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The Impact of Technological Progress on the Future of Work: Insights from a Survey on Alternative Employment Contracts in OECD Countries

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Abstract
Technology is changing how individuals work and the nature of the job contracts they take. New job market realities include gig work, working for multiple employers, part-time, and on short-term contracts. This study aims to understand whether individuals believe that technological change will lead their industries to experience an increase in alternative work contracts, including self-employment as well as temporary and multiple employer contracts. Through an OECD survey carried out in 25 countries, we find that most individuals expect these work conditions to become more common. However, people's opinion highly depends on their country of residence and industry of work.

Keywords Future of work · Technological progress · Employment contracts · Survey study

Introduction

Work conditions are inherently intertwined with technological progress (Campbell, 2018). History abounds with technological discoveries that have radically reduced the physical effort work requires from humans, such as the motorization of agricultural machines which radically changed work conditions for farmers since the end of

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the 1950s (Segal, 2018). The introduction of computers in the workplace in the late 1960s kicked off a significant technological revolution comparable in scope to the industrial evolution (Frey & Osborne, 2017). This has led to two major disruptions (Busemeyer et al., 2022): digitalization, i.e., the proliferation of connected communication systems integrated in how work is done, and the widespread conversion to automation through machine learning techniques and artificial intelligence. While the effect of those disruptions is somewhat difficult to measure (Gries & Naud´e, 2022), this means that across sectors of the economy (Brynjolfsson & McAfee, 2012), tasks are increasingly performed by computers and robots instead of humans (Erickson & Norlander, 2022; Meacham et al., 2021; Schlogl et al., 2021). This affects the work life of many (Chui et al., 2016). While introducing digital technology may ease up difficult or lengthy tasks, it also triggers socioeconomic change, a process referred to as digitization (Hirsch-Kreinsen, 2016). Anticipating how technological progress will impact work conditions is thus of paramount importance to mitigate social costs (Autor et al., 2023).

As no combination of indicators can predict the breadth of that change, we turn to workers to understand their expectations vis-a`-vis their work conditions. To assess current expectations, we have teamed up with the Organization for Economic Co-operation and Development (OECD) and asked workers from member-state countries for their opinion on the relationship between technological change and the multiplication of alternative job contracts in their industries.

Research shows that national context matters as countries are asymmetrically affected by technological disruption (Eichhorst et al., 2020; Nedelkoska & Quintini, 2018). However, it also indicates that technological change impacts some industries more than others. Knowledge intensive and highly digitalized sectors are more likely to be already impacted: media, telecommunications, and consumer financial services are among the most disrupted industries (Grossman, 2016). On the other hand, capital-intensive sectors, such as education and health care, have the potential for further digitalization (Gandhi et al., 2016). The World Economic Forum (2021) alerts on the fact that specific professions are at risk. While some jobs will be untouched, others will require a much more significant interaction between workers and new technologies. Other jobs will disappear. Many predict that most jobs will fall in the second category: they will not entirely disappear but will require great adaptation to incorporate new technologies as these trigger productivity (Segal, 2018; Frey & Osborne, 2017; World Economic Forum, 2016). However, technological disruptions are still likely to impact the social welfare of those whose jobs would disappear. Digitalization and automation can also force part of the population to resort to alternative or "non-standard" employment contracts, i.e., temporary contracts, contracts with multiple employers, and self-employment, as labor markets adjust to new conditions.

While technological disruptions may affect whether a job is relevant, they also affect work conditions. Recently, the lockdowns of the COVID-19 crisis have demonstrated that remote work, or work from home is possible thanks to the digitalization of labor processes (Erickson & Norlander, 2022). The switch from office-based to remote activities challenges the relationship between workers and employers. It can impact their obligations to one another, including, at its core, the type of contract that binds them professionally.

Our paper is structured as follows: We present the survey questions and data in the "Survey Data and Descriptive Statistics" section. The "Methodology and Results" section discusses the model framework and results. We present the model selection in the "Model Selection" section and the results in the "Results from Random Forest Modeling" section. We discuss our findings in the "Discussion" section and conclude in the "Conclusion" section.

Survey Data and Descriptive Statistics

This study is based on a cross-national survey co-developed with the OECD called "Risks That Matter" (OECD, 2021b) to collect information on the impact of technology on the workplace. The survey consists of two questionnaires: the "core questionnaire" which captures participants' opinions on selected current and emerging risks affecting society (OECD, 2020b), and the "background questionnaire" recording socioeconomic characteristics of the respondents (OECD, 2020a). The survey was carried out in September and October 2020 and recruited individuals in 25 OECD member States through a professional online panel provider. A total of 25,814 responses were recorded, with at least 1000 in each country. Sampling targets have been used to ensure the overall sample is representative in each country by sex, age classes, education level, income level, and worker status. Since, in practice, filling each quota with the exact required number of respondents is nearly impossible, weights are estimated for each response to correct for any under- or over-representation based on the five criteria. After application, the weighted sample should match all five specific sampling targets. By extension, it should also be nationally representative of these five criteria.[1]

Survey Questions and Available Data

In this study, we consider three statements that stem from the "core questionnaire" which included, in 2020, a section about digitalization, technology, and change in work conditions (OECD, 2020b, question 28). The question was addressed to individuals currently in employment, or that have been in employment in the past, and respondents were asked to refer to their current or most recent job. The original text of the question and the three statements were as follows:

Thinking more generally about the industry in which you work, how do you think the industry will change over the next 5 years as a result of digitalization and technological progress?

[1] In each country, the sampling criteria and categories were as follows: sex (men, women), age groups (18–24, 25–34, 35–44, 45–54, 55–64), education level (low/medium education, high education), income level (national equivalized disposable income deciles in 2019), and worker status at the end of 2019 (not employed, employee on a permanent contract, employee on a fixed-term/temporary contract, self-employed). In each country, weights sum up to 1000, i.e., weights are not population-corrected, and each country has equal weight regardless of the population size. See also OECD (2021b, Box 1.1).

(S1) Technology will lead to more people becoming self-employed and working for themselves.
(S2) Technology will lead to more people working on temporary or fixed-term contracts.
(S3) Technology will lead to more people working for multiple employers at the same time.

The possible answer options for each statement were very unlikely, unlikely, likely, very likely, and don't know. Through the answers, we aim to document if workers feel that technology is pushing them to change the typical job contracts that govern their positions.

While the question is focused on industry, it ultimately relates to the lived experiences of respondents that can be situated in a national and industry-specific context. By studying the respondents' answers, we can understand what workers think about these trends to explore more in-depth population differences and the factors that may cause them. By developing multiple models, we confirm and quantify the important differences in the population based on country and industry, and unveil the patterns hidden in our dataset. The nature of the statements (S1) to (S3) required the respondents to be working. Hence, these statements are analyzed on a reduced sample of 24,592 respondents.[2]

Explanatory Variables from the Background Questionnaire

Socio-Demographics, Education, and Social Class

The first two socio-demographic variables in our study are the respondents' gender (*GE*) and age group (*AG*). Further, we consider the current country of residence of the respondent (*CTR*) and aggregate information about the level of education (*ED*), yielding two groups, those with and without higher education. Finally, we asked participants about their self-perceived social class. In the variable *SC*, we distinguish lower, middle, and upper class.

Living Arrangements

Further, we use information on the size of the town where individuals live (*ST*) and whether they own or rent their house (*HT*). In addition, we consider the respondents' marital status (*MS*) and differentiate those who are married or in a registered partnership from the rest. We also record if the respondents' spouse or partner is employed (*PE*). Finally, living arrangements also include information on whether the respondents care for children (*CH*).

[2] We ignore the responses of 1219 participants that have never been employed (i.e., we only consider respondents indicating options (a) "currently employed" and (b) "currently not employed, but have been employed in the past" in question S12 of the background questionnaire) and three responses with incomplete answers.

Current Job and Employment Status

Our data include a comprehensive list of information on the respondents' work environment. The employment status (*ES*) indicates whether a respondent is employed, and the type of employment (*TE*) records whether a respondent works as an employee or is self-employed. The type of contract (*TC*) captures whether the current position is permanent, temporary, or without a contract. Moreover, participants indicate their situation of working full- or part-time (*PS*) and the company size (*CS*) where they work. The role in the current job is coded in the type of occupation variable (*TO*). Since our study focuses on the impact of the trends from technology, the industry (*IN*) where the individual works is potentially relevant.

Online Platform Work and Use of Digital Technologies

Further, we include information capturing the participants' experience using digital technology at work. More specifically, the questionnaire inquires about how often respondents use digital information (*DI*) or complex technology (*CT*) at work, as well as whether they have had experience with online platforms to find gig work (*GG*), i.e., income earning outside a traditional employment relationship. Table 1 summarizes the explanatory variables used in the present study. In Table 2 in the Appendix, we provide more details, including, for each variable, a brief description, the categories, and the identification number linking to the original survey question.

Descriptive Statistics

Comprehensive descriptive statistics are available in the report by OECD (2021b). In this study, we specifically focus on the perception of the likelihood of the three trends and potential differences among countries and industries.

Overall Perceived Likelihood of the Trends

The recorded answers for the three statements (S1) to (S3) serve as response variables in our study. Respondents indicated their opinion on a four-level Likert scale for each statement or answered with "don't know," Since we primarily focus on responses indicating a clear opinion, we omit those with the latter answer in our model. We further aggregate the four options into a binary answer. Building two groups, we aggregate the answers "very unlikely" and "unlikely" into *unlikely*, and "likely" and "very likely" into *likely*. In Table 3, we report the shares of answers in each category for each statement, along with the number of respondents and the sum of weights. The shares are calculated based on the respondents' weights in the sample.

Overall, 59.3% of the respondents think technology will lead to more self-employment (S1), whereas 66.7% feel that technology will lead to more temporary or fixed-term employment contracts (S2). Similarly, 65.5% of individuals believe

Table 1 Summary of the explanatory variables

Variable	Label
Socio-demographics, education and social class	
GE	Gender
AG	Age
CTR	Country
ED	Education
SC	Social class
Living arrangements	
ST	Size of town
HT	Housing type
MS	Marital status
PE	Partner's employment
CH	Children
Current job and employment status	
ES	Employment status
TE	Type of employment
TC	Type of contract
PS	Professional status
CS	Company size
TO	Type of occupation
IN	Industry
Online platform work and use of digital technologies	
DI	Digital information
CT	Complex technology
GG	Gig economy

Table 2 Distribution of the perceived likelihood of the three trends in statements (S1) to (S3)

Statement	Answer			Sample		Sample for model	
	Unlikely	Likely	Don't know	*N*	(Weights)	*N*	(Weights)
S1: trend to self-employment	26.5%	59.3%	14.2%	24,592	(24,391.1)	21,079	(20,940.5)
S2: trend to temporary contracts	19.2%	66.7%	14.1%	24,592	(24,391.1)	21,142	(20,949.9)
S3: trend to multiple employers	21.3%	65.5%	13.2%	24,592	(24,391.1)	21,383	(21,168.7)

The reported answer options "unlikely" and "likely" aggregate the original responses "very unlikely"/ "unlikely" and "likely"/ "very likely," respectively. Respondents who answered "don't know" are excluded from the sample used in the modeling. The reported shares are calculated based on the weights of the responses

Table 3 Optimal logistic regression and random forest models for the responses in statements (S1) to (S3)

	Model	Variables	*F*-score	Accuracy
(S1)	LRM	*CTR+AG+ED+ES+TC+ST+CH+PS+CS+IN+DI+CT+GG*	67.4%	60.0%
	RFM	*CTR+IN+TO+ST+SC+AG+CT+GE+GG*	95.2%	93.5%
(S2)	LRM	*CTR+GE+AG+ES+TC+SC+ST+MS+PE+CH+PS+TO+IN +DI+CT+GG*	67.4%	57.7%
	RFM	*CTR+AG+IN+TO+GG+CT+CS+SC*	95.4%	93.0%
(S3)	LRM	*CTR+AG+ED+SC+PS+CS+TO+IN+DI+CT+GG*	65.3%	56.1%
	RFM	*CTR+IN+TO+ST+SC+GE+AG+CS*	95.5%	93.3%

"LRM" and "RFM" stand for logistic regression model and random forest model, respectively. The variables (see Table 1) are ordered along decreasing AIC contribution in LRM and decreasing variable importance in RFM

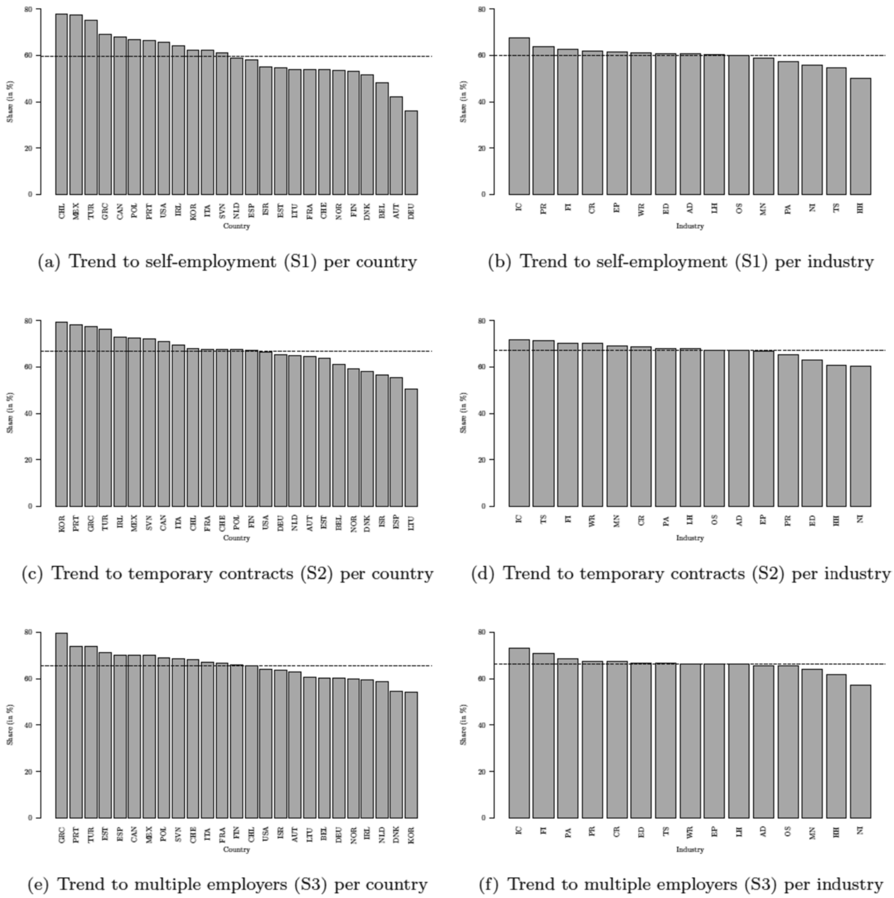
that technology will increase the number of people working for multiple employers simultaneously (S3). The trend toward self-employment is perceived as less likely when compared to the other two trends. In the following, we detail the respondents' perceptions by country and by industry.

Country and Industry Statistics

The above overall results (Table 3) show that most individuals regard all three statements as likely to become true for their industry within the next 5 years. However, we find substantial differences among countries and industries. In the graphs in Fig. 1, we report the shares of respondents that consider the trends as likely to happen in each country and industry. The numerical values underlying the graphs as well as the country and industry codes used are available in Table 4 in the Appendix.

Trend to Self-Employment (S1) Among the three trends, technology leading more people to be self-employed is considered the least likely in most countries (see Fig. 1a). Germany (36.2%), Austria (42.0%), and Belgium (48.1%) stand out for having the lowest likelihood levels. In contrast, nearly 80% of the respondents consider the trend likely in the two Latin American countries included in the survey: Chile (77.7%) and Mexico (77.3%). The same opinion prevails in Turkey (75.0%) and Greece (69.2%). Regarding the industries (see Fig. 1b), we find that employees in the sectors of information and communications (67.7%), professional activities (63.9%), and finance and insurance (62.6%) are most numerous to envision a future with more self-employment. In contrast, respondents from sectors related to human health (50.2%), transportation and storage (54.7%), and public administration (57.3%) are less likely to consider self-employment.

Trend to Temporary Contracts (S2) This trend is considered particularly likely in South Korea (79.4%), Portugal (78.1%), Greece (77.5%), and Turkey (76.2%), whereas this is the least true in Lithuania (50.5%). Levels of approval below 60% are also found in three other countries, namely, Spain (55.5%), Denmark (58.0%), and



(a) Trend to self-employment (S1) per country
(b) Trend to self-employment (S1) per industry
(c) Trend to temporary contracts (S2) per country
(d) Trend to temporary contracts (S2) per industry
(e) Trend to multiple employers (S3) per country
(f) Trend to multiple employers (S3) per industry

Fig. 1 Perceived likelihood of the three trends per country and industry. Note: The country and industry codes (*x*-axis of the graphs) are defined in Table 4 in the Appendix. The shares are expressed in % and are calculated based on the weights of the respondents in the sample. The dashed line represents the overall sample share

Norway (59.0%). An illustration of the results is given in Fig. 1c. We also observe that in 21 out of the 25 countries (the exceptions are Chile, Spain, Lithuania, and Mexico) more respondents view the increase in temporary or fixed-term contracts as more likely than an increase in self-employment (see Table 4 in the Appendix). Workers in the sectors of information and communications (71.5%), finance and insurance (70.2%), and transportation and storage (71.5%) are more likely to perceive a future with more temporary or fixed-term contracts. On the other hand, human health (60.7%) and education industries (63.1%) are the least likely to see such evolution. It is worth noting that, unlike in the case of the statement (S1), no industry-level perception yields values below 60%.

Table 4 Estimated partial dependence coefficients and marginal effects along the countries

Model of the perceived likelihood of the trends to…						
Countries	Self-employment (S1)		Temporary contracts (S2)		Multiple employers (S3)	
	PD	ME	PD	ME	PD	ME
Austria	−0.14	−12.29	0.20	−5.52	0.14	−5.59
Belgium	−0.01	−9.03	0.20	−5.67	0.15	−5.47
Canada	0.31	−1.13	0.27	−4.00	0.23	−3.47
Chile	0.38	0.50	0.21	−5.42	0.18	−4.64
Denmark	0.17	−4.49	0.18	−6.22	0.16	−5.00
Estonia	0.15	−5.12	0.17	−6.47	0.27	−2.27
Finland	0.13	−5.49	0.21	−5.31	0.25	−2.85
France	0.16	−4.90	0.22	−5.14	0.23	−3.27
Germany	−0.08	−10.86	0.18	−6.13	0.13	−5.85
Greece	0.29	−1.65	0.30	−3.05	0.32	−1.19
Ireland	0.25	−2.56	0.29	−3.47	0.17	−4.85
Israel	0.17	−4.53	0.23	−4.85	0.20	−4.16
Italy	0.21	−3.68	0.25	−4.38	0.17	−4.84
Korea	0.21	−3.52	0.26	−4.04	0.07	−7.28
Lithuania	0.18	−4.40	0.12	−7.58	0.13	−5.91
Mexico	0.32	−0.96	0.26	−4.23	0.20	−4.06
Netherlands	0.23	−2.96	0.22	−5.01	0.15	−5.28
Norway	0.21	−3.54	0.22	−5.08	0.17	−4.93
Poland	0.33	−0.75	0.30	−3.06	0.30	−1.64
Portugal	0.29	−1.55	0.35	−1.87	0.30	−1.72
Slovenia	0.25	−2.60	0.28	−3.56	0.22	−3.49
Spain	0.21	−3.68	0.14	−7.04	0.27	−2.33
Switzerland	0.19	−4.14	0.23	−4.77	0.19	−4.33
Turkey	0.37	0.28	0.37	−1.57	0.28	−2.07
USA	0.35	−0.03	0.30	−3.18	0.24	−3.04
Average effect		58.81		60.60		59.09

"PD" and "ME" (in %) stand for partial dependence coefficients and marginal effects, respectively

Trend to Multiple Employers (S3) Regarding the third statement concerning how technology will lead individuals to work for multiple employers in the next 5 years, almost 80% of the population in Greece considers it to be likely. In addition, Portugal (74.0%), Turkey (74.0%), Estonia (71.1%), Spain (70.3%), and Canada (70.2%) complete the group of countries with high expectations for that trend. On the other extreme, we find South Korea (54.2%) and Denmark (54.6%), where respondents support (S2) the least (see Fig. 1e). Only in the industries of information and communications (73.2%) and finance and insurance (71.0%) we find levels of approval above 70%. In contrast, the human health sector (61.8%) as well as manufacturing

(64.0%) are the sectors where the expectation of switching to multi-employer contracts due to technological progress is lowest.

In the next section, we set up a model to better understand what factors drive these responses.

Methodology and Results

Model Selection

We are interested in deriving the characteristics that affect an individual's response to each of the three statements. Up to here, we have only considered descriptive statistics on the overall effects based on the country and the industry where the respondent lives and works, respectively. Nevertheless, the available data allows us to test a rich set of covariates. We consider the set of the 20 variables presented in Table 1. In the following, using an explanatory model, we aim to understand the most relevant variables driving the recorded responses.

Assessing who feels at risk is a classification exercise as individuals have been placed in the two categories "likely" and "unlikely" based on their responses. This problem is typically solved using logistic regression models (LRMs). However, classification methods such as random forest models (RFMs) have become prominent in recent years as they perform well in multiple fields (Genuer & Poggi, 2020). Therefore, we approach this classification problem by fitting both LRMs and RFMs to our data, so that we can choose what we consider to be the best models in terms of model performance and the principle of parsimony.

As observed in Table 3, most individuals (around two-thirds) belong to the groups having answered "likely" throughout the three statements. Unbalanced datasets are problematic in machine learning methods as computers tend to focus on the most prevalent class (Menardi & Torelli, 2014). We train our models using upsampled data and assess their performance to overcome this. We use the weights associated with each response (also see "Descriptive Statistics" section).

In Table 5, we summarize the results regarding variable selection and model performance for each statement and model. In the case of the LRMs, we present the combination of variables that we found to minimize the Akaike information criterion (AIC). In the case of the RFMs, we display the most parsimonious RFM achieving an F-score of over 95% in statements (S1), (S2), and (S3).[3] We provide the model performance in terms of *F*-score and accuracy. RFMs perform better in all statements, resulting in models with fewer covariates and superior performance

[3] For the implementation in R, we use an algorithm available in the ranger package (Wright and Ziegler, 2017). The *F*-score is a widely accepted indicator of performance that considers class imbalance.

Table 5 Estimated partial dependence coefficients and marginal effects along the industries

Model of the perceived likelihood of the trends to…

Industries	Self-employment (S1)		Temporary contracts (S2)		Multiple employers (S3)	
	PD	ME	PD	ME	PD	ME
Essential primary	0.19	−4.15	0.24	−4.65	0.22	−3.72
Manufacturing	0.17	−4.65	0.24	−4.58	0.14	−5.55
Construction and real estate	0.19	−4.09	0.25	−4.26	0.21	−3.97
Wholesale and retail	0.22	−3.42	0.28	−3.62	0.20	−4.02
Transportation and storage	0.19	−4.17	0.29	−3.41	0.21	−3.85
Leisure and hospitality	0.23	−3.00	0.30	−3.19	0.23	−3.41
Information and communications	0.28	−1.96	0.30	−3.05	0.28	−2.06
Finance and insurance	0.26	−2.45	0.29	−3.50	0.27	−2.48
Professional activities	0.24	−2.90	0.26	−4.05	0.24	−3.04
Administration and support	0.22	−3.31	0.24	−4.69	0.23	−3.32
Public administration	0.19	−3.97	0.21	−5.34	0.22	−3.67
Education	0.20	−3.79	0.21	−5.38	0.21	−3.83
Human health	0.13	−5.68	0.19	−5.97	0.16	−5.15
Other services	0.20	−3.70	0.22	−5.08	0.18	−4.48
No information	0.23	−3.11	0.23	−4.89	0.17	−4.93
Average effect		58.81		60.60		59.09

"PD" and "ME" (in %) stand for partial dependence coefficients and marginal effects, respectively

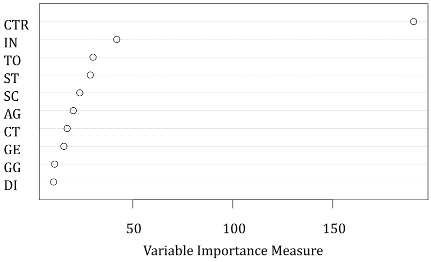
indicators. Based on these findings, we retain the RFMs for our analyses. Since RFMs belong to the family of non-parametric models, they do not rely on coefficients and significance like logistic regression. To interpret the results regarding the direction and magnitude of the effects, we present an analysis of variable importance to understand the most relevant covariates affecting people's opinions.[4] In addition, we perform a partial dependence coefficient analysis (Friedman, 2001) for each statement.[5]

Results from Random Forest Modeling

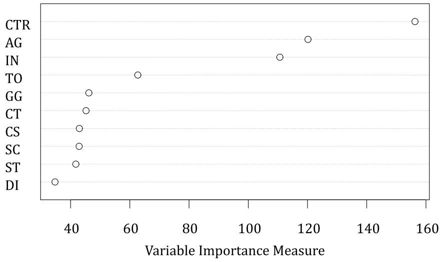
In the following, we present the main findings of our analysis. We start by reporting the ranking of the different variables' importance in each statement. Using the

[4] To assess variable importance, we resort to a version of the impurity method developed to correct previously identified biases (Nembrini et al., 2018) and double-check the results under a permutation approach.

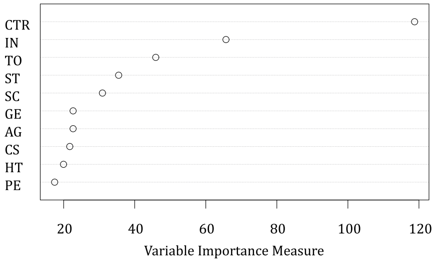
[5] We use the R package PDP to perform the partial dependence analysis. The partial dependence coefficient of a subcategory in a variable can be interpreted as the average effect resulting from the model when all responses are assumed to belong to this subcategory while keeping all other characteristics intact.



(a) Trend to self-employment (S1)



(b) Trend to temporary contracts (S2)



(c) Trend to multiple employers (S3)

Fig. 2 Illustration of the variable importance measure of the ten most important factors driving the perception of the three trends in the statements (S1) to (S3)

optimal RFMs given in Table 5, we lay out the effects of each variable using the partial dependence coefficients introduced in the "Model Selection" section. Finally, we detail our results and specifically focus on differences among industries and countries.

Variable Importance

As illustrated in Fig. 2, our analysis confirms that the country of residence *CTR* is one of the main predictors of the responses in all three statements. Next, the respondents' industry *IN* also plays a central role throughout all statements: it is the second most important covariate defining the response in statements (S1) and (S3); it occupies the third position in the model for statement (S2). We observe that the role of the age group *AG* of the respondent is second in terms of importance in the trend to temporary contracts (S2). Furthermore, the type of occupation *TO* completes the top three factors in (S1) and (S3) while it ranks fourth in (S2). More elements appear when completing the five most important factors: the size of the town *ST* where respondents live and the individuals' social class *SC* are relevant in statements (S1) and (S3). In addition to the type of occupation *TO*, using platforms to find gig work *GG* is an important effect in (S2).

In Table 6, 7, and 8, we report the effects for the variables retained in the final models (cf. Table 5). We disclose the estimated partial dependence coefficients (PD) for the three statements. We then consider the average predicted probability for the perceived likelihood in each model and compare it to the effect quantified by the

Table 6 Estimated correlation between the partial dependence coefficients and social indicators

Perceived likelihood of the trends to…			
Indicator	Self-employment (S1)	Temporary contracts (S2)	Multiple employers (S3)
Social spending	−0.55	−0.27	0.10
Unemployment spending	−0.48	−0.24	−0.01
Labor market spending	−0.54	−0.39	−0.05
Unemployment rate	0.24	0.13	0.48
Involuntary part-time rate	0.18	−0.15	−0.02
Self-employment rate	0.44	0.42	0.23
Part-time employment rate	−0.24	−0.22	−0.50
Temporary employment rate	0.38	0.24	0.13

PD coefficient. By doing this, we assess how much a person's probability changes for the average individual when modifying only one characteristic and keeping all others constant. This is what is called the marginal effect (ME). As expected (cf. the descriptive statistics in Table 3), we observe that the majority of individuals are classified in the "likely" perception category with high "average effects" of 58.81% for (S1), 60.60% for (S2), and 59.09% for (S3).

Results per Country

In Table 6, we observe three negative coefficients among the countries' PD coefficients in the model for statement (S1). The most prominent effect is that of Austria (PD = −0.14), followed by Germany (PD = −0.08), and Belgium (PD = −0.01). This can be interpreted as follows: taking all respondents with their actual characteristics but assuming them to be from a particular country, we would end up with an average probability declining by 12.29% if all were Austrians, 10.86% if all were German, and 9.03% if all were Belgians. In contrast, if all respondents were from Chile, the probability would roughly equal the overall average (ME = 0.50% close to zero).

For the trend to temporary contracts (S2), we only observe positive PD coefficients, indicating that, for all countries, the perceived likelihood is above 50%. Our model confirms the Lithuanians' lower perception (PD = 0.12), translating into a marginal probability effect of −7.58%. A similar effect is also observed in Spain (PD = 0.14) and Estonia (PD = 0.17), translating into marginal effects of −7.04% and −6.47%, respectively. Furthermore, respondents from Portugal, Turkey, Poland, and Greece perceive the likelihood close to the global average.

For the trend regarding multiple employers (S3), our results show that, across countries, the probability of the development to be likely remains higher than 50%. However, in several countries, the perceived likelihood is substantially reduced from the average level of 59.09%. For example, the marginal effects are −7.28% for Korea, −5.91% for Lithuania, −5.85% for Germany, −5.59% for Austria,

Table 7 Estimated partial dependence coefficients and marginal effects for variables other than country and industry

Model of the perceived likelihood of the trends to…						
Variables	Self-employment (S1)		Temporary contracts (S2)		Multiple employers (S3)	
	PD	ME	PD	ME	PD	ME
Size of town <10k	0.13	−5.53			0.16	−5.06
10–100k	0.21	−3.70			0.22	−3.71
100+	0.32	−0.97			0.25	−2.82
No info	0.28	−1.83			0.23	−3.30
Social class						
Lower class	0.19	−4.10	0.29	−3.37	0.17	−4.75
Middle class	0.20	−3.77	0.22	−5.12	0.21	−3.88
Upper class	0.21	−3.52	0.21	−5.25	0.23	−3.34
No info	0.22	−3.39	0.28	−3.63	0.27	−2.43
Type of occupation						
Manager	0.20	−3.89	0.21	−5.27	0.20	−4.01
Professional	0.17	−4.62	0.17	−6.31	0.18	−4.61
Technician	0.20	−3.93	0.23	−4.92	0.20	−4.17
Clerical	0.21	−3.46	0.33	−2.49	0.24	−3.15
Service	0.21	−3.49	0.28	−3.70	0.20	−4.18
Manual	0.20	−3.94	0.27	−3.88	0.21	−3.78
No info	0.22	−3.36	0.27	−3.95	0.19	−4.47
Age group						
18–24	0.24	−2.95	0.11	−7.94	0.17	−4.82
25–34	0.22	−3.32	0.13	−7.38	0.15	−5.42
35–44	0.17	−4.61	0.16	−6.67	0.17	−4.82
45–54	0.17	−4.52	0.29	−3.32	0.23	−3.31
55–64	0.21	−3.70	0.41	−0.47	0.26	−2.54
Gender						
Male	0.20	−3.79			0.20	−4.15
Female	0.20	−3.76			0.21	−3.94
Other	0.17	−4.48			0.22	−3.55
Complex technology Everyday	0.24	−2.72	0.25	−4.42		
Sometimes	0.24	−2.80	0.26	−4.23		
Never	0.13	−5.61	0.21	−5.37		
No info	0.13	−5.61	0.21	−5.37		

Table 7 (continued)

Model of the perceived likelihood of the trends to…						
Gig economy						
Never	0.15	– 5.14	0.20	– 5.72		
A few times	0.31	– 1.01	0.28	– 3.75		
Occasion-ally	0.30	– 1.43	0.36	– 1.81		
Regularly	0.25	– 2.52	0.33	– 2.37		
Company size <10			0.25	– 4.30	0.22	– 3.52
10–249			0.22	– 5.01	0.20	– 4.21
250+			0.22	– 5.08	0.18	– 4.68
No info			0.31	– 2.85	0.24	– 3.10
Average effect		58.81		60.60		59.09

"PD" and "ME" (in %) stand for partial dependence coefficients and marginal effects, respectively

and – 5.47% for Belgium. One of the reasons could be that these individuals see the future of work as a problem of scarcity or simply that social rights have preserved jobs that offer full employment. In contrast, the results in Greece and Portugal, where such situations already exist, are closest to average.

Results per Industry

We observe from Table 7 that being employed in the human health sector (PD = 0.13) results in a decrease of 5.68% in the perceived likelihood of the trend to self-employment (S1). In contrast, we find that the highest PD coefficient is predicted for individuals from the sectors of information and communications and finance with marginal effects yielding – 1.96% and – 2.45%, respectively.

Regarding the trend to temporary contracts (S2), workers of the human health sector (PD = 0.19, ME = 5.97), education (PD = 0.21, ME = – 5.38%), and public administration (PD = 0.21, ME = – 5.34%) are found to envision the lowest likelihoods. In contrast, working in the sectors of information and communications (PD = 0.30, ME = 3.05%), leisure and hospitality (PD = 0.30, ME = – 3.19%), and finance and insurance (PD = 0.29, ME = – 3.50%) relate to a higher perceived likelihood for temporary contracts in their sector.

Finally, for the trend (S3), our model results suggest that working in manufacturing (PD = 0.14, ME = 5.55%), human health (PD = 0.16, ME = 5.15%), or other services sectors (PD = 0.18, ME = – 4.48) makes a person less inclined to consider likely working for multiple employers in the next 5 years. In contrast, those in information and communications (PD = 0.28, ME = – 2.06%) and finance and insurance (PD = 0.27, ME = – 2.48) expect this to be an important trend.

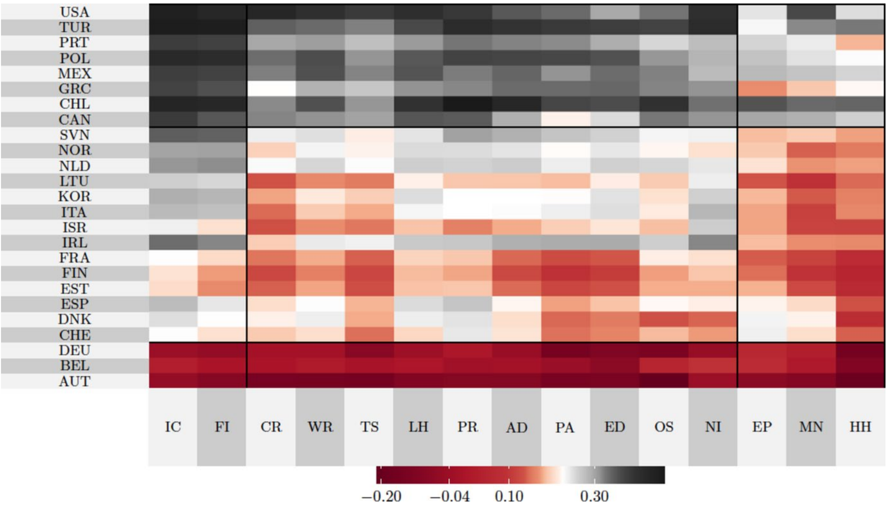


Fig. 3 Graphical representation of the estimated partial dependence coefficients along the country-industry combinations for the trend to self-employment (S1)

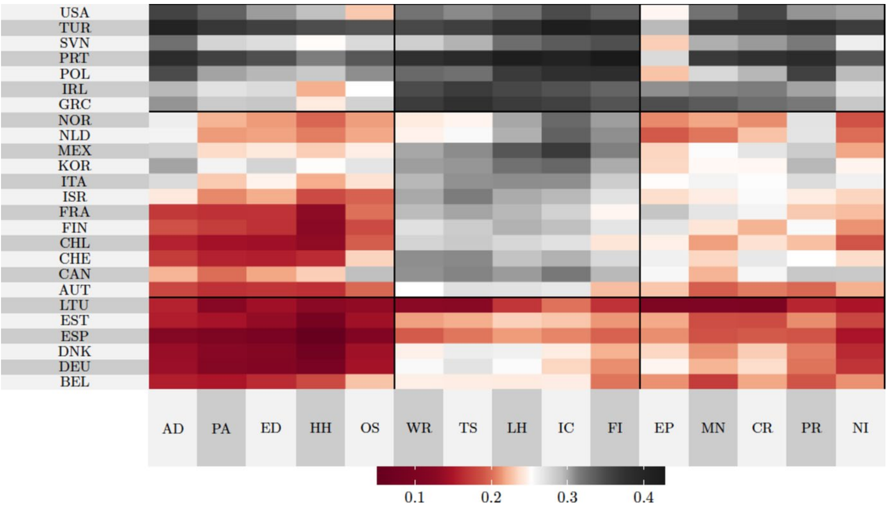


Fig. 4 Graphical representation of the estimated partial dependence coefficients along the country-industry combinations for the trend to temporary contracts (S2)

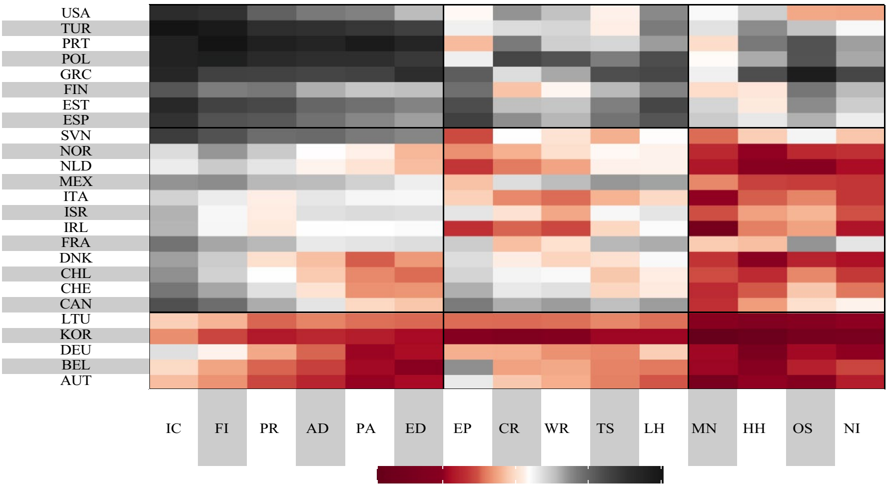


Fig. 5 Graphical representation of the estimated partial dependence coefficients along the country-industry combinations for the trend to multiple employers (S3)

Country-Industry Crossed Effects

Since both country *CTR* and industry *IN* variables are among the factors that best explain the perceived likelihood for the trends (S1) to (S3), we now analyze the crossed effects among countries and industries. To proceed, we continue to resort to the partial dependence coefficients of the RFMs. We graphically illustrate the results through "heatmaps" in Figs. 3, 4, and 5 for each of the three statements. In the illustrations, we cluster both countries and industries in three groups based on the coefficients.[6] These groups differentiate countries and industries along the likelihood perception for the statements found.

With Fig. 3, we can identify differences among industries and countries in the perceived likelihood of (S1). We see, for example, how Austria, Belgium, and Germany form a cluster characterized by a large skepticism of workers switching to self-employment due to technology. In the three countries, this skepticism is present in all industries (negative or low estimations of the partial difference coefficients). We observe a second cluster formed by Switzerland, Denmark, Spain, Estonia, Finland, France, Ireland, Israel, Italy, Korea, Lithuania, Netherlands, Norway, and Slovenia. To a large extent, these countries are characterized by coefficients that are mixed and more moderate in relative terms. Indeed, we find differences among industry groups: for instance, the cluster composed of the information and communications, and the finance and insurance sectors tends to have a higher perceived likelihood when compared to the sectors of essential primary, manufacturing, and human health. Finally, we observe a third cluster, with respondents from countries believing in greater

[6] Both clustering and heatmaps are done using the package superheat (Barter, 2022), which is available in R. The clustering method used relies on *K*-means.

adoption of self-employment. This group includes Canada, Chile, Greece, Mexico, Poland, Portugal, Turkey, and the USA.

Regarding the trend to temporary contracts (S2), see Fig. 4, we find that a cluster of seven countries yields particularly low PD coefficients. These are Belgium, Germany, Denmark, Spain, Estonia, and Lithuania. The skepticism regarding switching to temporary contracts is particularly strong in administration, education, human health, and other services. Another group of countries, including Austria, Canada, Switzerland, Chile, Finland, France, Israel, Italy, Korea, Mexico, the Netherlands, and Norway, is characterized by more moderate positions. Finally, Greece, Ireland, Poland, Portugal, Slovenia, Turkey, and the USA form a group of nations characterized by a strong belief that temporary contracts will become more customary in the next 5 years. We also observe that respondents from selected industries consider the trend (S2) more likely than others. For instance, we see that workers in leisure and hospitality, information, and communications, as well as finance and insurance are particularly inclined to believe in a bigger adoption of temporary contracts. This industry group is complemented by wholesale and retail, and transportation and storage.

Finally, we document that Austria, Belgium, Germany, Korea, and Lithuania are characterized by a low trust in the trend (S3), as shown in Fig. 5. On the other hand, respondents from countries like Spain, Estonia, Finland, Greece, Poland, Portugal, Turkey, and the USA consider a turn to multiple employers more likely. In the latter countries, the belief stands through all economic sectors. Regarding the industries, we find evidence that employees in the information and communication sector and in finance and insurance, professional activities, administration, and education feel more likely to resort to working for multiple employers due to technological advances. Note, however, that this does not hold throughout all country clusters. We also observe that in manufacturing, human health, and other services, the opposite holds, i.e., multiple employers are less imagined.

Relationship with Countries' Social Indicators

Since we find patterns by country of origin in all statements, we further assess the potential relationship between the countries' partial dependence coefficients and OECD indicators related to social security and the labor markets. These indicators (see Table 9) include levels of social spending (i.e., benefits, direct in-kind provision of goods and services, and tax breaks with social purposes, see OECD, 2021g), unemployment spending, and labor market spending (i.e., unemployment services, training, benefits, hiring subsidies, and job creations in the public sector, as well as unemployment benefits, see OECD, 2021d). OECD indicators include unemployment, self-employment, part-time employment, and temporary employment rates.[7]

[7] The availability by year of the respective indicators changes per indicator and country. To keep the choice of year consistent for all countries within an indicator, we chose the latest year for which all countries had information available at the moment of the analysis. Because of this, unemployment spending indicators used (OECD, 2021e) correspond to those of the year 2017. In contrast, social spending (OECD, 2021g), labor market spending (OECD, 2021d), and involuntary part-time rates (OECD, 2021a) correspond to the year 2018. Finally, rates of unemployment (OECD, 2021i), self-employment (OECD, 2021f), part-time (OECD, 2021c), and temporary work (OECD, 2021h) correspond to the year 2019.

From Table 9, we observe a strong negative correlation between the trend to self-employment (S1) and levels of social spending (− 0.55), unemployment spending (− 0.48), and labor market spending (− 0.54). This signals that countries, where individuals consider the likelihood of a turn to self-employment lower (low PD coefficients), are those with higher levels of social, unemployment, and labor market spending. This highlights how spending in a system of integrated benefits, including education, policies to incentivize job creation, and classical cash benefits could be key to reducing the potential negative consequences of the type of job contract linked to this trend. Still considering the trend (S1), we find a positive correlation of 0.44 with the self-employment rate. This signals that economies where individuals tend to consider (S1) more likely, already experience higher levels of self-employment. This also shows that respondents' expectations are somewhat grounded in trends they already observe.

Regarding the trend toward temporary contracts (S2), the correlations with the social indicators are much weaker when compared to those with the trend (S1). Moderate-level correlations are found in the case of labor spending (− 0.39) and the self-employment rate (0.42). In the case of the trend to multiple employers (S3), we observe a correlation of 0.48 with the observed unemployment rate, signaling that workers in economies with high unemployment rates tend to expect work relationships with multiple employers to increase. In contrast, the correlation of − 0.50 found in the case of part-time employment rates may indicate that part-time employees are likely to work reduced hours instead of resorting to multiple contracts with different employers to obtain a full-time salary equivalent.

Effects from Other Variables

Considering the different variables of interest (see Table 8 for the numerical results), our analysis signals an effect of the size of the town where people live on the perceived likelihood of the trends due to technology. We observe that the smaller the town where respondents live, the lower the perceived likelihood of the trends (S1) and (S3). The social class also plays an important role. We find belonging to a lower social class comes with a lower perception of upcoming self-employment (S1) or working for multiple employers (S3).

Middle or upper-class participants do not trust that technology will bring temporary contracts. Regarding the segments along the type of occupation, managers, and professionals share the same low perceived likelihood of the trend to temporary contracts (S3). Indeed, the group of professionals is somewhat reluctant to believe in any of the three statements. In contrast, being a clerical worker, for example, makes an individual more likely to see a shift toward temporary employment contracts in the next 5 years.

The effects found for the age groups differ along the three statements. We find that the younger the individuals, the more likely they see a future of work with more self-employment. In contrast, the older they are, the more likely they believe in a shift toward temporary employment contracts and situations with multiple employers. The respondent's gender is only relevant in trends (S1) and (S3). We observe that the difference between men and women is small, with women slightly more inclined to see multiple employer situations arrive.

When differentiating respondents along their usage of complex technology, an effect is only relevant in the case of the trends (S1) and (S2). In both trends, we identify two groups. Those who use (sometimes or every day) complex technology at work are more likely to envision the trends when compared to those who never use it. Similarly, regarding contact with the gig economy, we find that those without experience in the gig economy have the lowest perceived likelihood of acknowledging trends (S1) and (S2). Finally, the size of the company where people work plays a role in the perception of the trends (S2) and (S3): we observe that in smaller companies, the likelihood for temporary and multiple employer relationships is higher.

Discussion

National context matters. Our results show that respondents' country of residence is the most important variable in explaining their expectations regarding the future of work and alternative job contracts. This corroborates previous studies which found that countries are asymmetrically affected by technological disruptions (Boeri et al., 2020; Eichhorst et al., 2020; Nedelkoska & Quintini, 2018). We interpret these results as the impact of national labor markets on expectations regarding technological progress. Our findings corroborate previous classifications of OECD labor markets. Indeed, OECD countries are institutionally heterogeneous (Erlinghagen, 2019) and can be classified into four groups: liberal labor markets (e.g., UK, Ireland, and the USA) where regulation is low, corporate labor markets (e.g., Germany, Austria, and Belgium) where some jobs are more protected than others depending on skills, flexicurity labor markets (e.g., Denmark) which are based both on labor flexibility and a consequent welfare state, and Mediterranean labor markets (e.g., Spain, Italy, and France) where flexibility is based on agerelated variations in job security levels (Barbieri, 2009). We find that expectations thus tend to vary according to the degree of flexibility that characterizes national markets. Indeed, for self-employment (S1) and multiplication of employers (S3), respondents from Austria, Belgium, and Germany, which are all corporate labor markets, expect changes in the job market the least, underlining that classic forms of employment are still relatively protected in those countries. Ultimately, this result could also confirm the importance of social norms in employer-employee relationships, as pointed out by research (Abraham et al., 2022).

Nevertheless, the importance of the sector of employment should not be discarded. Some industries that constantly stand out in our results have been previously identified as extreme cases of new technology adoption (Gandhi et al., 2016; Grossman, 2016). This is the case for the financial industry, which ranks in the top 3 for the perceived likelihood of all the trends (S1), (S2), and (S3), and within which "Fintech" firms are imposing themselves as the dominant business model (PWC, 2020). The information and communication industry has also been highly disrupted: the technological revolution is accelerating through the development of robotic process automation in processes such as report generation, customer service, order processing, and price tracking (Marr, 2019). In the old economy, all these tasks would have been performed by humans. In addition, the introduction of 5G wireless technology will bring along new tendencies in the industry since it will support more connected devices (Marr, 2019). In this sense, our results document that workers in these industries already perceive changes in their work environment, making them feel more at risk of being subjected to alternative employment contracts. In contrast, the human health sector is usually identified as an industry with relatively less technological disruption (Grossman, 2016) and is consistently ranking in the bottom 3 for the perceived likelihood in (S1), (S2), and (S3).

While country and industry are respectively the first and second variables of importance for the trends (S1) and (S3), findings show that age trumps industry when it comes to the expectation regarding the multiplication of temporary contracts (S2), with older generations more likely to perceive change. This is probably because older generations compare today's conditions to the conditions they knew and consider that the conditions in which new generations enter the labor market may be less favorable—or even hope-inspiring—than it was to them. However, younger generations are not as pessimistic. Similarly, the occupation type and the town size are also important predictors. Our findings point toward urban workers in the services sector as those are the most likely to expect a multiplication of temporary-term contracts.

Ultimately, our results indicate that technological disruptions will likely impact labor markets and generations asymmetrically. Anticipating the impact of technological progress is thus of paramount importance to adapt labor markets to future shocks and prevent negative externalities on social welfare and ultimately build the future of the "gig economy" (Balakrishnan, 2022; Probert & Wajcman, 1988). Indeed, these perceptions from individuals may be well justified as technology is expected to reduce the demand for human work (see, for example, Paolillo et al., 2022). While there is no apparent one-size-fits-all solution to these expected changes, policy-makers must anticipate rather than react to them. Indeed, technological advancements lead to complete re-hauls of the labor market rather than simple adjustments. Supporting change while mitigating social externalities is thus highly relevant. For instance, the negative consequences of temporary contracts can be counteracted with wage guarantees, training, and supplementary pension savings for temporary and self-employed workers (Jerg et al., 2021; S¨oderqvist, 2017). Employers can be subject to the obligation to offer a permanent contract after having renewed an employee's contract three consecutive times; this is the case, for instance, after recent reforms in the Netherlands (Government of the Netherlands, 2021). Countries like Denmark and the Netherlands exemplify how flexicurity can help overcome these challenges and provide workers with the necessary social protection provisions to face changing labor markets (European Comission, 2020). Moreover, research shows that the relation between skills and unemployment flows is remarkably robust (Stijepic, 2021), reinforcing the argument that a training and skill-building oriented approach could combat unemployment effectively. Such reforms, however, come at the cost of more extensive social welfare and social security expenses, and it remains open if public opinion, while aware of the changes ahead, supports the cost of these changes.

Conclusion

Technology is evolving rapidly, affecting how people perform their tasks at work. In this study, based on a cross-national survey co-developed with the OECD, we document that most individuals feel that technology will likely lead to the multiplication of alternative work contracts, but there are important variations across countries and sectors. We show that around two thirds of participants believe in increased self-employment due to technology, and that temporary work and contracts with multiple employers will become more prominent in their industry. However, as we have shown, people's opinions vary substantially depending on the country of residence and industry.

Technological advancements make people in countries like Germany, Austria, and Belgium feel less threatened by alternative work contracts. In contrast, respondents envision a more imminent turn to non-standard work forms in countries like the USA, Turkey, Portugal, Poland, or Greece. In our discussion, we link these findings to labor market environments. We also observe that the respondents' views are correlated with social indicators such as levels of unemployment spending or labor market spending. Regarding the industry, on the one hand, we find that those working in the human health sector tend to feel less at risk of being driven into self-employment, temporary contracts, or multi-employer contracts. On the other hand, workers in the finance and insurance sectors and those from the information and communications sectors feel more at risk (see also Knotz et al., 2023).

Overall, we expect our work to help public authorities peek at the future of work and anticipate changes in the labor markets. We believe that the analysis of interactions developed by industry and country can help policy-makers identify the most significant challenges and potential solutions based on the composition of the economic sectors. Governments can expect a more considerable disruption in labor markets when higher adoptions of alternative work contracts are anticipated in industries that are key for the country. Finally, it is also relevant for authorities to understand people's perception of risk and reflect on the factors that may affect it inside the national reality, especially when those disruptions need adaptation of the social security.

Appendix

Table 8 Summary of the variables considered in the study

Variable	Label	Description	Categories	Ref
Socio-demographics, education and social class				
GE	Gender	Gender of the respondent	Male, female, other	B2
AG	Age	Age group of the respondent (calculated from year of birth)	18–24, 25–34, 35–44, 45–54, 55–64 years	B3
CTR	Country	Current country of residence	24 countries, see Table 9	B4
ED	Education	Highest educational level attained	Higher education (h + i), no higher education (a + b + c + d + e + f + g)	B6
SC	Social class	Self-perceived social class of the respondent and the household	Lower class (a + b), middle class (c), upper class (d + e), no info. (f)	B38
Living arrangements				
ST	Size of town	Population of the town of residence	< 10k (a + b), 10k–100k (c + d), 100k + inhabitants (e + f), no info. (g)	B16
HT	Housing type	Housing ownership at the current place of living	Owner (a + b), tenant (c + d + e)	B17
MS	Marital status	Current marital status	Married/registered partnership (b), other (a + c + d + e)	B18
PE	Partner's employment	Employment status of the spouse or partner	Employed (a), other (b + c + those not living with a partner)	B20
CH	Children	Respondent being a parent	Children (a), no children (b)	B21
Current job and employment status				
ES	Employment status	Employment status at the moment of survey	Employed (a), unemployed (b), never been employed (c)	B12
TE	Type of employment	Indicator whether the respondent is (self-)employed	Employee (a), self-employed (b), other (*ES* = 6 "employed")	B13
TC	Type of contract	Type of employee contract of the respondent	Permanent (a), temporary (b), without a contract (c), other (*TE* = 6 "employee")	B14

Table 8 (continued)

Variable	Label	Description	Categories	Ref
PS	Professional status	Description of current job situation	Full-time (a + b), part-time (c + d), no paid work (e + f + g + i + j + k + l), retired (h)	B25
CS	Company size	Number of workers in the company or firm	< 10 (a + b), 10–249 (c), 250 + (d), no info (e + f)	B26
TO	Type of occupation	Role in the current or most recent job	Manager (a), professional (b), technician (c), clerical (d), service (e), manual (f + g + h + i), no info. (j + k)	B27
IN	Industry	Economic sector of the current or most recent work	14 industries, see Table 9	B28
Online platform work and use of digital technologies				
DI	Digital information	Frequency of usage of digital information and communication technologies at work	Everyday (a + b), sometimes (c + d + e), never (f), no info. (g)	B29
CT	Complex Technology	Frequency of usage of complex technology (robots, specialist software) at work	Everyday (a + b), sometimes (c + d + e), never (f), no info. (g)	B30
GG	Gig economy	Usage of an app or online platform to find gig work	Never (a), a few times (b), occasionally (c), regularly (d)	B31
Trends from technology and government action (response variables)				
*S*1	Trend to self-employment	Technology will lead to more people becoming self-employed and working for themselves	Unlikely (1 + 2), likely (3 + 4), other (5)	C28a
*S*2	Trend to temporary contract-sTechnology will lead to more people working on temporary or fixed-term contracts	Unlikely (1 + 2), likely (3 + 4), other (5)	C28b	*S*2
*S*3	Trend to multiple employersTechnology will lead to more people working for multiple employers at the same time	Unlikely (1 + 2), likely (3 + 4), other (5)	C28c	*S*3

In the last column, explanatory variables (B…) are referenced from the background questionnaire (OECD, 2020a), while response variables (C…) come from the core questionnaire (OECD, 2020b). The category "no info." stands for "no information" and corresponds to answers like "I don't know," "not applicable," "I would rather not answer," and "can't choose"

Table 9 Perceived likelihood of the three trends per country and industry

Perceived likelihood (shares in %) of the trends to…				
Category	Code	Self-employment (S1)	Temporary contracts (S2)	Multiple employers (S3)
Countries				
Austria	AUT	42.0	64.6	63.0
Belgium	BEL	48.1	61.1	60.4
Canada	CAN	68.0	70.8	70.2
Chile	CHL	77.7	67.8	65.5
Denmark	DNK	51.5	58.0	54.6
Estonia	EST	54.5	63.9	71.1
Finland	FIN	53.2	67.0	65.9
France	FRA	54.0	67.7	66.9
Germany	DEU	36.2	65.1	60.2
Greece	GRC	69.2	77.5	79.8
Ireland	IRL	64.2	72.7	59.6
Israel	ISR	55.1	56.7	63.8
Italy	ITA	62.2	69.4	67.0
Korea	KOR	62.4	79.4	54.2
Lithuania	LTU	54.0	50.5	60.8
Mexico	MEX	77.3	72.4	70.0
Netherlands	NLD	58.9	64.8	58.9
Norway	NOR	53.5	59.0	59.9
Poland	POL	66.7	67.7	69.0
Portugal	PRT	66.5	78.1	74.0
Slovenia	SVN	61.1	72.2	68.5
Spain	ESP	58.0	55.5	70.3
Switzerland	CHE	53.9	67.7	68.3
Turkey	TUR	75.0	76.2	74.0
USA	USA	65.8	66.4	64.0
Industries				
Essential primary	EP	61.4	66.8	66.5
Manufacturing	MN	59.0	69.0	64.0
Construction and real estate	CR	61.8	68.5	67.5
Wholesale and retail	WR	61.04	70.1	66.5
Transportation and storage	TS	54.7	71.5	66.6
Leisure and hospitality	LH	60.4	67.8	66.4
Information and communications	IC	67.7	71.5	73.2
Finance and insurance	FI	62.6	70.2	71.0
Professional activities	PR	63.9	65.2	67.6
Administration and support	AD	60.6	67.2	65.7
Public administration	PA	57.3	68.0	68.6
Education	ED	60.7	63.1	66.9
Human health	HH	50.2	60.7	61.8
Other services	OS	60.0	67.2	65.4
No information	NI	55.7	60.2	57.1

Table 9 (continued)

The shares are expressed in % and are calculated based on the weights of the respondents in the sample. Information on industries stems from question B28 (OECD, 2020a) with the following aggregations: EP includes answer options a, b, d, and e; CR includes f and l; LH includes i and r

Author Contribution JW designed the analysis and contributed to the whole writing process. AUM conducted the analysis and wrote the first draft. TD wrote subsequent drafts.

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Availability of Data and Materials The data supporting this study's findings are available on the OECD's website. Data are also available from the authors upon reasonable request.

Declarations

Competing Interests JW is part of the Enterprise for Society (E4S) Center's initiative on shaping the future of work and is also with the Swiss Finance Institute, Lausanne, Switzerland.

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