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Automation, Skills and the Future of Work: What do Workers Think?

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Abstract

We exploit a survey data set that contains information on how 11,000 workers across advanced and emerging market economies perceive the main forces shaping the future of work. In general, workers feel more positive than negative about automation, especially in emerging markets. We find that negative perceptions about automation are prevalent among workers who are older, poorer, more exposed to job volatility, and from countries with higher levels of robot penetration. Perceptions over automation are positively viewed by workers with higher levels of job satisfaction, higher educational attainment, and from countries with stronger labor protection. Workers with positive perceptions of automation also tend to respond that re-education and retraining will be needed to adapt to rapidly evolving skill demands. These workers expect governments to have a role in shaping the future of work through protection of labor and new forms of social benefits. The demand for protection and benefits is more significant among women and workers that have suffered job volatility.

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I. INTRODUCTION

The fear of automation is turning into the collective angst of our times. The concern of associated job losses has dominated the public debate, both in popular media and in policy discussions. Almost everyone following the news has been exposed to headlines such as "Robots Will Destroy Our Jobs—and We're Not Ready for It" and endless discussions on what could be the jobs of future. According to a recent review (Winick, 2018), the most commonly cited numbers in such journalistic pieces come from three sources: a 2013 Oxford study that said 47 percent of US jobs are at high risk of automation in the next few decades, an OECD study suggesting that 9 percent of jobs in the organization's 21 member countries are automatable, and a McKinsey report which affirmed that 400 to 800 million jobs worldwide could be automated by 2030.[2] While there is little evidence on the extent of human displacement by robots (Autor and Salomon, 2018; Acemoglu and Restrepo, 2019), such predictions have shaped public perceptions to the point that increasingly large majorities of people believe that robots will be doing much of the work done by humans within 50 years. This in turn is building concerns of how difficult it would be for ordinary people to find jobs and increasing inequality.

There are early signs that perceptions about how automation can affect our future may already be impacting people's behavior. There is evidence from the US 2016 presidential elections showing that "automation in recent years tilted the electorate into opting for radical political change" (Frey, Berger and Chen, 2018). Concerns about automation are increasingly reflected in policy proposals too. For example, Andrew Yang, a 2020 Democrat Presidential Candidate, is running on a platform that promises to implement universal basic income for every American adult funded by a new tax on the companies benefiting most from automation. Thus, understanding what factors shape public perceptions of automation may provide valuable insights into ongoing economic and political developments.

[2] The related references are: Frey and Osborne (2013), Arnt, Gregory and Zierahn (2016) and Manyika and others (2017).

In this paper, we address this issue. Specifically, we examine the factors that explain whether workers have a positive or a negative perception of how automation will shape the future of their own work. We do so by exploiting the information contained in a survey conducted by provided by Boston Consulting Group's Henderson Institute (BHI) on the Future of Work (BHI, 2018). This survey, conducted in May 2018, interviewed 11,000 workers across 11 advanced and emerging economies to understand how they perceive the forces that shape the future of work. The uniqueness of this database resides in its wide country coverage and in the number of questions that allow us to relate the workers' perceptions to their personal characteristics, employment characteristics, and policy preferences. In addition, this survey deliberately excludes highly-educated workers, and focuses instead on understanding the perceptions of less educated and lower income workers and middle-skilled workers.

We start by examining the role of personal and employment characteristics in explaining perceptions of automation.[3] In line with our expectation, we find that negative perceptions about how automation will affect the future of work are prevalent among workers who are older, poorer, and exposed to job volatility. Furthermore, workers with higher levels of job satisfaction and higher educational achievements tend to have positive perceptions. Exploiting regional heterogeneity, we find that respondents from emerging market economies are likely to have a more favorable view of automation than respondents from advanced economies. This finding is consistent with the evidence that about half of the total decline in labor shares in advanced economies can be attributed to the impact of technology (Dao et al., 2017).

Next, to better understand perceptions, we explore the role of labor market characteristics. Specifically, we examine the role of labor market's exposure to new technologies (i.e. *degree of automation*) and labor protection laws (i.e. *degree of protection*) in explaining perceptions. We find that while survey respondents from countries with higher *degree of automation* are likely to perceive automation negatively, respondents from countries with higher *degree of protection* are likely to view automation positively.

[3] We use the term automation to refer broadly to new technologies in the workplace—such as automation and artificial intelligence as posed as a question in the survey

Finally, we analyze how workers intend to respond to rapidly evolving skill demands stemming from automation. We find that workers that have a positive perception of how automation will impact the labor market tend to acknowledge that reeducation and retraining will be needed. These workers also expect governments to have a role in shaping the future of work through government protection and new forms of social benefits. Some of our results could have policy implications. For example, because the demand for protection and new benefits is more significant among women and workers that have suffered job volatility, policymakers could consider better-targeting these groups when designing new programmes to cushion the effects of technological change.

This paper is structured as follows. The next section reviews the survey literature on workers attitudes towards innovation, technological change, and robotization. Section III describes data and presents main stylized facts. Section IV focuses on the factors that explain the perception of workers towards automation, and it dedicates two sub-sections to understand regional heterogeneity and labor market characteristics that explain perceptions. Section V studies what workers' expectations about how to respond to in terms of reeducation, retraining, government protection and new social benefits. Section VI summarizes the main findings and concludes.

II. Literature Review

Predictions on the number of jobs which will possibly be automated in the next 10 to 20 years vary considerably, and new estimates are likely to keep being released by research institutions, think tanks, and corporations. MIT Technology Review mapped the most recent studies and concluded: "we have no idea how many jobs will actually be lost to the march of technological progress" (Winick, 2018).

Despite the lack of concrete evidence for substitution of human labor by robots, public perception tends to show that citizens are generally pessimistic when it comes to the possibility of losing their jobs to machines. Public opinion surveys that have looked at attitudes towards automation, and new technologies in general, have found that a majority of people are concerned that the use of robots and artificial intelligence will cause more jobs to disappear than new jobs to be created (see

Table I for a summary of these surveys). More importantly, large majorities think that ordinary people will have a hard time finding jobs as a result of automation (Eurobarometer, 2017; Pew, 2018).

How individuals view the impact of technology on their employment outcomes have typically been associated with their education levels. Early surveys of U.S. workers have shown that even before the impact of technology became a trendy research topic, perceptions of job security tended to increase with schooling (Manski and Straub, 1999).[4] These results have recently been confirmed with new data. U.S. Workers with a lower education background are less optimistic about the impact of technology in general and feel more vulnerable in their jobs than workers who are college graduates (Gallup, 2017, 2018).

Cross country surveys have also shown that workers with lower education levels were more worried when thinking about the future of work than those with higher education levels, although the share of workers who were worried did not exceed one in three workers (PwC, 2017 and Fuze, 2018). In addition to education levels, restricted access to information make people more worried about the impact of automation on their jobs (Eurobarometer, 2017).

Table 1. Recent Public Opinion Surveys

2017 Gallup Surveys[5]	Gallup surveys looked specifically at how workers perceive the impact of technology over their personal situation: • April-May 2017, a survey of 1,100 U.S. workers found that 26 percent of U.S. workers thought it was likely that their job would be eliminated by new technologies, automation, artificial intelligence or robots within the next 20 years. About 13 percent said this would happen within the next five years. College graduates were significantly less likely than others to fear that

[4] This paper analyzed the responses of 3600 persons interviewed from 1994 through early 1998 via the nationwide Survey of Economic Expectations. It found that subjective probabilities of job loss tend to decrease with schooling and subjective probabilities of good search outcomes tend to increase with schooling; hence composite job insecurity tends to decrease with schooling. Self-employed workers see themselves as facing less job insecurity than do those who work for others.

[5] Newport (2017, 2018); Reinhart (2018)

	their jobs would be eliminated in five years. But expectations of replacement in 20 years were very similar across all education levels. • September-October 2017, the Northeastern University/Gallup survey of 3,300 Americans looked at attitudes toward artificial intelligence (AI) and its effect on their lives and work. 73 percent of Americans said that they expected AI to destroy more jobs than it would create. Employed Americans with less than a bachelor's degree were almost twice as likely to feel their jobs at risk than those with a four-year degree or more.
2017 Eurobarometer Survey	In May 2017, The European Commission published a Eurobarometer survey presenting European citizens' opinions on the impact of digitization and automation on daily life. Approximately 28,000 EU citizens from different social and demographic categories were interviewed. Attitudes towards robots and artificial intelligence were generally positive but they depended greatly on the education level and the exposure to information: respondents who had heard, read or seen something about artificial intelligence in the last 12 months were more likely to have a positive view of artificial intelligence and robots. 74 percent of respondents expressed concerns that the use of robots and artificial intelligence could cause more jobs to disappear than new jobs to be created.
2018 Pew Survey	In September 2018, the Pew Research Center published a report by Wike and Stokes (2018) with results from its annual study of public opinion (a survey covering 1,000 respondents in each of 10 countries—Greece, Japan, Canada, Argentina, Poland, Brazil, South Africa, Italy, Hungary, United States) focused on perceptions around the impact of automation and technology in general. Overall, most respondents believed that increasing automation would have negative consequences for jobs. Interestingly, in most countries, pessimism about jobs lost to technology was correlated with views about the current state of the economy. When it comes to the question of the responsibility for preparing the workforce for the future, respondents saw a clear role for the government, but many also highlighted a role for individuals.
2017 PwC Survey	In 2017, PwC commissioned a survey of 10,000 workers, retired people, unemployed and students in China, India, Germany, the UK and the US. The analysis focused on the difference in perceptions across generations

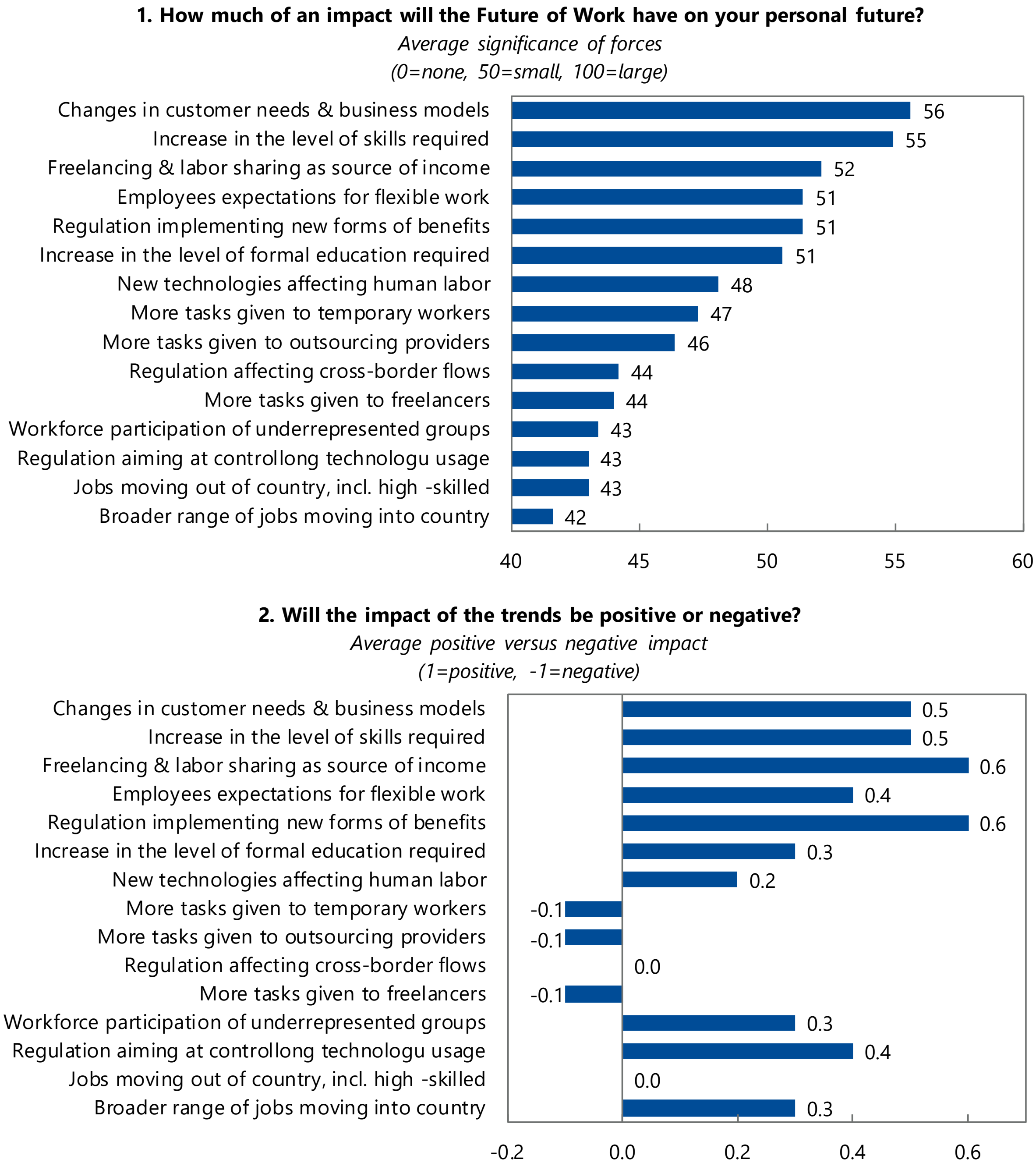
	(e.g. baby boomers, Gen X, Millennials, Gen Z) and across countries. PwC found that those respondents with fewer years of formal education were more worried when thinking about the future of work. 30 percent of respondents with basic education were worried about their future, while only 13 percent of university graduates, and 11 percent of post-graduates showed similar concerns.
2018 Fuze Survey	In 2018, cloud communications and collaboration platform provider Fuze commissioned a survey of 6,600 knowledge workers in private sector organizations with more than 500 employees, across 9 countries: Australia, Canada, France, Germany, the Netherlands, Scandinavia, Spain, the UK, and the United States. They found that 66% are not worried about the impact of automation on their jobs.

The BHI (2018) survey used in this paper provides us with relevant information needed to test the role of education in explaining workers' attitudes towards automation. Specifically, it classifies the respondents into four levels of educational attainment. Moreover, for our purposes, this new database allows us to connect the workers' views on automation with their current job satisfaction, their past job volatility, and the respondents' other personal characteristics in terms of age, gender and income level. Finally, this survey provides answers to questions that had not been asked before in this context such as on the need for re-education or retraining and the role of governments in preparing workers for managing the impact of automation on the future of work.

III. Data and Stylized facts

The BCG survey is based on interviews of 11,000 workers in 11 countries: the US, the UK, Germany, France, Spain, Sweden, Japan, India, Indonesia, China, and Brazil. The survey deliberately excludes highly-educated workers—those with top tier universities' bachelor's degrees, master's degrees, and higher. Instead, it focuses on understanding the perceptions of less educated and lower income workers (60-to-85 percent of respondents with household income below their respective national averages) and middle-skilled workers. Thus, providing us with insights on the views of those with education levels below a four-year college degree.

Figure 1. Forces Shaping the Future of Work



Source: Boston Consulting Group (2018).

The workers surveyed were presented with a framework of 15 forces expected to shape the future of work and were asked which trends were likely to have a positive or negative impact on their own personal situation. Changing customer needs, more skills and education, more freelancing and flexibility were all mentioned among the top forces shaping the future workplace. New technologies affecting human labor, such as automation and artificial intelligence, were ranked in the middle among the forces likely to have an impact on the respondents' personal future (Figure 1, left). Thus, workers think 'automation' is only part of the Future of Work story. On average, the expected impact of automation and artificial intelligence was deemed to be slightly positive (Figure 1, right).

For this paper, we build the main dependent variable using the responses from the two questions that ask about workers' perceptions regarding the impact of automation and artificial intelligence on the future of work. First, "How much of an impact new technology at workplace (e.g., automation, AI) will have on your own personal future?" Second, "Do you believe the impact to be positive or negative?" We combine responses to these two questions to build the variable *automation* that takes values 1, 2 and 3 corresponding to negative, neutral, and positive attitude towards new technologies.[6] After cleaning our data, we end up with 7,689 respondents distributed largely evenly across our countries with lowest number of respondents in Japan (504) and highest in India (837).

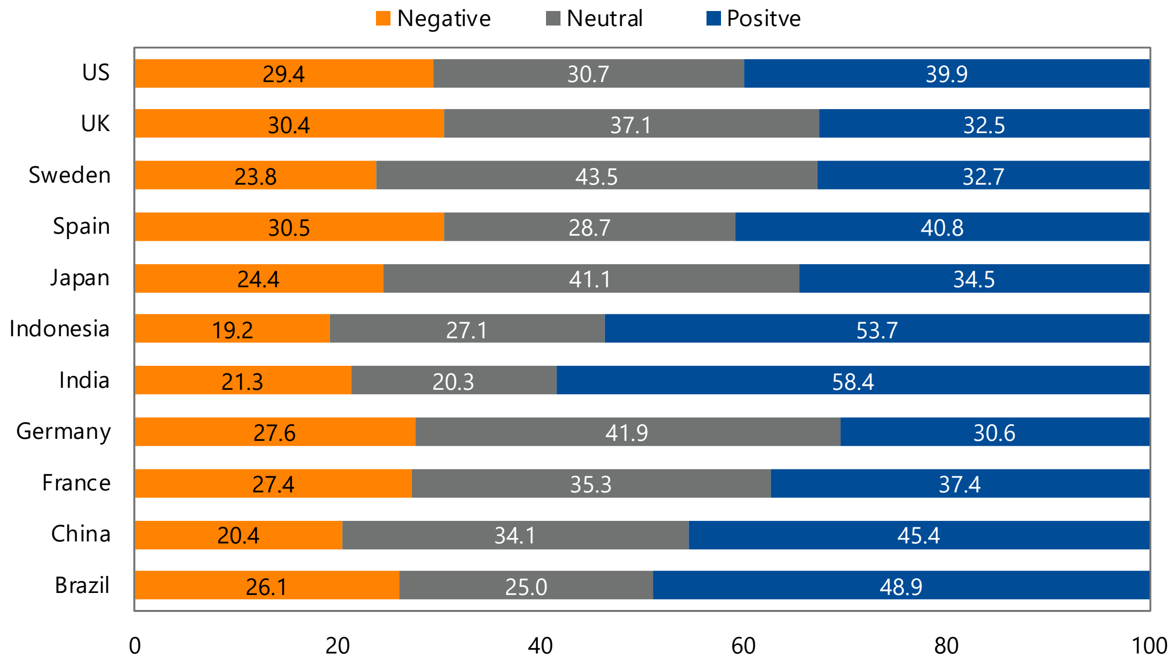
On average, the workers' perceptions about the impact of technology on the future of work are positive. [7] 41.3 percent of workers think that new technologies (automation, AI) will have a positive impact in the workplace, while only 25.5 think the effect will be negative. Country differences are important (Figure 2). For example, in India, Indonesia more than 50 percent of respondents have a positive opinion about the effect that automation will have in the workplace, whereas in Germany, or Sweden this percentage barely surpasses 30 percent.

[6] For section 5, we use this variable as an independent factor explaining the worker's attitudes towards reskilling and government policies. We use dummies generated as follows: *automation_pos* takes value 1 when *automation* equals 3 (positive), and takes value 0 otherwise; *automation_neg* takes value 1 when automation equals 1 (negative) and takes value 0 otherwise.

[7] While the questions are not exactly comparable across surveys, positive perceptions about automation and the future of work seem to be higher among respondents in BCG (2018) survey than in previous surveys mentioned in Table 1.

Figure 2. The Effect of Automation on the Future by Country

(Percent of respondents)



Sources: Boston Consulting Group (2018); and IMF staff calculations.

Potentially, a wide range of factors could explain the workers' perception of the effect of automation on the future of work. To capture the most important personal characteristics, we look at key aspects such as educational attainment, age, income level and gender. Initial associations between the workers' views on automation and those personal characteristics can be summarized as follows (Figure 3):

- More educated people (especially college graduates) have a more positive view of the impact of technology on the future of work compared to respondents with lower levels of education.

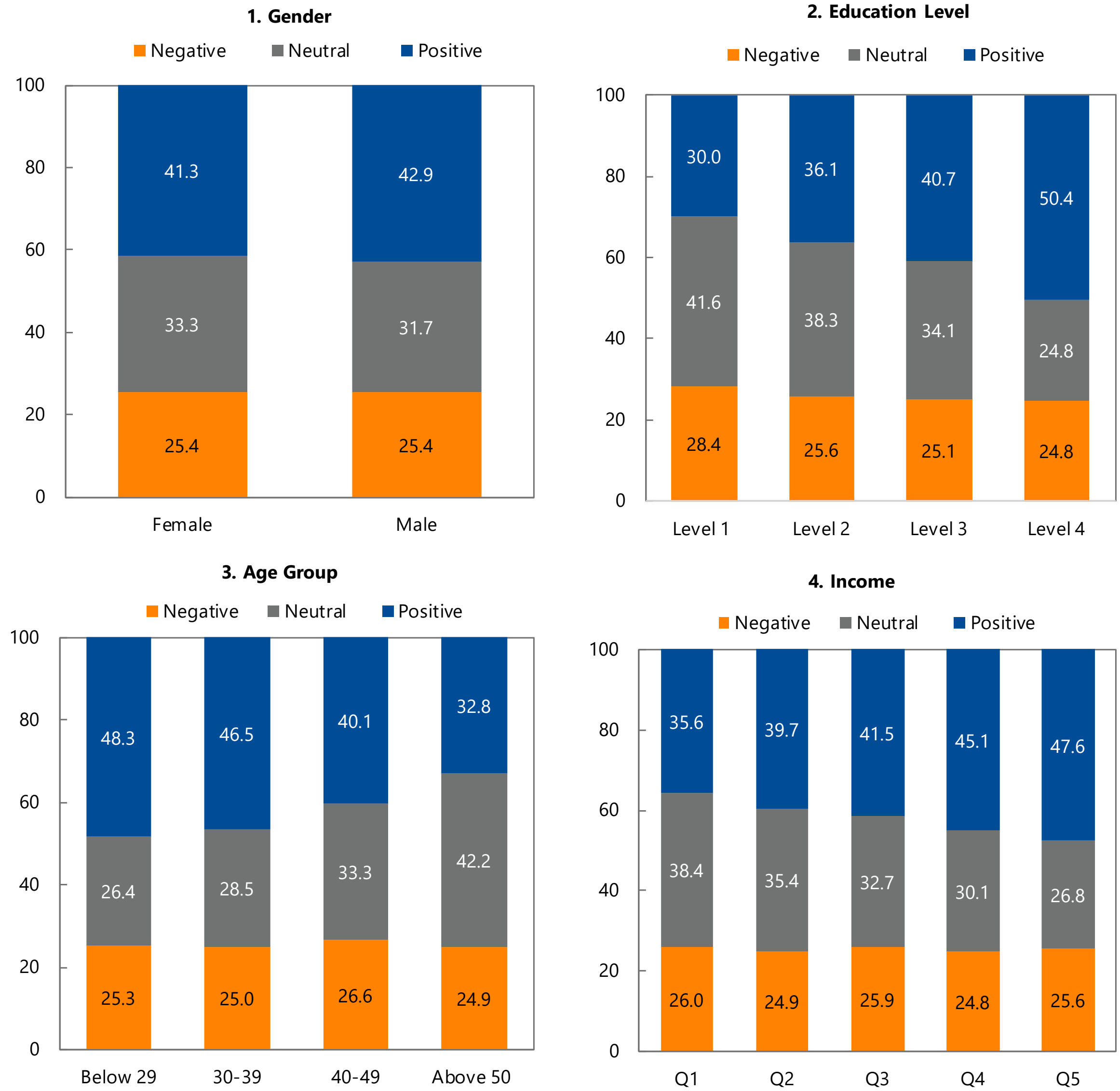
- Older respondents tend to be less positive about the effect of technology on the future of work. The difference between younger workers below 29 years old and older workers above 50 years old is substantial.

- Respondents form higher income quintiles are clearly more positive about the impact of technology on the future.

Gender instead does not seem to be an issue, although the proportion of respondents that have a negative view about automation is slightly higher among women that among men.

Figure 3. The Effect of Automation on the Future by Personal Characteristics

(Percent of respondents)



Sources: Boston Consulting Group (2018); and IMF staff calculations.

IV. AUTOMATION AND THE FUTURE OF WORK

In this section, we exploit the richness of our data to assess more rigorously which factors shape survey respondents' perceptions of the effect of automation, or more broadly new technologies, on the future of work.

Specifically, we estimate the following model conditional on different combinations of country and industry fixed effects.

$$automation_{i,j,c} = \alpha + \beta PC_{i,j,c} + \gamma EC_{i,j,c} + \varepsilon_{i,j,c} \quad (1)$$

where $automation_{i,c}$ is a variable that captures the perception of how a survey respondent i in industry j in country c view the impact of new technologies on her own future, and takes the value negative (1), neutral (2), or positive (3). $PC_{i,c}$ is a vector that captures respondent characteristics and includes the following variables: edu captures the level of education and takes a value between 1 to 4 with 1 corresponding to lowest level of education (1 = middles school or less; 2 = trade school/vocational training; 3 = high school; and 4 = two/three-year college), age_group is a variable that takes the a value between 1 to 4 with 1 corresponding to the youngest age cohort (1 = 18-29; 2 = 30-39; 3 = 40-49; and 4 = 50-75), $income$ is the income from paid work after taxes that takes five categories (where 1 is the lowest income quintile by country in the sample and 5 is the highest), and $female$ is a dummy variable that takes value 1 if the respondent is female, 0 otherwise. $EC_{i,c}$ is a vector that captures employment characteristics and includes the following variables: $job\_happiness$ is a proxy for job satisfaction that takes the value 1 (unhappy), 2 (neutral), and 3 (happy) in response to a question on "How happy are you with your current employment situation?", $job\_volatility$ that captures the frequency of job changes in the last five years and takes the value 1 (not at all), 2 (once or twice) and 3 (three or more times), and $contingent$ which is a dummy variable taking value 1 when respondents are self-employed, temporary workers, company owners, or unemployed workers[8], and takes value 0 otherwise.[9]

Our results from ordered logit (or proportional odds) model estimations are reported in Table 1. We start by exploring the relationship between perceptions and personal characteristics (see column 1 of Table 1). Specifically, we note that respondents with higher levels of education are likely to have a more favorable perception of the impact of technology on the future of their work. To interpret these coefficients, we use odds ratios. Associated odds ratios for these set of

[8] Contingent workers in this survey would include the following: self-employed (e.g. a tradesperson, independent professional, freelancer) or small entrepreneurs with no or less than 5 employees; temporary workers employed by staffing agencies (e.g. Randstad, Adecco) or similar companies; company owners with 5 or more employees are also considered contingent workers; and unemployed workers.

[9] Non-continent workers in this survey would include the following: Salaried employee in a large company (50 employees or more); and salaried employee in a small company (less than 50 employees).

regressions are reported in Table A.1 in the Annex. For example, an increase in educational outcome from high school to college leads to the odds of being more favorable about the impact of technology on the future of work to be 1.7 times larger, all else equal. In other words, for an increase from high school to college, *ceteris paribus*, we observe a 70 percent increase in the odds of being more positive about the impact of automation.

Income too is positively associated with favorable perceptions of the impact of technology on the future of work. An increase from the fourth to fifth income quintile leads to a 30 percent increase in the odds of being more positive about the impact of automation. Age, however, is negatively associated with favorable perceptions towards technology indicating that older respondents are less likely to favorably perceive the impact of automation on the future of their work. Finally, we note that the odds of female respondents being more favorable is about 8 percent lower than male respondents. All these results are in line with our expectations.

We extend our specification further by including the vector of employment characteristics. Results from our estimations are reported in column 2 of Table 1. We find that none of the above results are affected by the inclusion of additional controls. Moreover, in line with our expectations, we find that the variable $job\_happiness$ is positively associated with a more favorable perception of the impact of new technologies on the future of work while the variable $job\_volatility$ is negatively associated. *Contingent* workers have a statistically significant view of the impact of new technologies on the future of work.

It is still possible that unobserved heterogeneity across countries or industries might be driving our results. To control for this possibility, we estimate our baseline specification conditional on different combinations of country and industry fixed effects. Columns 3-5 report the results of estimations that include country effects, industry effects, and the combination of both. Finally, in column 6 we include country-industry pair fixed effects that controls for all country-industry specific shocks. The main results discussed above are robust to the inclusion of fixed effects and remain comparable in magnitudes. However, we note that the $female$ dummy, $job\_volatility$, and the dummy capturing *Contingent* workers lose statistical significance in some specifications.[10] [11]

Table 1 – Automation and the Future of Work: Baseline

Variables	automation	automation	automation	automation	automation	automation
2.edu	0.193**	0.183**	0.251***	0.174**	0.242***	0.233***
	(0.079)	(0.080)	(0.084)	(0.080)	(0.084)	(0.085)
3.edu	0.269***	0.269***	0.234***	0.262***	0.228***	0.223***
	(0.069)	(0.070)	(0.074)	(0.070)	(0.074)	(0.076)
4.edu	0.500***	0.479***	0.367***	0.460***	0.351***	0.350***
	(0.076)	(0.076)	(0.084)	(0.077)	(0.085)	(0.086)
2.age_group	-0.054	-0.075	-0.052	-0.074	-0.051	-0.049
	(0.063)	(0.063)	(0.064)	(0.063)	(0.064)	(0.065)
3.age_group	-0.242***	-0.272***	-0.196***	-0.268***	-0.195***	-0.188***
	(0.064)	(0.065)	(0.066)	(0.065)	(0.067)	(0.068)
4.age_group	-0.370***	-0.424***	-0.248***	-0.411***	-0.244***	-0.242***
	(0.058)	(0.061)	(0.065)	(0.061)	(0.065)	(0.066)
2.income	0.112*	0.094	0.094	0.089	0.09	0.103
	(0.064)	(0.065)	(0.065)	(0.065)	(0.065)	(0.066)
3.income	0.131**	0.105	0.105	0.098	0.1	0.108
	(0.066)	(0.066)	(0.066)	(0.066)	(0.067)	(0.068)
4.income	0.247***	0.214***	0.218***	0.203***	0.210***	0.211***
	(0.067)	(0.067)	(0.068)	(0.068)	(0.068)	(0.069)
5.income	0.284***	0.232***	0.243***	0.217***	0.232***	0.227***
	(0.069)	(0.069)	(0.070)	(0.070)	(0.070)	(0.072)
female	-0.067	-0.072*	-0.051	-0.065	-0.053	-0.048
	(0.043)	(0.043)	(0.043)	(0.044)	(0.044)	(0.045)
contingent	0.133***	0.129***	0.044	0.147***	0.064	0.069
	(0.045)	(0.045)	(0.046)	(0.046)	(0.047)	(0.049)
2.job_happiness		0.209***	0.184***	0.203***	0.182***	0.437***
		-0.065	-0.066	-0.065	-0.066	(0.057)
3.job_happiness		0.410***	0.435***	0.408***	0.433***	-0.055
		(0.055)	(0.056)	(0.055)	(0.056)	(0.049)
2.job_volatility		-0.079*	-0.064	-0.073	-0.058	-0.157
		(0.048)	(0.048)	(0.048)	(0.048)	(0.097)
3.job_volatility		-0.211**	-0.180*	-0.198**	-0.167*	-0.190*
		(0.094)	(0.094)	(0.094)	(0.095)	(0.109)
Observations	7,689	7,689	7,689	7,689	7,689	7689
Country Dummies	No	No	Yes	No	Yes	No
Industry Dummies	No	No	No	Yes	Yes	No
Country-Industry Dummies	No	No	No	No	No	Yes
Sample	All	All	All	All	All	All
Estimation	Ologit	Ologit	Ologit	Ologit	Ologit	Ologit

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

[10] This result is probably driven by the fact that there are more contingent workers in emerging economies (particularly in India and Indonesia), and they overall exhibit a positive view towards the impact of new technologies on the future of work. As a result, the country fixed effects absorb the statistical significance of the dummy variable. We therefore drop this variable in subsequent regressions.

[11] Similar results are obtained when we run the regressions including a dummy variable to identify workers of the gig economy. Only 4 percent of workers declare gig or platform economy as a primary source of income, and 13 percent report it as a secondary source of income. Gig-economy workers are younger (60 percent are between 18 and 35 years old) and more educated (43 percent are college educated) than the sample average. Again, in this case the effect of Indian and Indonesian respondents (a large majority of which are young, educated and welcoming technological change) is significant.

This table reports a set of regression where the dependent variable is automation - a variable that captures the perception of how survey respondents view the impact of new technologies on their own future, and takes the value negative (1), neutral (2), or positive (3).

A. Regional heterogeneity

In this subsection, we explore the regional heterogeneity of our data by undertaking sub-sample regressions. We estimate our original model conditional on country-industry pair fixed effects, the most stringent specification, separating the respondents from advanced, European, [12] and emerging economies. The results are reported in Table 2.

Three observations stand out. First, we note that only older respondents from advanced and European economies, but not emerging market economies, are likely to have a negative perception of the impact of technology on the future of their work. The coefficients on age_group for emerging market economies although negative are not statistically significant. Second, the positive impact of income levels is now restricted to advanced and European countries. The coefficients for emerging economies are not statistically significant. Finally, we note that female respondents from advanced and European economies have a statistically significant negative perception of the effects of automation on the future of their work.

Taken together, these sets of results indicate that the impact of new technologies on the future of work is perceived in a more negative light by older and female respondents in advanced economies. More broadly, respondents from emerging market economies are likely to have a favorable view. This observation is in line with the evidence from literature that suggests technology have contributed to greater substitution of capital for labor in advanced economies than in emerging market economies (Dao et al., 2017).

[12] Our country groupings in this section are the following: Europe (Germany, France, Spain, Sweden); Advanced (Germany, France, Spain, Sweden, the US, the UK, and Japan); and Emerging (India, Indonesia, China, and Brazil).

Table 2 – Automation and the Future of Work: Regional Heterogeneity

Variables	automation	automation	automation
2.edu	0.223**	0.227**	0.222***
	(0.101)	(0.104)	(0.172)
3.edu	0.150	0.145	0.346***
	(0.096)	(0.103)	(0.130)
4.edu	0.316***	0.259***	0.453***
	(0.097)	(0.118)	(0.085)
2.age_group	-0.065	-0.034	-0.033
	(0.097)	(0.118)	(0.085)
3.age_group	-0.243***	-0.164	-0.107
	(0.094)	(0.115)	(0.101)
4.age_group	-0.310***	-0.264***	-0.051***
	(0.086)	(0.105)	(0.128)
2.income	0.153*	0.098	0.031
	(0.084)	(0.097)	(0.106)
3.income	0.199**	0.202**	-0.028
	(0.087)	(0.103)	(0.109)
4.income	0.314***	0.236***	0.032
	(0.089)	(0.104)	(0.110)
5.income	0.284***	0.309***	0.115
	(0.092)	(0.107)	(0.116)
female	-0.136**	-0.180**	-0.083
	(0.059)	(0.070)	(0.073)
2.job_happiness	0.139	0.098	0.242***
	(0.087)	(0.107)	(0.105)
3.job_happiness	0.411***	0.367***	0.482***
	(0.072)	(0.086)	(0.092)
2.job_volatility	-0.039	-0.114	-0.075
	(0.065)	(0.076)	(0.076)
3.job_volatility	-0.169	-0.137	-0.116
	(0.124)	(0.154)	(0.157)
Observations	4,607	3,317	3,082
Country-Industry Dummies	Yes	Yes	Yes
Sample	Advanced	Europe	Emerging
Estimation	Ologit	Ologit	Ologit

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

This table reports a set of regression where the dependent variable is automation - a variable that captures the perception of how survey respondents view the impact of new technologies on their own future, and takes the value negative (1), neutral (2), or positive (3). Columns 1, 2, and 3 correspond to sub-sample regressions for advanced, European, and emerging economies respectively.

B. Labor Market Characteristics

Some individual country characteristics such as labor market characteristics might help us better understand what drives regional heterogeneity and the determinants of workers' perceptions. We explore this idea in this section by focusing our attention on two labor market characteristics at the country level. Specifically, we explore the role of labor market's exposure to new technologies (i.e. *degree of automation*) and labor protection laws (i.e. *degree of protection*) in explaining perceptions of how technology would affect the future of work. To this end, we augment our regressions specified in equation 1 with the inclusion of country level characteristics to equation (2) below.

$$y_{i,j,c} = \alpha + \beta PC_{i,j,c} + \gamma EC_{i,j,c} + \delta CC_c + \varepsilon_{i,j,c} \qquad (2)$$

where CC_c is a vector that includes: rob_c which is the number of robots per thousand workers based on the data from International Federation of Robotics, a proxy for degree of automation in labor markets, and lri_c which is an index from Centre for Business Research at Cambridge University that captures the difficulty for firms to terminate labor contracts, a measure of degree of protection in labor markets. This labor regulation index takes a value between '0' and '1' where '0' stands for no protection or the lowest protection offered to workers, and '1' stands for the maximum or highest protection offered.[13][14]

Our results from ordered logit estimations of equation (2), conditional on industry fixed effects, are reported in Table 3.[15] At the outset we would like to note that none of our results relating to personal and employment characteristics discussed in the two previous sections are affected by including labor market characteristics variables. Education, age, and income have expected signs and remain strategically significant.

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[13] The CBR Labour Regulation Index Dataset ('CBR-LRI') provides data on labor laws in 117 countries. For our purposes, we focus on the area of labor law coded in the dataset relating to dismissal. We use a simple average of 9 variables under section C (from 16 to 24) on the Regulation of dismissal which includes Legally mandated notice period, Legally mandated redundancy compensation, Minimum qualifying period of service for normal case of unjust dismissal, Law imposes procedural constraints on dismissal, Law imposes substantive constraints on dismissal, Reinstatement normal remedy for unfair dismissal, Notification of dismissal, Redundancy selection, and Priority in re-employment. Please see Adams, Z., Bishop, L. and Deacon, S. (2016) CBR Labour Regulation Index (Dataset of 117 Countries) (Cambridge: Centre for Business Research) for further details.

[14] We also run regressions whereby labor market characteristics are defined by levels of unemployment and spending in active labor market policies (ALMPs). None of these variables are significant determinants of the views that survey respondents have about the future of work. For brevity, these additional tests are not reported, but are available from authors upon request.

[15] We cannot include country or country-industry pair fixed effects in this specification since our key explanatory variables of interest, proxy for exposure to new technology and labor protection, is at the country level.

Furthermore, for our purposes we note that the labor market characteristics are statistically significant determinants of perceptions. In column 1 of Table 3 we include the latest figures for the number of robots per thousand workers in our estimation (rob_c). We find that the point estimate is negative and statistically significant. This indicates that respondents from countries with higher levels of robot penetration, on average, are less likely to have a favorable view of the impact of automation on the future of work. We notice an 8 percent decline in the odds of being more favorable about the impact of technology on the future of work for a one-unit increase in the number of robots per thousand workers. The coefficient on the latest value for labor regulation index (lri_c), reported in column 2, is positive and statistically significant suggesting that respondents from countries with higher levels of labor protection on average are likely to have a favorable view of how technology affects the future of work. A one unit increase in the *labor regulation index* increases the odds of being positive about the impact of automation by nearly 60 percent. Finally, in column 3 we jointly estimate the impact of the two country characteristics. Both of these results hold and are comparable in magnitudes.

We also undertake a robustness check by replacing the latest values of our labor market characteristics with the average for last few years available. For robot penetration and labor market regulation, we use the averages for the period 2000-2016 and 2009-2013 respectively. Results of these regressions are reported in Table A.2 in Appendix I. Our results are robust to using the averages instead of the latest available figures. However, we note that in the joint estimation, the number of robots per thousand workers loses statistical significance.

Table 3 – Automation and the Future of Work: Labor Market Characteristics

Variables	automation	automation	automation
2.edu	0.213***	0.167**	0.206**
	(0.081)	(0.080)	(0.081)
3.edu	0.254***	0.324***	0.303***
	(0.070)	(0.071)	(0.072)
4.edu	0.415***	0.500***	0.451***
	(0.077)	(0.077)	(0.078)
2.age_group	-0.064	-0.080	-0.070
	(0.063)	(0.063)	(0.063)
3.age_group	-0.243***	-0.268***	-0.246***
	(0.066)	(0.065)	(0.067)
4.age_group	-0.353***	-0.380***	-0.336***
	(0.063)	(0.062)	(0.063)
2.income	0.085	0.088	0.090
	(0.065)	(0.065)	(0.065)
3.income	0.093	0.096	0.099
	(0.066)	(0.066)	(0.067)
4.income	0.195***	0.199***	0.201***
	(0.067)	(0.068)	(0.068)
5.income	0.219***	0.210***	0.222***
	(0.070)	(0.070)	(0.070)
female	-0.060	-0.071	-0.061
	(0.044)	(0.044)	(0.044)
2.job_happiness	0.185***	0.173***	0.162**
	(0.065)	(0.065)	(0.065)
3.job_happiness	0.392***	0.390***	0.377***
	(0.055)	(0.055)	(0.055)
2.job_volatility	-0.075	-0.072	-0.073
	(0.048)	(0.048)	(0.048)
3.job_volatility	-0.185**	-0.193**	-0.188**
	(0.094)	(0.094)	(0.094)
rob16	-0.076***		-0.065***
	(0.014)		(0.015)
lri13		-0.474***	-0.386***
		(0.105)	(0.108)
Observations	7,689	7,689	7,689
Country-Industry Dummies	Yes	Yes	Yes
Sample	All	All	All
Estimation	Ologit	Ologit	Ologit

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

This table reports a set of regression where the dependent variable is automation - a variable that captures the perception of how survey respondents view the impact of new technologies on their own future, and takes the value negative (1), neutral (2), or positive (3). In addition to the original specification, columns 1 and 2 include labor market characteristics (latest values) that proxy *degree of automation* and *degree of protection* in an economy individually. Column 3 jointly estimates them.

V. Automation, Reskilling and Government Policies

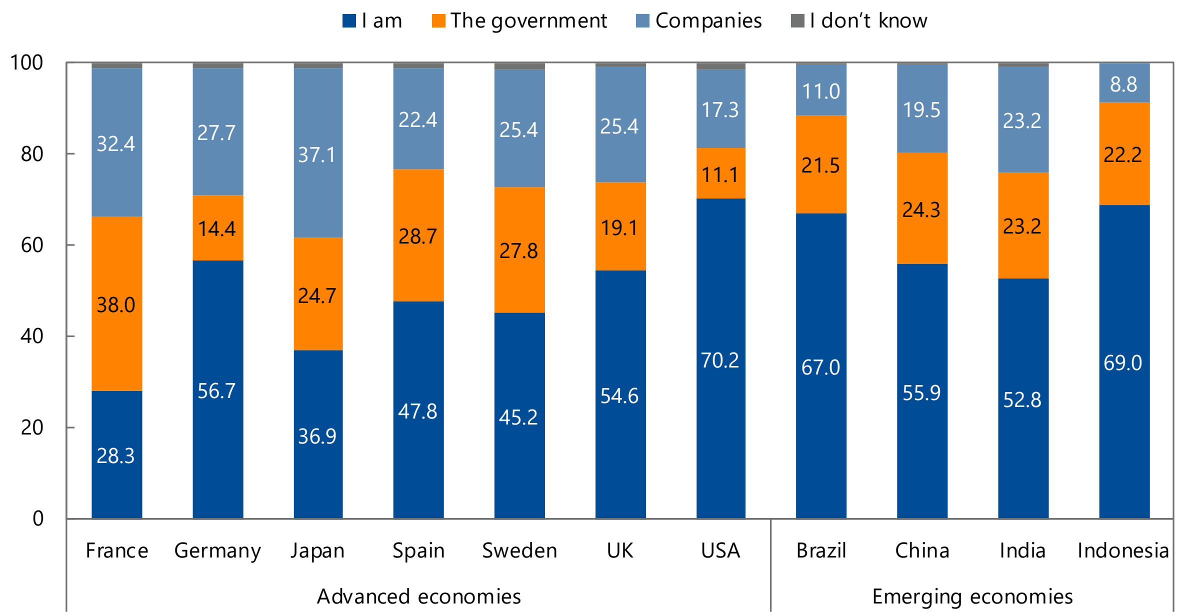
In this final section of the paper we explore workers' perception about reskilling and government policies.

A. Reskilling

When workers are asked how much of an impact the future of work forces would have on their own personal future, nearly 55 percent of respondents expect new technologies to continuously raise skills requirements. Also, workers consider themselves as first responsible to prepare to the future of work, instead of the companies or the government (Figure 4). With the exception of the United States (where more than 70 percent of workers consider that they are the first responsible to prepare for the future of work), the sense of personal responsibility is higher in emerging market economies than in advanced economies. The perception that the government should be the first responsible is only prevalent in France, but other advanced economies like Spain or Sweden also show numbers close to 30 percent of respondents who think the government should play a leading role. In Germany and Japan, instead, workers consider that companies have a higher role to play than governments in this adaptation process.

Figure 4. Who is Responsible for Preparing you for the Future of Work forces?

(Number of respondents divided by 100)

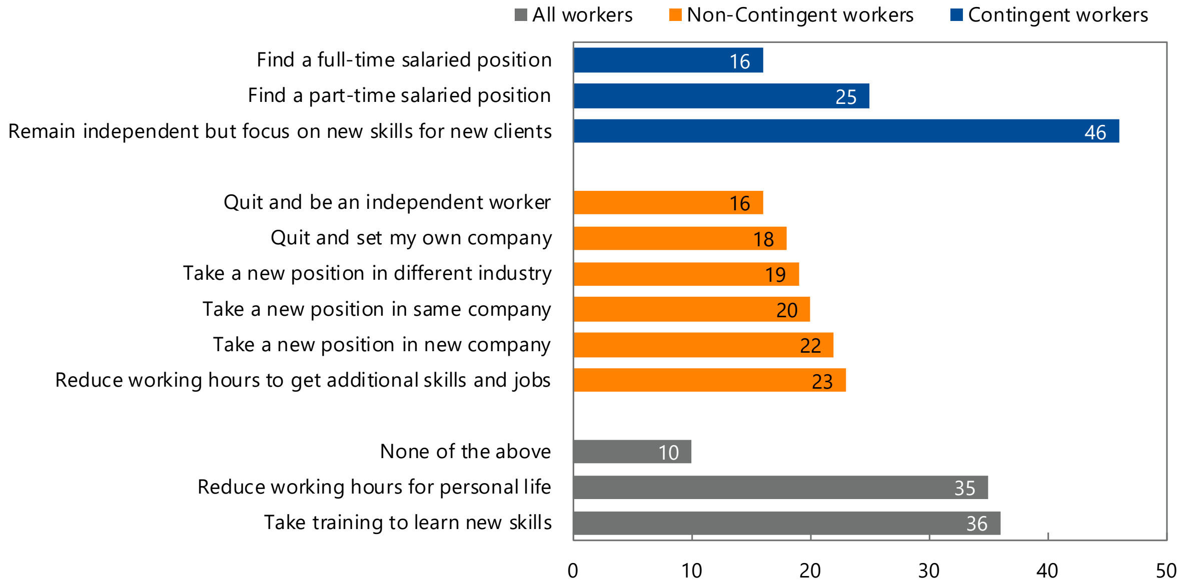


Sources: Boston Consulting Group (2018); and IMF staff calculations.

If their choices were not limited by financial or practical considerations, most workers would build up their skills and take more time for themselves (Figure 5). This is specially the case for independent workers, 46 percent would prefer to remain independent but focus on building new skills. In comparison, only 22 percent of non-contingent workers would reduce the number of hours they dedicate to their employers to rebuild their skillset. When asked about the obstacles that prevent workers from acting, most workers won't take a training or reduce their hours because of financial constraints. However, they also point to lack of time and clarity of options available to them (Figure 6).

Figure 5. Which of The Following Things Could You Imagine Doing?

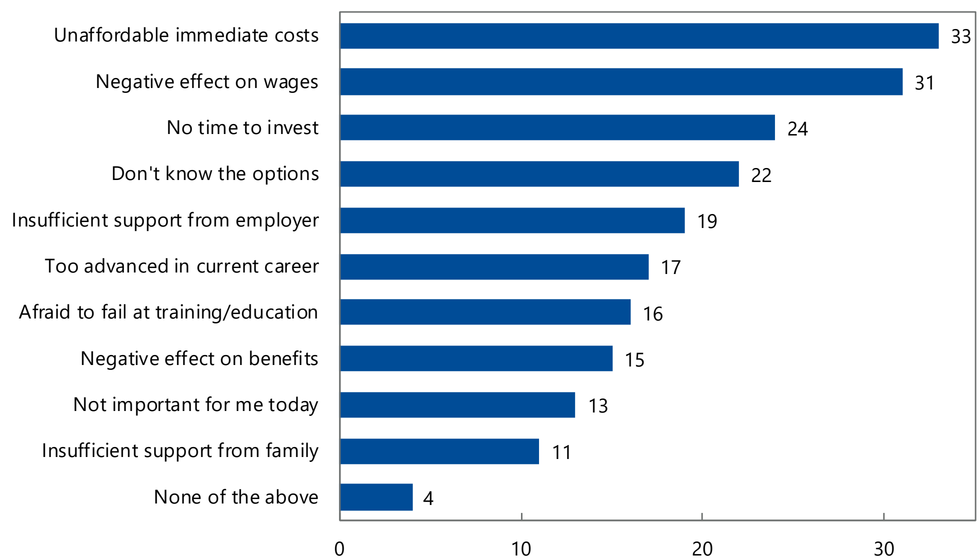
(Percent of respondents)



Sources: Boston Consulting Group (2018); and IMF staff calculations.

Figure 6. Which Obstacles Prevent You from Taking These Actions?

(Percent of respondents)



Sources: Boston Consulting Group (2018); and IMF staff calculations.

To understand how personal characteristics and workers' perception of automation influence their view towards reskilling and adapting to the future of work, we estimate the following model conditional on different combinations of country and industry fixed effects.

$$Reskilling_{i,\mathrm{j},c} = \alpha\ + \beta PC_{i,\mathrm{j},c} + \gamma EC_{i,\mathrm{j},c} + \delta automation\_pos_{i,\mathrm{j},c} + \varepsilon_{i,\mathrm{j},c} \qquad (3)$$

where $Reskilling_{i,j,c}$ takes the form of two dependent variables named $Reeducation_{i,j,c}$ and $Retraining_{i,j,c}$. These two variables capture how survey respondents i in industry j in country c view respectively the changing workforce structure as 'needing more formal education to find a job' (reeducation) or 'more-on-the job training require to keep up' (retraining). These two variables take three values: negative (1), neutral (2), or positive (3). As in the baseline specification, $PC_{i,\mathrm{j},c}$ is a vector that captures respondent characteristics. Finally, we include a dummy variable $automation\_pos_{\mathrm{i,j},c}$ which takes value 1 when respondents had a positive view of automation and takes value zero for those that have a neutral or negative view.

Results are reported in table 4. Columns 1 and 2 report the results for the reeducation variable. Higher levels of educational attainment, higher income levels, job happiness and a positive perception of how automation will impact the future of work are all associated with a positive view towards reeducation. Columns 3 and 4 report the results for the retraining variable. In this case, results are similar to those for the reeducation variable, with few important exceptions: the preexisting level of educational attainment is not a significant explanatory factor of the respondent's attitude towards retraining. Instead, age and gender become important factors; middle-age workers and women have a more positive view towards on-the-job training than other groups.

B. Government policies

Preparing for the future of work not only entails reeducation and retraining. Workers also see a role for government policies, in the form of government protection or new benefits. The final exercise of this paper consists in running similar regressions as those performed before on the variables that measure the attitude of workers toward these government policies. We estimate the following equation:

$$GovPolicies_{i,\mathrm{j},c} = \alpha\ + \beta PC_{i,\mathrm{j},c} + \gamma EC_{i,\mathrm{j},c} + \delta automation\_pos_{i,\mathrm{j},c} + \varepsilon_{i,\mathrm{j},c} \qquad (4)$$

where $GovPolicies_{i,j,c}$ takes the form of two dependent variables named $Gov\_protection_{i,j,c}$ and $Gov\_Benefits_{i,j,c}$. These two variables capture how survey respondents i in industry j in country c view respectively the expected reactions of governments to the effect of technologies in the labor market. Two options are considered 'protection of existing forms of work' (gov_protection) or 'the regulation of new forms of benefits' (gov_benefits). These two variables take three values: negative (1), neutral (2), or positive (3). The vector of independent variables is the same as in equation (3) above.

Results in table 5 show that women and those workers who have suffered a job volatility are more positively associated with expecting government protection. These two characteristics are also important determinants of the attitude towards new benefits. Interestingly, older workers have a more negative view of the development of government protection and new benefits. While the survey does not additional information that can explain this association, this result could be consistent with older workers fearing the dismantling of existing benefits (like pensions) to redirect spending towards those new programs to compensate those affected for the technological change.

Table 4 – Reskilling and the Future of Work

Variables	reeducation	reeducation	reeducation	retraining	retraining
2.edu	0.282***	0.228**	0.274***	0.054	-0.011
	(0.090)	(0.090)	(0.090)	(0.093)	(0.093)
3.edu	0.283***	0.220***	0.275***	0.078	0.007
	(0.081)	(0.081)	(0.082)	(0.084)	(0.085)
4.edu	0.549***	0.451***	0.546***	0.221**	0.114
	(0.091)	(0.091)	(0.091)	(0.094)	(0.095)
2.age_group	0.002	0.015	-0.002	0.170**	0.182***
	(0.066)	(0.066)	(0.066)	(0.067)	(0.068)
3.age_group	0.103	0.158**	0.104	0.153**	0.204***
	(0.069)	(0.069)	(0.069)	(0.071)	(0.072)
4.age_group	0.053	0.148**	0.036	0.009	0.102
	(0.066)	(0.067)	(0.067)	(0.069)	(0.070)
2.income	0.016	-0.008	0.011	0.052	0.026
	(0.068)	(0.068)	(0.069)	(0.069)	(0.070)
3.income	0.139**	0.1	0.139**	0.193***	0.153**
	(0.071)	(0.071)	(0.071)	(0.072)	(0.073)
4.income	0.137*	0.077	0.138*	0.248***	0.178**
	(0.070)	(0.071)	(0.071)	(0.072)	(0.073)
5.income	0.145**	0.071	0.159**	0.297***	0.223***
	(0.071)	(0.071)	(0.071)	(0.074)	(0.075)
female	-0.05	-0.034	-0.05	0.091*	0.116**
	(0.046)	(0.046)	(0.046)	(0.047)	(0.048)
automation_pos		0.803***			0.882***
		(0.050)			(0.052)
2.job_happiness	0.214***	0.184***	0.202***	0.207***	0.163**
	(0.069)	(0.069)	(0.069)	(0.071)	(0.071)
3.job_happiness	0.362***	0.299***	0.306***	0.279***	0.208***
	(0.059)	(0.059)	(0.059)	(0.060)	(0.060)
2.job_volatility	-0.055	-0.058	-0.027	0.038	0.034
	(0.050)	(0.050)	(0.050)	(0.051)	(0.052)
3.job_volatility	-0.115	-0.094	-0.101	-0.205*	-0.18
	(0.105)	(0.108)	(0.106)	(0.109)	(0.111)
Observations	7,689	7,689	7,689	7,689	7,689
Country-Industry Dummies	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All
Estimation	Ologit	Ologit	Ologit	Ologit	Ologit

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

This table reports a set of regressions where ‘reskilling’ takes the form of two dependent variables named ‘reeducation’ or ‘retraining’. These two variables capture how survey respondents view respectively the changing workforce structure as ‘needing more formal education to find a job’ or ‘more-on-the job training require to keep up’. These two variables take three values: negative (1), neutral (2), or positive (3). In addition to the original specification, columns 2 and 4 include a dummy variable taking value 1 for those respondents that had a positive view of automation and takes value zero for those that have a neutral or negative view.

Table 5 – Government Policies and the Future of Work

Variables	gov_protection	gov_protection	gov_benefits	gov_benefits
2.edu	-0.044	-0.096	0.143	0.089
	(0.088)	(0.087)	(0.091)	(0.092)
3.edu	0.112	0.057	0.246***	0.189**
	(0.081)	(0.080)	(0.085)	(0.085)
4.edu	0.137	0.055	0.280***	0.185*
	(0.090)	(0.090)	(0.095)	(0.096)
2.age_group	-0.053	-0.037	-0.068	-0.057
	(0.068)	(0.068)	(0.069)	(0.069)
3.age_group	-0.092	-0.039	-0.171**	-0.120*
	(0.070)	(0.070)	(0.071)	(0.072)
4.age_group	-0.223***	-0.138**	-0.263***	-0.175**
	(0.067)	(0.068)	(0.069)	(0.070)
2.income	-0.035	-0.053	-0.124*	-0.148**
	(0.070)	(0.070)	(0.073)	(0.073)
3.income	0.003	-0.03	0.024	-0.009
	(0.069)	(0.069)	(0.073)	(0.074)
4.income	0.037	-0.026	0.082	0.016
	(0.071)	(0.071)	(0.074)	(0.074)
5.income	0.084	0.017	0.008	-0.068
	(0.072)	(0.072)	(0.075)	(0.076)
female	0.083*	0.102**	0.167***	0.190***
	(0.046)	(0.046)	(0.048)	(0.048)
automation_pos		0.753***		0.796***
		(0.050)		(0.052)
2.job_happiness	-0.061	-0.1	0.061	0.021
	(0.069)	(0.069)	(0.071)	(0.072)
3.job_happiness	0.028	-0.041	0.092	0.025
	(0.057)	(0.058)	(0.060)	(0.061)
2.job_volatility	0.171***	0.172***	0.104**	0.107**
	(0.050)	(0.050)	(0.051)	(0.052)
3.job_volatility	0.047	0.07	0.059	0.092
	(0.107)	(0.109)	(0.109)	(0.111)
Observations	7,689	7,689	7,689	7,689
Country-Industry Dummies	Yes	Yes	Yes	Yes
Sample	All	All	All	All
Estimation	Ologit	Ologit	Ologit	Ologit

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

This table reports a set of regressions where the dependent variables are 'government protection' or 'government benefits' - two variables that capture respectively how survey respondents view the changing role of government 'in protecting human employment from the effects of automation' or in 'providing new forms of benefits to regular workers'. These two variables take three values: negative (1), neutral (2), or positive (3). In addition to the original specification, columns 2 and 4 include a dummy variable taking value 1 for those respondents that had a positive view of automation and takes value zero for those that have a neutral or negative view.

VI. CONCLUSIONS

Using survey data obtained from 11,000 workers in advanced and emerging economies, we have performed an empirical analysis to understand how workers see ongoing technological change and the deployment of massive automation, robotization and artificial intelligence in the workplace. In general, workers feel more positive than negative about this transformation, although the positive attitude is more evident in emerging market than in advanced economies.

Our econometric exercises show that negative views about automation and artificial intelligence are prevalent among older, poorer workers, among those who have suffered recent job volatility and in countries with high robot penetration. At the same time, job satisfaction in the current position, higher levels of education (especially in emerging countries), and strong labor protection are associated with more positive views.

Most respondents are ready to prepare themselves for the future of work, and consider the government only partially responsible to help them navigate this process. At the same time, companies are expected to also play an important role (an expectation which is stronger among advanced economies' workers). The barriers than workers mention are lack of time and lack of financial resources. If both were available, a majority would decide to retraing in order to prepare for the future.

Finally, workers that have a positive perception of how automation will impact the workplace tend to respond positively about the need to reeducate and retrain to respond to rapidly evolving skill demands. These workers also expect governments to have a role in shaping the future of work through government protection and new forms of social benefits. Some of our results could have policy implications. Additional fiscal space could be needed to finance major reskilling programs and/or new social benefits. Even within existing budgets, because the demand for protection and new benefits is more significant among women and workers that have suffered job volatility, policymakers could consider better-targeting these groups when designing new programmes to cushion the effects of technological change.

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Annex:

Table A.1 – Automation and the Future of Work: Baseline, Odds Ratios

Variables	automation	automation	automation	automation	automation	automation
	Odds ratios	Odds ratios	Odds ratios	Odds ratios	Odds ratios	Odds ratios
2.edu	1.202**	1.191**	1.284***	1.181**	1.273***	1.261***
	(0.095)	(0.095)	(0.107)	(0.094)	(0.106)	(0.107)
3.edu	1.311***	1.312***	1.264***	1.302***	1.256***	1.250***
	(0.091)	(0.092)	(0.094)	(0.091)	(0.094)	(0.095)
4.edu	1.654***	1.619***	1.443***	1.591***	1.421***	1.420***
	(0.125)	(0.123)	(0.121)	(0.122)	(0.120)	(0.123)
2.age_group	0.0946	0.0926	0.949	0.928	0.950	0.952
	(0.059)	(0.058)	(0.060)	(0.059)	(0.061)	(0.061)
3.age_group	0.783***	0.760***	0.822***	0.764***	0.824***	0.830***
	(0.050)	(0.049)	(0.055)	(0.050)	(0.055)	(0.056)
4.age_group	0.690***	0.653***	0.783***	0.663***	0.788***	0.789***
	(0.040)	(0.040)	(0.051)	0.041	(0.051)	(0.052)
2.income	1.110	1.090	1.095	1.086	1.090	1.105
	(0.071)	(0.070)	(0.071)	(0.070)	(0.071)	(0.072)
3.income	1.128*	1.100	1.106	1.092	1.100	1.109
	(0.074)	(0.073)	(0.073)	(0.072)	(0.073)	(0.075)
4.income	1.263***	1.223***	1.238***	1.210***	1.227***	1.227***
	(0.084)	(0.082)	(0.083)	(0.082)	(0.083)	(0.084)
5.income	1.311***	1.245***	1.269***	1.227***	1.254***	1.247***
	(0.090)	(0.086)	(0.088)	(0.086)	(0.088)	(0.089)
female	0.929*	0.925*	0.948	0.932	0.946	0.951
	(0.040)	(0.040)	(0.041)	(0.041)	(0.042)	(0.043)
2.job_happiness		1.234***	1.202***	1.288***	1.199***	1.195***
		(0.080)	(0.079)	(0.080)	-0.079	(0.080)
3.job_happiness		1.511***	1.547***	1.508***	1.544***	1.550***
		(0.083)	(0.087)	(0.083)	(0.087)	(0.088)
2.job_volatility		0.923*	0.938	0.927	0.943	0.946
		(0.044)	(0.045)	(0.044)	(0.046)	(0.046)
3.job_volatility		0.815**	0.838*	0.826**	0.850*	0.858
		(0.076)	(0.079)	(0.078)	(0.080)	(0.083)
Observations	7,689	7,689	7,689	7,689	7,689	7689
Country Dummies	No	No	Yes	No	Yes	No
Industry Dummies	No	No	No	Yes	Yes	No
Country-Industry Dummies	No	No	No	No	No	Yes
Sample	All	All	All	All	All	All
Estimation	Ologit	Ologit	Ologit	Ologit	Ologit	Ologit

Standard errors in parenthese Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1 ***p<0.01, **p<0.05, *p<0.1

This table reports odds ratios from a set of regression where the dependent variable is automation - a variable that captures the perception of how survey respondents view the impact of new technologies on their own future, and takes the value negative (1), neutral (2), or positive (3).

Table A.2 – Automation and the Future of Work: Labor Market Characteristics, Averages

Variables	automation	automation	automation
2.edu	0.196**	0.166**	0.190**
	(0.080)	(0.080)	(0.080)
3.edu	0.266***	0.321***	0.311***
	(0.070)	(0.071)	(0.072)
4.edu	0.420***	0.500***	0.457***
	(0.077)	(0.077)	(0.078)
2.age_group	-0.066	-0.080	-0.070
	(0.063)	(0.063)	(0.063)
3.age_group	-0.248***	-0.268***	-0.251***
	(0.066)	(0.065)	(0.066)
4.age_group	-0.363***	-0.384***	-0.350***
	(0.062)	(0.062)	(0.063)
2.income	0.087	0.088	0.090
	(0.065)	(0.065)	(0.065)
3.income	0.093	0.096	0.098
	(0.066)	(0.066)	(0.067)
4.income	0.195***	0.198***	0.201***
	(0.067)	(0.068)	(0.068)
5.income	0.218***	0.210***	0.220***
	(0.070)	(0.070)	(0.070)
female	-0.061	-0.071	-0.063
	(0.044)	(0.044)	(0.044)
2.job_happiness	0.187***	0.175***	0.166**
	(0.065)	(0.065)	(0.065)
3.job_happiness	0.388***	0.391***	0.376***
	(0.055)	(0.055)	(0.055)
2.job_volatility	-0.077	-0.073	-0.074
	(0.048)	(0.048)	(0.048)
3.job_volatility	-0.185**	-0.193**	-0.188**
	(0.094)	(0.094)	(0.094)
rob16	-0.066***		-0.054***
	(0.014)		(0.015)
lri13		-0.438***	-0.351***
		(0.104)	(0.108)
Observations	7,689	7,689	7,689
Country Dummies	No	No	No
Industry Dummies	Yes	Yes	Yes
Country-Industry Dumm	No	No	No
Sample	All	All	All
Estimation	Ologit	Ologit	Ologit

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

This table reports a set of regression where the dependent variable is automation - a variable that captures the perception of how survey respondents view the impact of new technologies on their own future, and takes the value negative (1), neutral (2), or positive (3). In addition to the original specification, columns 1 and 2 include labor market characteristics (period averages) that proxy *degree of automation* and *degree of protection* in an economy individually. Column 3 jointly estimates them.