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Sustainable Employment in the Age of Digitalisation:

challenges, obstacles, and opportunities

CONTRAT N° B2/191/P3/SEAD

SEAD Working Paper 2024.02

The effects of the digital revolution on individuals' labor market outcomes

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THE EFFECTS OF THE DIGITAL REVOLUTION ON INDIVIDUALS' LABOR MARKET OUTCOMES

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1. Introduction

Technological changes restructure the economy in which the labor demand in some occupations is growing while it is declining in other occupations. The aim of this paper is to study the direct effects of these technological changes on individuals labor market outcomes in Belgium. Most of the studies on the effects of the digital revolution focus on automation. Yet, we agree that technological changes do not just replace human labor, it also complements workers and creates new jobs. Our objectives are thus to estimate the effects of both occupations growth, a measure that takes into account both the disappearance and the creation of jobs, and automation potential. Our individuals labor market outcomes are individuals' employment and unemployment probabilities, unemployment duration, health and income. For each of these outcomes measures, we perform four types of analysis: (1) a descriptive statistics analysis in which we examine how their means differ by occupations' growth and automation potential groups, (2) a linear regression analysis in which we estimate the direct effect of occupations growth and automation potential on each of these measures, (3) we study how the effects have evolved over time and (4) we study how the effects differ by gender, age and education. The European Labor Force Survey (EU-LFS) is used for our analyses and we focus on the period 2011-2021.

The general fear in the literature is that the digital revolution (e.g. big data analytics, web-enabled markets, the internet of things and machine learning) are threatening many jobs and occupations because of automation. Yet, economists and other scholars argue that various mechanisms compensate for labor-saving technologies: automation does not just substitute labor, it can also complement labor, raise employment in the design of new technologies and increase labor demand because of increasing productivity and falling product prices (Autor, 2014 & 2019; Vivarelli, 2015; DeCanio, 2016; Acemoglu & Restropo, 2018; Gregory et al. 2019). Indeed, as productivity increases with technological progress, the cost of production falls and prices are likely to fall (assuming product markets are competitive). If consumers respond to falling prices by consuming more, then more workers are needed both in the market experiencing technological changes but also in other markets when consumers decide to spend their extra income on other goods. The results is that technological changes restructure the economy where the labor demand in some occupations is growing while it is declining in other occupations (a detailed review of the literature is given in Deschacht (2021)). Theoretical and empirical studies explain that the occupations that are declining mainly represents occupations involving many routine tasks, since these tasks can more easily be automated, and those that are growing mainly represent occupations involving non-routine tasks. Because, routine tasks are particularly performed by middle-skilled and non-routine tasks by high-skilled and low-skill workers, technological changes lead to a decrease in the share of middle-skilled workers and to an increase in the shares of low- and high-skilled workers.

This restructuration of the economy has some consequences on the labor market. First, it could lead to increasing unemployment rate. Even if economists argue that technological changes do not reduce overall employment, there could still be structural unemployment when workers in the declining occupations who lose their jobs lack the necessary skills to find jobs in rising occupations. Unemployment may also arise when the returns firms make from the fall in production costs do not lead to a reduction of products prices or to the hiring of new workers (Economist, 2017; European Commission, 2019). Second, the digital revolution and occupational change create both opportunities and threats for the quality of jobs (Peña-Casas et al., 2018). On the one hand, technology replace workers in performing routine, repetitive and hard physical jobs so that job quality in that dimension could be expected to improve. On the other hand, the digital revolution has allowed for a better monitoring of workers by management, which may increase effort levels, the intensity of work and mental stress (Gallie, 2017). Finally, technological changes have some effects on income and inequalities. Since technology is routine-biased, new technologies leads to an increase in the demand for non-routine tasks who are located at the tails of the wage distribution and to a decrease in the demand for non-routine middle-wage jobs (Autor, Levy, & Murnane, 2003; Autor D. , 2014). This increases income inequalities since the wages of high-skilled rise as labor supply responds slowly to the increased demand in these jobs (Autor, 2014) while the wages of low-skilled jobs do not rise because it is relatively easy to enter these jobs. This results into wage polarization in which the wage premium of high-skilled relative to low-skilled workers increases.

This paper contributes to the literature in a number of ways. First, we propose a new measure of the digital revolution which is the occupations growth. Most of literature so far has focused on automation which only consider the substitution of jobs by new technologies and does not consider the creation of new jobs. We thus believe that studying the effects of occupations growth, which better characterize the digital revolution, can provide new lights on it actual effects on labor market outcomes. Second, we try to estimate the direct effect of these changes on labor outcomes which attempts to answer the question on whether technological changes actually affect individuals' labor market outcomes. It is important for policy makers to understand how workers are affected by technologies and which workers are affecting the most. …?

The rest of the chapter is organized as follows. The next two sections, respectively, present our methods and data. In Section 4, the results of our different estimation analyses are given and Section 5 contains a conclusion.

2. Methods

The aim of the paper is to study the effects of the digital revolution on individual labor market outcomes. In order to do so, we perform the following linear model

$$Y = \beta_0 + \beta_1 \mathrm{DR} + \beta_2' X' + \varepsilon$$

where our dependent variable Y represents our 5 different measures for individuals' labor market outcomes: employment, unemployment, unemployment duration (in months), non-employment because of health problems and income deciles.

As explained before, the digital revolution introduces changes in the structure of the economy where the labor demand is growing in some occupations and declining in others. Our independent variables on the measures of the digital revolution, DR, thus include a dummy for growing occupations (ISCO groups 21 to 26 and 31, 33, 34 and 53) vs declining occupations (ISCO groups 72 to 75), occupations growth rates and the automation potential of occupations. The growing/declining occupations and the occupations growth rate were calculated based on a previous analysis of the Belgian Labor force survey (Deschacht & Detilleux, 2022). In this study, we ranked occupations based on changes in the absolute number of workers in each of these occupation between 1986 and 2020. The 10 occupations with the biggest positive changes represent the growing occupations and the 4 occupations with the biggest negative changes the declining occupations. To obtain the occupations growth rates we took the log of the ratio between the absolute number of workers in each occupations in 2020 and the one in 1986. This variable thus represent the percentage change in the number of workers between 1986 and 2020. We obtained the occupations potential from the study of Schaffters (2019) who, building on the work of Frey and Osborne (2017) and applying a novel class probability estimation model to (principally) the O*NET data, determined the probability of a certain occupation to be automatable, i.e. the automation potential. Note that, all these three measures were constructed based on the individuals' occupations measured on the ISCO-08 classification and represent the current occupations for the employed individuals and the previous occupations for the non-employed.

For each combination between our dependent and the independent variables, we run two models: one without control variables (X') and one with the control variables sex, age, Belgian and education. Information on the construction and definition of the dependent, independent and control variables are given in Appendix A.

We perform two separate additional analyses to investigate how the effect β_1 evolve over time and how it differs by gender, age and education. In the first analysis, we run the above regression models separately for each year and present the results in a figure. This allows us to check whether the effects of our measures for the digital revolution on individuals labor market outcomes have remained constant over time or not. In the second analysis, we perform interaction analyses in which the independent variable for growing occupations is interacted with gender, age and education. These interactions allow us to study whether the effects differ in these groups.

3. Data

The European Labor Force Survey (EU-LFS), that we obtained from Eurostat, is used in this report. The EU-LFS covers many different European countries over the period from 1983 to 2021, but we focus on Belgium and we restrict the analysis to the period from 2011 on because of the break in the ISCO classification from the ISCO-88 to the ISCO-08 in that year. The sample consists of employed, unemployed and non-employed Belgian individuals aged 21 to 65. Note that, the sample is further restricted to the employed and unemployed individuals for the analyses on unemployment, to the unemployed individuals for the analyses on unemployment duration and to the employed individuals for the analyses on income deciles.

Table 1 presents the descriptive statistics. The results for our dependent variables on individuals labor market outcomes show that 66 percent of individuals in our sample are employed while about 6 percent of them are non-employed because of health problems. Among the sample of employed and unemployed individuals, there is about 8 percent of unemployed and their mean unemployment duration is about 26 months long. The mean income deciles for the employed individuals is rightly at around 5.5. Unfortunately, the exact monthly income is not given in the EU-LFS, only the income deciles which is measured on a scale from 1 to 10 representing the different deciles.

For the independent variables, we find that around 85 percent of the individuals are or were previously in growing occupations (ISCO groups 21 to 26 and 31, 33, 34 and 53) compared to 15 percent in declining occupations (ISCO groups 72 to 75). The maximum growth rate is 1.845 meaning that the number of workers in that occupation has more than doubled between 1986 and 2020. The mean automation potential is 0.52 which means that on average, the occupations of workers have a probability to be automatized in the future of 0.5.

The results for the control variables indicate that 51 percent of individuals in our sample are women, that the average age is approximately 44 and that 88 percent are citizen of Belgium. Finally, we find that more than 70 percent of individuals in our sample have at least an upper secondary education.

Table 1: Descriptive statistics of main variables

		N	Mean	SD	Min	Max
Dependent variables						
Employed		478,710	0.66	0.47	0	1
Unemployed		342,727	0.08	0.26	0	1
Unemployment duration (in months)		18,667	25.89	29.18	0	120
Not-employed because of health problems		478,710	0.06	0.24	0	1
Income (deciles)		259,281	5.64	2.87	1	10
Independent variables						
Growing occupations		165,749	0.85	0.35	0	1
Occupations growth rate		385,554	0.43	0.51	-0.731	1.845
Automation potential		385,474	0.52	0.33	0.006	0.987
Controls						
Female		478,710	0.51	0.50	0	1
Age (in years)		478,710	43.85	12.75	21	65
Belgian		477,786	0.88	0.32	0	1
Education:	Early childhood education	478,710	0.04	0.19	0	1
	Primary education	478,710	0.06	0.24	0	1
	Lower secondary education	478,710	0.16	0.37	0	1
	Upper secondary education	478,710	0.36	0.48	0	1
	Post-secondary non-tertiary education	478,710	0.02	0.14	0	1
	Tertiary education	478,710	0.36	0.48	0	1

Note: The sample consists of individuals from Belgium between 2011 and 2021 (pooled data). The independent variables are constructed from the occupations of the individuals which represent the current ISCO08 (2 digits) occupations for the employed and previous ISCO08 (2 digits) occupations for the not-employed. Appendix A gives an explanation on the construction of the variables.

4. Results

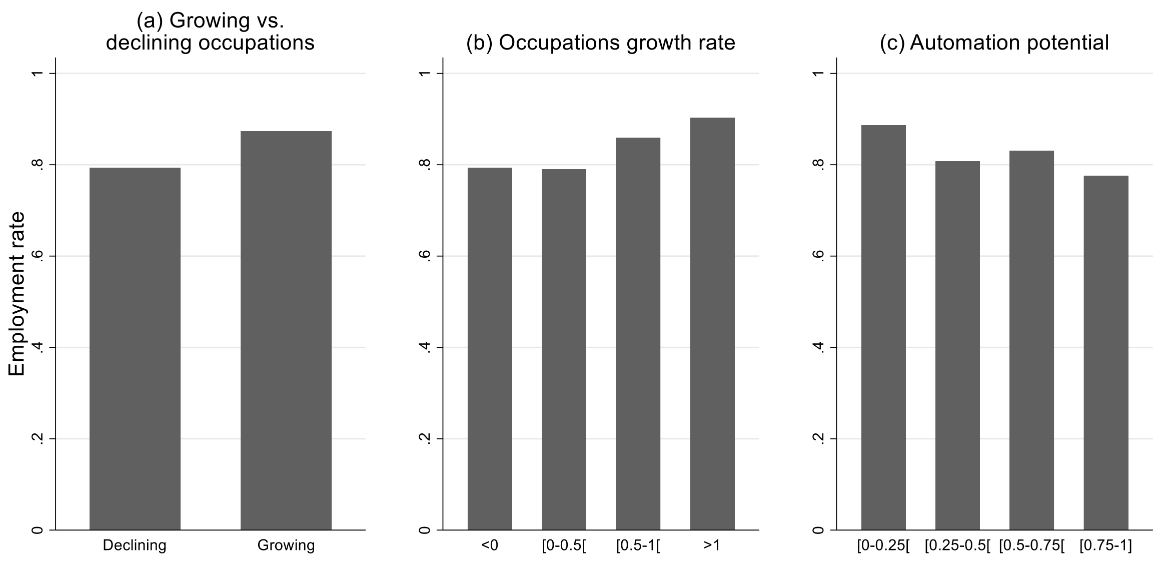
In the 5 following sections, we present the results on the effects of our measures for the digital revolution on the 5 different individuals labor outcomes measures that we have selected, each section representing one dependent variable. All sections have the same structure: we first present the mean of our dependent variable breaking down by occupations growth and automation potential groups, next, the results of our regression model (1) are presented and, finally, we perform our two additional analyses on how the effects evolve over time or differ by sex, age and education.

4.1. Employment probability

In this section, we are interested in the effects of our digital revolution measures on workers probability of being employed. The full sample is thus considered in this section and the variable of interest is a dummy indicating whether the individual is employed vs not-employed.

In Figure 1, we present the employment probabilities by growth and automation potential of occupations. In the first figure, the mean employment probabilities of individuals currently or previously in growing (ISCO groups 21 to 25 and 31, 33, 34 and 53) and declining occupations (ISCO groups 72 to 75) are given. The results show that the mean probability is larger in the former group at around 85 percent compared to 79 percent in the latter group. Next, we give the employment rate separately by 4 occupations growth rate groups. These groups represent occupations with a growth rate that is below 0, between 0 and 0.5, between 0.5 and 1 and above 1. That is, the first group represents occupations that have declined over the past 30 years while group 4 represents occupations that have more than doubled over the same period. We find that the employment probability is larger in occupations that have grown more rapidly over the past three decades. The last figure present the employment probability in the 4 automation potential groups which represent 0.25 point intervals and the results show that the employment probability is larger in occupations with lower automation potential.

Figure 1: Employment rates by growth and automation potential of occupations



Note: Belgian population aged 21-65 for the period 2011-2021 (pooled data). N=165,749 for (a), N=385,554 for (b) and N=385,474 for (c).

For the list of growing and declining occupations in (a), see the main text.

Table 2 presents the results of the linear probability model (1) with the dummy for employment as dependent variable. The estimated effects of our three measures of the digital revolution, growing vs. declining occupations, occupations growth rates and occupations potential, are given separately.

All estimated coefficients have the expecting size in the sense that workers' probability to be employed today is higher when the workers are currently or were previously in growing occupations, in occupations with larger growth rate or in occupations with low automation potential. Particularly, we find that compared to individuals in declining occupations, those in growing occupations are 8 percent point more likely to be employed today (based on the model without controls). The estimate for the occupations growth rates suggests that when the number of workers in an occupation increases by 1 percent point, the probability of being employed of workers in this occupation increases by 7.5 percent point. Finally, we find that individuals in occupations with zero automation potential (those with no risk at all to be automated) have a predicted probability of being employed 12.8 percent point above the one of those in occupations with 100% automation potential (those completely at risk of being automated). The results are similar in the models with control variables where the estimated coefficients have the same sign and are again significantly different from zero, yet, they are smaller in absolute terms. All in all, our results suggest that workers in occupations that are more directly affected by technological changes (in the sense that the labor demand in these occupation is declining or that jobs in these occupations have high probability of being automated in the future) are less likely to be in employment.

Table 2: Effects of occupation growth and automation potential on the Pr. to be employed

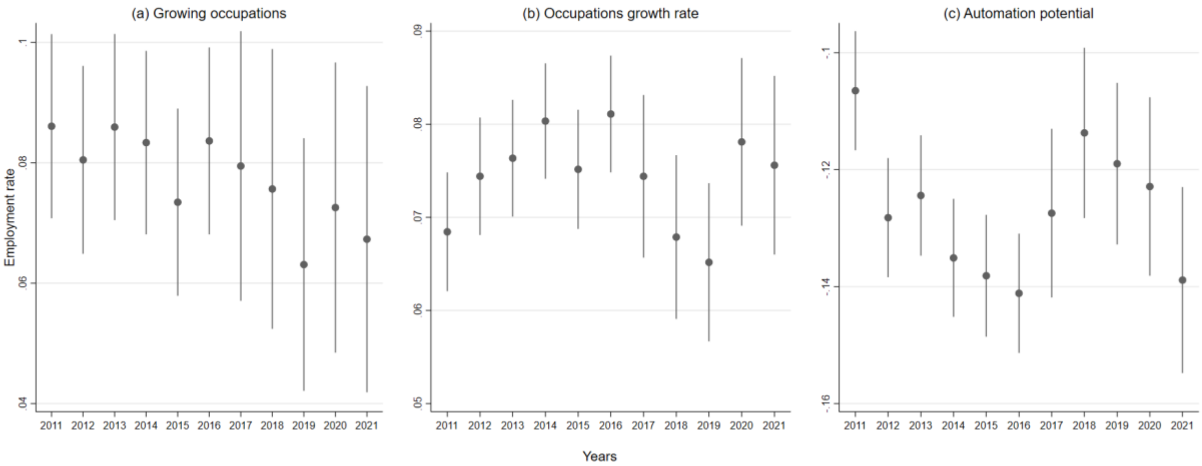
		Models	
		(1)	(2)
Growing occupations	Coeff	0.080***	0.028***
	(SE)	(0.003)	(0.003)
	N	165,749	165,627
Occupations growth rate	Coeff	0.075***	0.027***
	(SE)	(0.001)	(0.001)
	N	385,554	385,032
Automation potential	Coeff	-0.128***	-0.057***
	(SE)	(0.002)	(0.002)
	N	385,474	384,953
Controls (sex, age, Belgian and education)		No	Yes

Note: The dependent variable is a dummy variable indicating employment. Linear probability models with tests based on robust standard errors.

*** $p<0.01$; ** $p<0.05$ and * $p<0.1$

In Figure 2, we present our results on the changes in the estimated coefficients over time. In each of the three sub-figures, the horizontal axis gives the years and the vertical axis the values of the estimated coefficients. The estimates are obtained from the model without control variables. Similarly to the results in the above Table, we find that the effects of the dummy for growing occupations and of occupations growth rates on the probability to be employed are positive while the effects of the automation potential of occupations are negative and this is true in all years. Yet, we can see that the effects of growing occupations in (a) get closer to zero over time. Note that, this pattern disappears when the variable education is added as control in the models. There are also some variations in the effects of the occupations growth rates and automation potential over time, but we do not find any clear pattern.

Figure 2: Effects of occupation growth and potential automation on the Pr. to be employed, over time



In Table 3 we present the results of our interactions analyses. The estimates in the table explain how the effect of the dummy variable for growing occupations differ by sex, age and education. We find significant gender differences in the effect with women benefiting more than men. Indeed, we find in column (1) that women in growing occupations have predicted probability to be employed 3.4 percentage point higher than the one of men in growing occupations. We also find significant age differences with the effects of growing occupations on employment probability increasing with age. Finally, column (3) show that the effects of being in a growing occupations on the Pr. to be employed do not vary significantly between individuals with less than secondary education, but the effect is significantly lower for individuals with a secondary education or more. The results are very similar in the last column where all interactions are included in the model. Overall, our results suggest the effect of being in a growing occupations is stronger for women, old and low educated workers.

Table 3: Differences in the effect of being in a growing occupation on employment by sex, age and education

	Models			
	(1)	(2)	(3)	(4)
Growing occupations	0.024***	-0.094***	0.082**	-0.041
	(0.003)	(0.010)	(0.033)	(0.034)
Growing occupations * Female	0.034***			0.033***
	(0.009)			(0.009)
Growing occupations * Age		0.003***		0.003***
		(0.000)		(0.000)
Growing occupations * Early childhood education (ref. group)				
Growing occupations * Primary education			0.025	0.015
			(0.037)	(0.037)
Growing occupations * Lower secondary education			-0.020	-0.022
			(0.033)	(0.033)
Growing occupations * Upper secondary education			-0.063*	-0.051
			(0.033)	(0.033)
Growing occupations * Post-secondary non-tertiary education			-0.100***	-0.077**
			(0.034)	(0.034)
Growing occupations * Tertiary education			-0.070**	-0.059*
			(0.033)	(0.033)
Controls (sex, age, Belgian and education)	Yes	Yes	Yes	Yes
Years and months fixed effects	Yes	Yes	Yes	Yes
Number of observations	165,627	165,627	165,627	165,627

Note: Growing occupations is a dummy variable distinguishing growing occupations from declining occupations (see the main text for details).

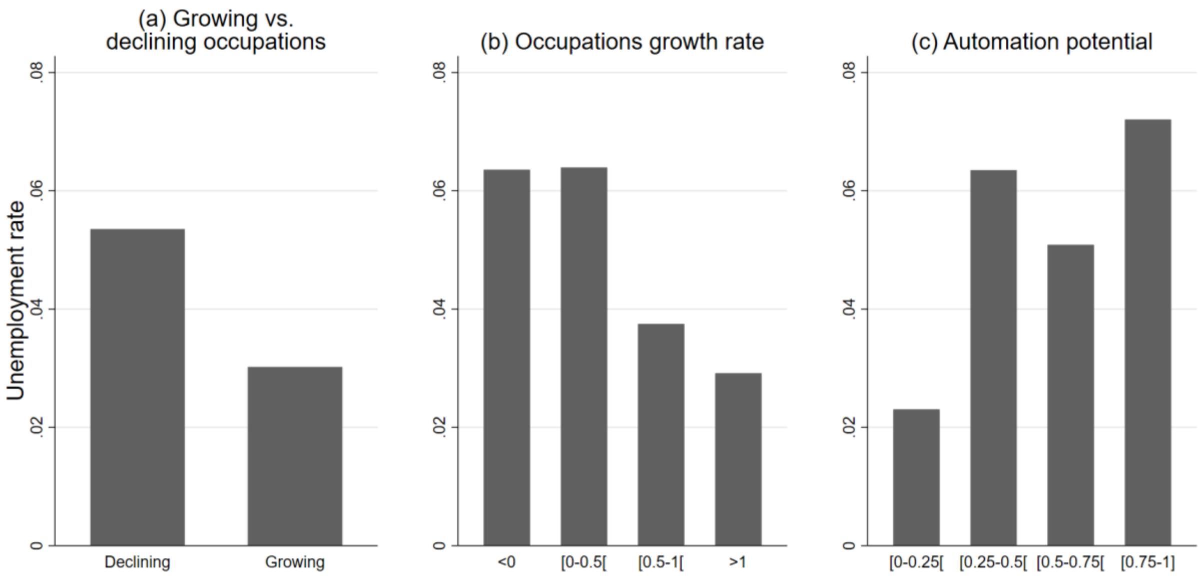
*** $p<0.01$; ** $p<0.05$ and * $p<0.1$

4.2. Effect on the probability of being unemployed

We now consider the effect of occupations growth and automation potential on the probability to be unemployed. The dependent in this section is a dummy variable that takes the value 1 when the individual is unemployed and 0 when the individual is employed.

In Figure 3, we present the mean unemployment probabilities by growing occupations, occupations growth rate and automation potential groups. The results in Figure (a) show that the unemployment probability is larger in declining occupations (at around 5.4 percent) than in growing occupations (at 3 percent). For occupations growth rate, we see that the mean unemployment is above 6 percent in occupations with growth rates below 0.5 while it is below 4 percent in occupations with growth rates above 0.5. The last sub-figure shows that the mean unemployment probability is at the highest (at 7.2 percent) in occupations with automation potential between 0.75 and 1 and at the lowest (at 2.3 percent) in occupations with automation potential below 0.25.

Figure 3: Unemployment rates by growth and automation potential of occupations



Note: Belgian population aged 21-65 for the period 2011-2021 (pooled data). N=147,738 for (a); N=334,596 for (b) and N=334,539 for (c). For the list of growing and declining occupations in (a), see the main text.

Table 4 presents the estimated effects of growing occupations, occupations growth rate and automation potential on the probability to be unemployed. The estimates for growing occupations suggest that individuals in growing occupations are, respectively in the model with and without controls, 2.3 or 0.5 percent point less likely to be unemployed compared to individuals in declining occupations. The estimates for occupations growth rate are similar with individuals in occupations experiencing larger positive growth rate being less likely to be unemployed. Particularly, we find that when the number of workers in an occupation increases by 1 percent point, the probability to be unemployed of individuals in this occupation decreases by 2.5 or 0.5 percent points, respectively in the model without and with controls. For automation potential, we find that a one percent point increase in the automation potential probability of occupations leads to a 0.054 or 0.028 point increase in the probability to be unemployed for the individuals in these occupations, again depending on whether we consider the model without or with controls.

Table 4: Effects of occupation growth and automation potential on the Pr. to be unemployed

		Models	
		(1)	(2)
Growing occupations	Coeff	-0.023***	-0.005**
	(SE)	(0.002)	(0.002)
	N	147,738	147,649
Occupations growth rate	Coeff	-0.025***	-0.007**
	(SE)	(0.001)	(0.001)
	N	334,596	334,177
Automation potential	Coeff	0.054***	0.028**
	(SE)	(0.001)	(0.001)
	N	334,539	334,121
Controls (sex, age, Belgian and education)		No	Yes

Note: The dependent variable is a dummy variable indicating unemployment. Linear probability models with tests based on robust standard errors.

*** p<0.01; ** p<0.05 and * p<0.1

The results on the evolution of the effects (calculated in the model without controls) over time are displayed in Figure 4. Again and in all years, we find negative estimates on the effects of growing occupations and occupations growth rate on the probability of being unemployed while those on the effects of the occupations automation potential are positive. The first two sub-figures on the effects of occupations growth show that the estimates are getting closer to zero over time, the effect of the dummy variable for growing occupations is not even longer significantly different from zero in 2021. There is no clear pattern for the estimated effects of the occupations automation potential since we find that it has become larger between 2011 and 2015, then decreased between 2015 and 2018 and stay approximately constant at around 0.045 between 2018 and 2021.

Figure 4: Effects of occupation growth and automation potential on the Pr. to be unemployed, over time

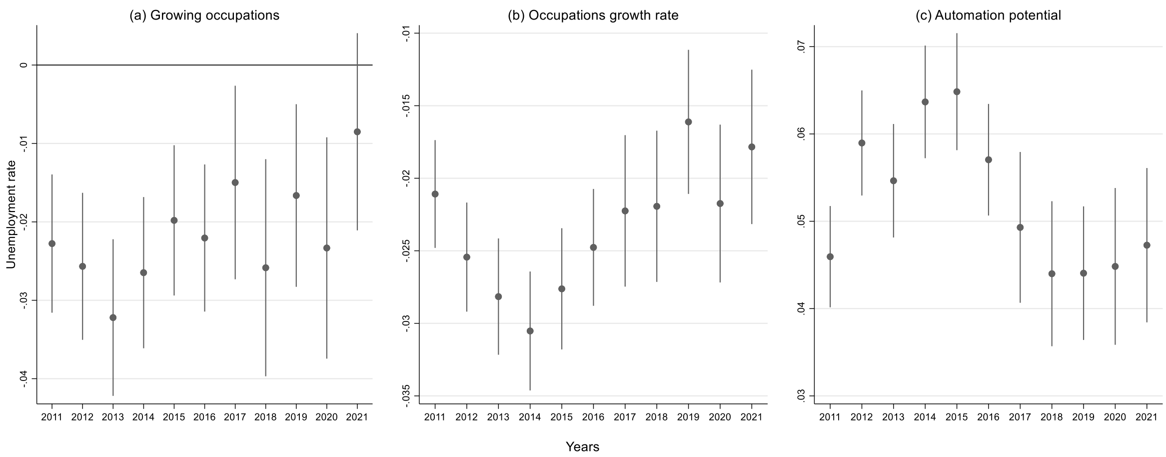


Table 5 presents the results on the interaction between the dummy variable for growing occupations and sex, age and education. The results indicate that there are again significant gender and age differences in the effects, but we do not find significant differences by education (column 3). The effect of the dummy for growing occupations on unemployment is larger in absolute terms for women compared to men and for young individuals. Both female and young individuals are less likely to be unemployed if they are in a growing occupations compared to male and older individuals. The effect is also larger in absolute terms individuals with at most early childhood education but the differences with higher education groups are not significant. Very similar results are found when all interactions are included in the model (column 4).

Table 5: Differences in the effect of being in a growing occupation on unemployment by sex, age and education

	Models			
	(1)	(2)	(3)	(4)
Growing occupations	-0.003	-0.039***	-0.030	-0.069***
	(0.002)	(0.007)	(0.025)	(0.027)
Growing occupations * Female	-0.013**			-0.013**
	(0.006)			(0.006)
Growing occupations * Age		0.001***		0.001***
		(0.000)		(0.000)
Growing occupations * Early childhood education (ref. group)				
Growing occupations * Primary education			0.021	0.019
			(0.029)	(0.017)
Growing occupations * Lower secondary education			0.022	0.019
			(0.026)	(0.029)
Growing occupations * Upper secondary education			0.029	0.021
			(0.025)	(0.026)
Growing occupations * Post-secondary non-tertiary education			0.033	0.032
			(0.026)	(0.025)
Growing occupations * Tertiary education			0.020	0.038
			(0.026)	(0.026)
Controls (sex, age, Belgian and education)	Yes	Yes	Yes	Yes
Years and months fixed effects	Yes	Yes	Yes	Yes
Number of observations	147,649	147,649	147,649	147,649

Note: Growing occupations is a dummy variable distinguishing growing occupations from declining occupations (see the main text for details).

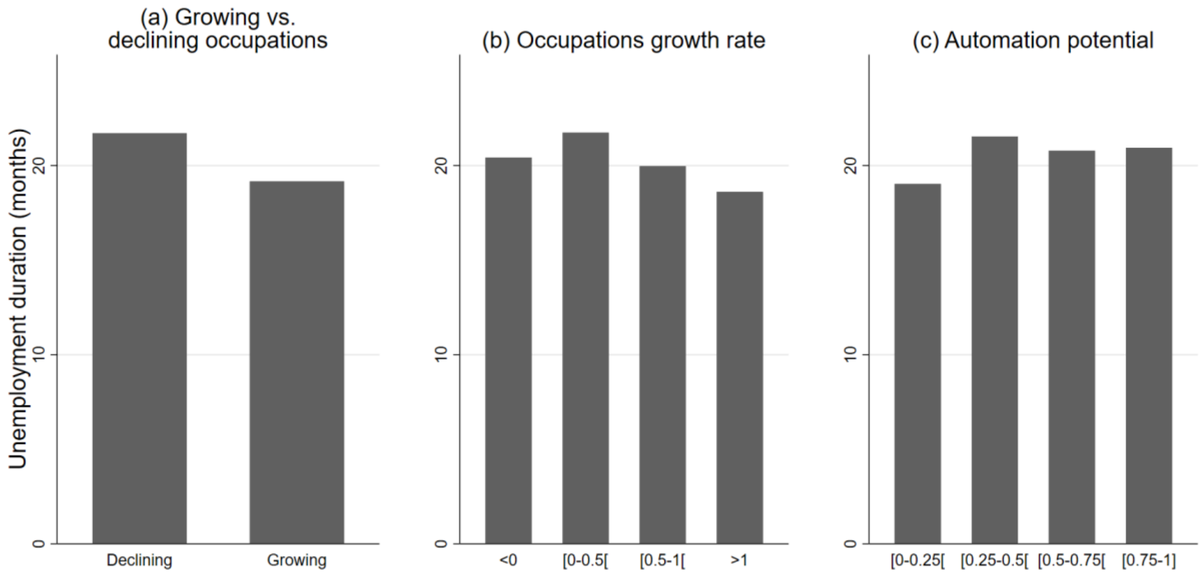
*** $p<0.01$; ** $p<0.05$ and * $p<0.1$

4.3. Effect on the unemployment duration among the unemployed

In this section, we analyze the effects of occupations' growth and automation potential on unemployment duration measured in months. This variable is only defined for the unemployed individuals. Note that because we focus on the unemployed sample, our independent variables are measured based on their previous occupations; their occupation before moving to unemployment.

Figure 5 presents the mean unemployment duration within occupations growth and automation potential groups. The mean differences between groups are less striking than in the two sections above. Still, we find that the mean unemployment duration is higher, at around 22 months, for unemployed individuals previously in a declining occupation compared to the one of those previously in a growing occupation, at around 19 months. Similar results are found for the occupations growth rate groups with unemployed individuals in occupations that have more than doubled over the past 30 years having lower mean unemployment duration compared to individuals in other growth rate groups. For differences by automation potential groups, there is a clear difference in the mean unemployment duration between unemployed individuals in occupations with automation potential below 0,25 and those in occupations with automation potential above 0,25. The mean unemployment duration is approximatively the same at around 21 months in all automation potential groups above 0,25.

Figure 5: Unemployment duration (in months) by growth and automation potential of occupations



Note: Belgian population aged 21-65 for the period 2011-2021 (pooled data). N=4,936 for (a); N=17,575 for (b) and N=17,567 for (c).
For the list of growing and declining occupations in (a), see the main text.

Table 6 presents the results of the linear model (1) where the dependent variable is the unemployment duration. The first estimate explains that the predicted unemployment duration is 2.5 months lower for the unemployed individuals that were previously in growing occupations compared to the unemployed individuals that were in declining occupations (in the model without control variables). The effect is also negative in the model with control variables but it is no longer significantly different from zero. The occupations growth rate also has a negative effect on the unemployment duration: we find that when the number of workers in an occupation in which unemployed individuals were previously increases by 1 percent point, their predicted unemployment duration increases by about 1 month. Again, the effect is not significantly different from zero in the model with control variables. The last estimated coefficient in the models without control variables indicates that unemployed individuals previously in occupations that had an 100% change of being automatized are in unemployment for about 2 months more compared to unemployed individuals previously in occupations with 0 chances of being automatized. The corresponding estimate in the model without control variables is around 1 month, but the effect is not significantly different from zero.

Table 6: Effects of occupation growth and automation potential on unemployment duration

		Models	
		(1)	(2)
Growing occupations	Coeff	-2.543***	-1.337
	(SE)	(0.744)	(0.856)
	N	4,936	4,916
Occupations growth rate	Coeff	-1.137***	-0.572
	(SE)	(0.351)	(0.369)
	N	17,575	17,472
Automation potential	Coeff	1.819***	1.470
	(SE)	(0.562)	(0.584)
	N	17,567	17,465
Controls (sex, age, Belgian and education)		No	Yes

Note: The dependent variable is unemployment duration measured in months. Linear models with tests based on robust standard errors.

*** p<0.01; ** p<0.05 and * p<0.1

The results on the evolution of the estimated effects of occupations growth and automation potential are presented in Figure 6. We obtained these estimates by regressing the models without control variables separately in each year between 2011 and 2021. Almost all estimates have the expected sign with growing occupations and occupations growth rate having negative effects on unemployment duration and occupations potential having positive effects. Yet, almost none of the estimated coefficients are significantly different from zero. There are also no clear changes in the estimated effects over time in this section.

Figure 6: Effects of occupation growth and automation potential on unemployment duration, over time

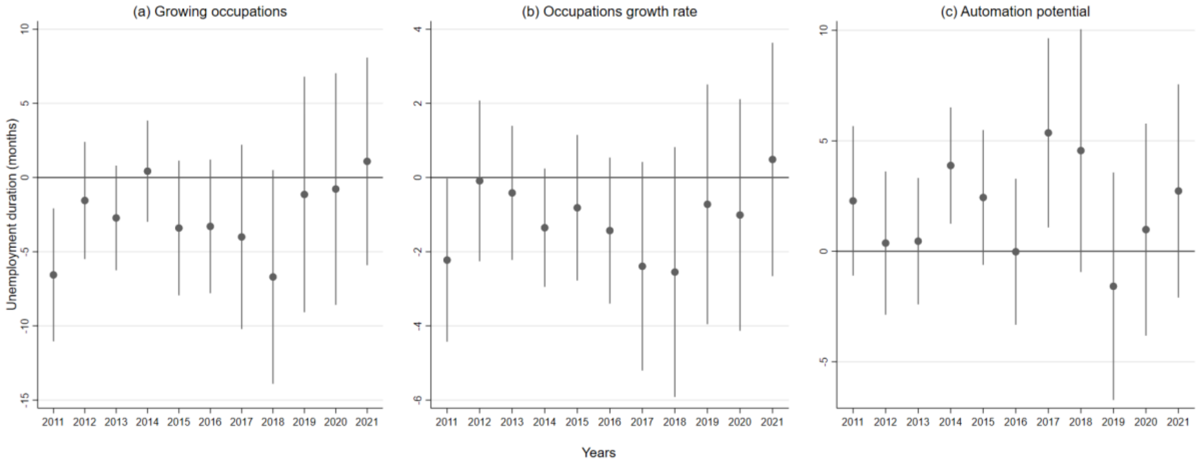


Table 7 shows how the effects of growing occupations on the unemployment duration differ by sex, age and education. Differently than before, we find significant differences by education but the effects do not significantly differ by gender and age. Indeed, while we again find that the effects are larger in absolute terms for women and younger individuals, the differences are not significant. The effect of the dummy for growing occupations is yet significantly larger for individuals with lower education levels. Our estimates suggest that the predicted unemployment duration for individuals previously in growing occupation and with a tertiary education is about 13 months lower compared to those with none or early childhood education. We can make similar conclusions for the comparisons with individuals having upper secondary education or post-secondary education.

Table 7: Differences in the effect of being in a growing occupation on unemployment duration by sex, age and education

	Models			
	(1)	(2)	(3)	(4)
Growing occupations	-0.966	-4.744*	9.960**	6.757
	(0.895)	(2.579)	(4.997)	(5.546)
Growing occupations * Female	-2.270			-2.269
	(2.062)			(2.203)
Growing occupations * Age		0.087		0.093
		(0.062)		(0.063)
Growing occupations * Early childhood education (ref. group)				
Growing occupations * Primary education			-11.134*	-11.563*
			(5.965)	(6.276)
Growing occupations * Lower secondary education			-10.089*	-10.189*
			(5.237)	(5.246)
Growing occupations * Upper secondary education			-12.418**	-12.413**
			(5.105)	(5.096)
Growing occupations * Post-secondary non-tertiary education			-6.038	-5.911
			(6.283)	(6.045)
Growing occupations * Tertiary education			-13.115**	-13.346**
			(5.492)	(5.592)
Controls (sex, age, Belgian and education)	Yes	Yes	Yes	Yes
Years and months fixed effects	Yes	Yes	Yes	Yes
Number of observations	4,916	4,916	4,916	4,916

Note: Growing occupations is a dummy variable distinguishing growing occupations from declining occupations (see the main text for details).

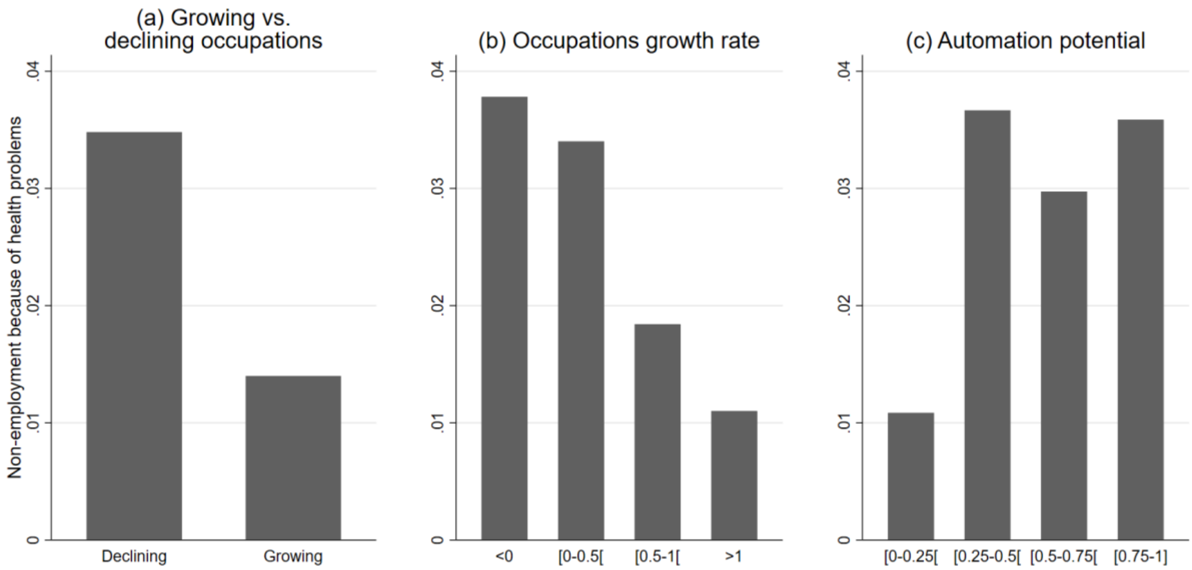
*** p<0.01; ** p<0.05 and * p<0.1

4.4. Effect on the probability to be not employed because of health problems

This section presents the results on the effects of our digital revolution measures on the dummy variable for non-employment because of health problems. This variable is defined for all employed and non-employed individuals and takes the value 1 when the individual reported being not-employed because of health problems and the value 0 otherwise.

Figure 7 presents the means of this measure by occupations growth and automation potential groups. We find that only 1.4 percent of individuals in growing occupations reported being non-employed because of health issues while 3.5 percent of individuals in declining occupations reported the same. The results are similar in the sub-figure (b) where the non-employment rate because of health problems is less than 2 percent in occupations with growth rates above 0.5 while it is more than 3 percent in occupations that have declined or grown slower over the past three decades. Concerning the results by automation potential groups, we find a clear difference between the percentage of individuals being unable to work due to health in occupations with automation potential below 0.25 and the one of individuals in occupations with automation potential above 0.25. While about 1 percent of individuals in the former occupations are unable to work due to health issues, 3 to 4 percent of individuals in the latter occupations are unable to work due to health issues. The results thus suggest that workers in occupations that are more strongly affected by the digital revolution (in the sense that the labor demand for their jobs has decreased or that their jobs are more at risk to be automated) have much higher chances to be unable to work today because of health problems.

Figure 7: Non-employment because of health problems by growth and automation potential of occupations



Note: Belgian population aged 21-65 for the period 2011-2021 (pooled data). N=22,947 for (a); N=68,535 for (b) and N=68,504 for (c). For the list of growing and declining occupations in (a), see the main text.

Table 8 presents the results of the linear probability model (1) with as dependent variable the dummy for non-employment because of health problems. Similarly to the results in Figure 7, the estimates in the table suggest that individuals in occupations that are in growing occupations or in occupations at high automation potential are more likely to be unable to work today because of health problems. Indeed, we find that compared to individuals currently or previously in declining occupations, individuals in growing occupations are 2.1 or 1.1 percent points, depending on whether or not the control variables are included in the model, less likely to be non-employed because of health issues. Similar results are found for the occupations growth rates where individuals in occupations with larger positive growth rates having lower probability to be non-employed because of health problems. Finally, we find that a one percent point increase in our occupational automation potential measure increases the individuals' probability of being unable to work due to health issues by 0.03 or 0.01 point, respectively in the model without and with control variables.

Table 8: Effects of occupation growth and automation potential on the Pr. to be not-employed because of health problems

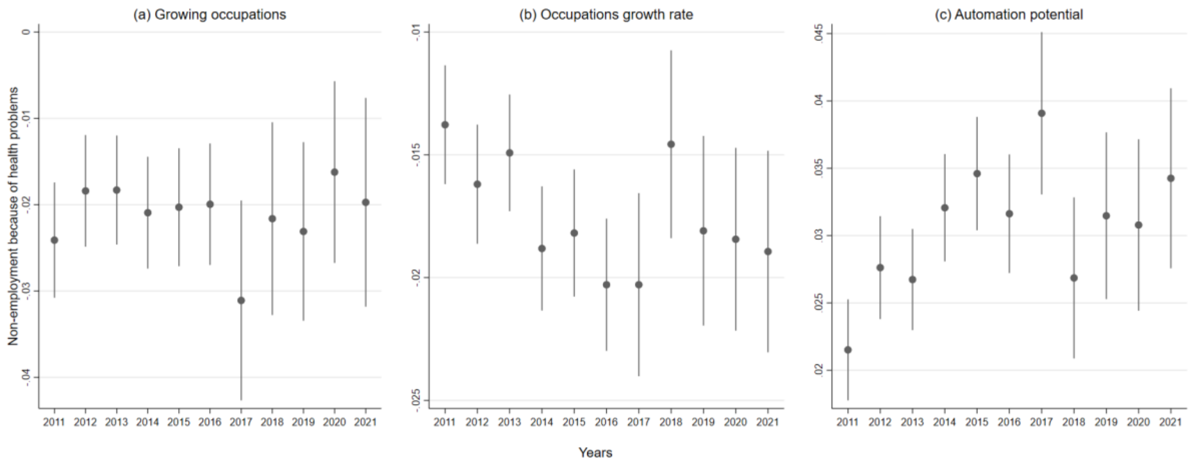
		Models	
		(1)	(2)
Growing occupations	Coeff	-0.021***	-0.011***
	(SE)	(0.001)	(0.001)
	N	165,749	165,627
Occupations growth rate	Coeff	-0.017***	-0.005***
	(SE)	(0.000)	(0.000)
	N	385,554	385,032
Automation potential	Coeff	0.030***	0.010***
	(SE)	(0.001)	(0.001)
	N	385,474	384,953
Controls (sex, age, Belgian and education)		No	Yes

Note: The dependent variable is a dummy variable indicating non-employed because of health problems. Linear probability models with tests based on robust standard errors.

*** p<0.01; ** p<0.05 and * p<0.1

Contrary to the previous results for which we did not find any clear pattern on the effects of automation potential over time, Figure 8 suggest that their effects on the probability to be not-employed due to health problems have become bigger over the period from 2011 to 2021. Particularly, we find that the effects grow from about 0.02 to 0.04 between 2011 and 2017 then drop to 0.027 in 2018 and grow again after 2018. Similar results are found for the effects of the occupations growth rate: the effects have become stronger between 2011 and 2017 before dropping closer to zero in 2018 and increasing again, in absolute terms, after 2018. No clear changes are observed on the effects of the dummy growing occupations which stay relatively constant over time at approximately -0.02 except in 2017 where the effects drops to -0.03.

Figure 8: Effects of occupation growth and automation potential on the Pr. to be not-employed because of health problems over time



We now investigate how the effects differ by gender, age and education (Table 9). While we find no significant differences by gender and education, we find that being in a growing occupations contribute more to older individuals. Indeed, the results in column (2) suggest that, at the mean age (44), the estimated effect of the dummy variable for growing occupations is -0.022 (0.022-0.001*44). That is, individuals aged 44 years old in growing occupations are 2.2 points less likely to be non-employed because of health problems than individuals aged 44 years olds in declining occupations. The corresponding image for individuals aged 50 years old is 2.8 points while it is only 0.008 points for individuals aged 30 years old.

Table 9: Differences in the effect of being in a growing occupation on the Pr. to be non-employed because of health problems by sex, age and education

	Models			
	(1)	(2)	(3)	(4)
Growing occupations	-0.010***	0.022***	-0.015	0.019
	(0.001)	(0.004)	(0.018)	(0.018)
Growing occupations * Female	-0.004			-0.004
	(0.005)			(0.005)
Growing occupations * Age		-0.001***		-0.001***
		(0.000)		(0.000)
Growing occupations * Early childhood education (ref. group)				
Growing occupations * Primary education			-0.005	-0.002
			(0.020)	(0.020)
Growing occupations * Lower secondary education			-0.006	-0.005
			(0.018)	(0.018)
Growing occupations * Upper secondary education			0.005	0.002
			(0.018)	(0.018)
Growing occupations * Post-secondary non-tertiary education			0.015	0.009
			(0.018)	(0.018)
Growing occupations * Tertiary education			0.009	0.006
			(0.018)	(0.018)
Controls (sex, age, Belgian and education)	Yes	Yes	Yes	Yes
Years and months fixed effects	Yes	Yes	Yes	Yes
Number of observations	165,627	165,627	165,627	165,627

Note: Growing occupations is a dummy variable distinguishing growing occupations from declining occupations (see the main text for details).

*** p<0.01; ** p<0.05 and * p<0.1

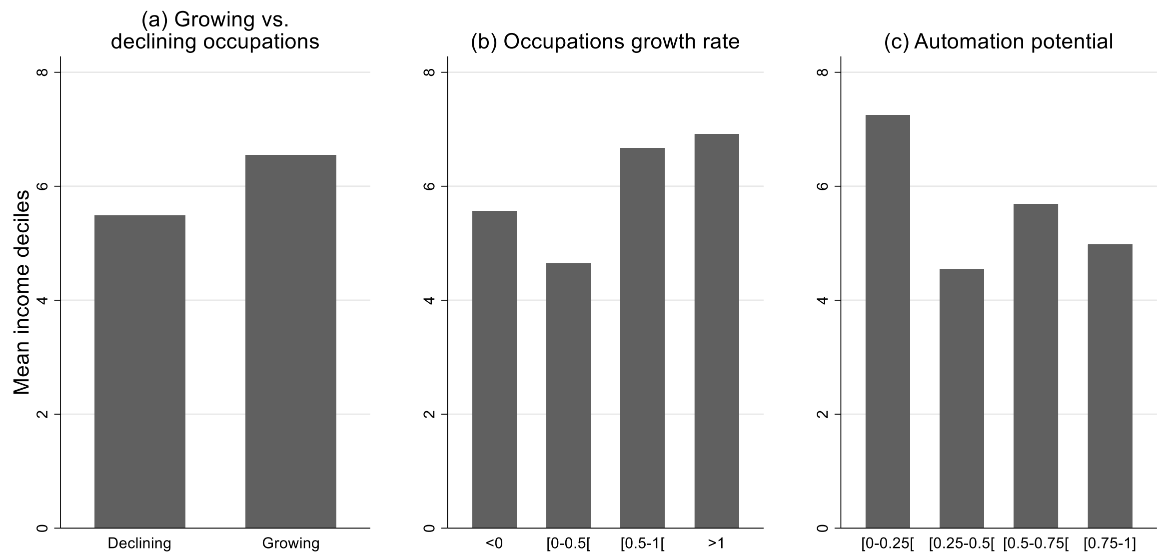
4.5. Effect on income deciles among the employed individuals

In this section, we analyze the effects of occupations growth and automation potential on income deciles. We do not have information on the previous income of non-employed individuals, hence the analysis is restricted to the employed sample in this section. Consequently, our independent variables are measured on workers' current occupations.

Figure 9 presents the mean income deciles by occupations growth and automation potential groups. It may seem curious to analyze deciles means, but unfortunately, the exact gross income of workers are not available in the EU-LFS only the categories in deciles. Still, some conclusions can be made since a higher decile mean in a certain group suggests higher average incomes in that group.

The results indicate that workers in growing occupations have, on average, higher income compared to workers in declining occupations. We also find clear differences in average incomes between workers in occupations with growth rates below 0.5 and those in occupations with growth rates above 0.5. The average incomes are larger in the latter occupations. The means are also very distinct for workers in occupations with automation potential below 0.25, who have higher incomes, and those in occupations with automation potential above 0.25.

Figure 9: Mean income deciles by growth and automation potential of occupations



Note: Belgian population aged 21-65 for the period 2011-2021 (pooled data). N=117,003 for (a); N=259,281 for (b) and N=259,245 for (c). For the list of growing and declining occupations in (a), see the main text.

We now look at the effects of the growing occupations, occupations growth rate and automation potential on income deciles (Table 10). Our results suggest that workers in growing occupations have an income decile about 1 or 0.7 point higher than workers in declining occupations, depending on whether we look at the model without or with control variables. The second row of estimates indicate that a one percent point increase in the number of workers in a certain occupation leads to a 1.5 or 0.7 point increase in the income deciles of workers in this occupation. In other words, our results suggest that workers in occupations that have grown faster in the past have higher income compared to those in occupations that have grown slower or declined. The opposite is true for automation potential since we find that the higher the automation potential of workers' occupations, the lower are their incomes.

Table 10: Effects of occupation growth and automation potential on income deciles

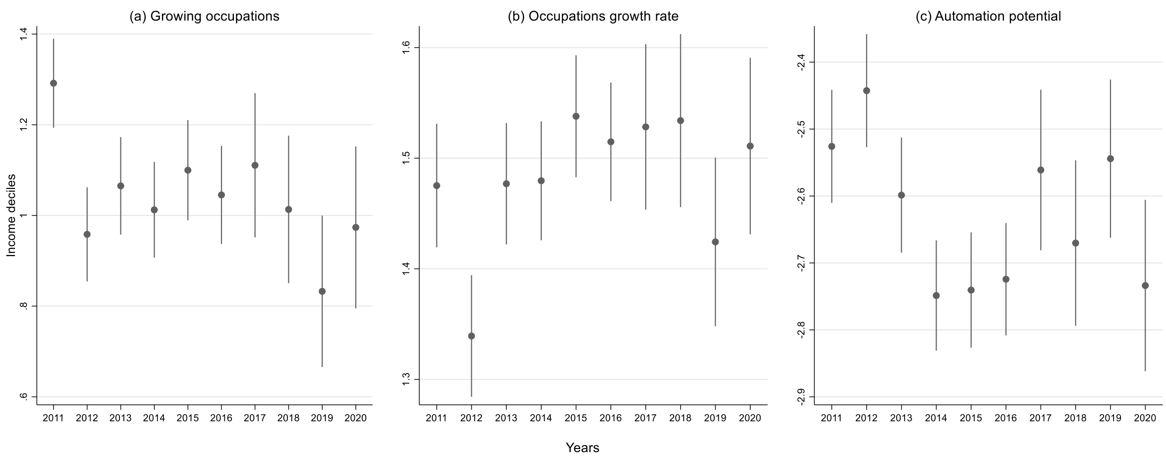
		Models	
		(1)	(2)
Growing occupations	Coeff	1.056***	0.728***
	(SE)	(0.020)	(0.021)
	N	117,003	116,944
Occupations growth rate	Coeff	1.478***	0.706***
	(SE)	(0.010)	(0.010)
	N	259,281	259,008
Automation potential	Coeff	-2.629***	-1.293***
	(SE)	(0.015)	(0.016)
	N	259,245	258,972
Controls (sex, age, Belgian and education)		No	Yes

Note: The dependent variable represents income deciles. Linear models with tests based on robust standard errors.

*** p<0.01; ** p<0.05 and * p<0.1

Figure 11 reveals how the effects on income deciles have evolved over the period from 2011 and 2021. In the first two sub-figures, we can see that the effects drop dramatically in 2012 and 2019 and that apart from these two drops, the effects are rather constant over time. No clear patterns is yet observed for the effects of automation potential on income deciles.

Figure 10: Effects of occupation growth and automation potential on income deciles over time



Finally, we present the results of our interactions analyses on income deciles. Overall, the results indicate that older and better educated workers benefit more from being in a growing occupations. Indeed, we find that the predicted income deciles of workers with tertiary education in growing occupations are approximately 1 points above the ones of workers with only early childhood education in growing occupations. We also find that the effect of being in a growing occupations on income deciles increase with age: for each additional age year, the predicted income decile of workers in growing occupations increases by 0.006 or 0.008 point (column 2 or 4). Yet, we do not find significant sex difference in model (1) and the difference is only significant at the 10% significance level in the model with all interactions.

Table 11: Differences in the effect of being in a growing occupation on income deciles by sex, age and education

	Models			
	(1)	(2)	(3)	(4)
Growing occupations	0.734***	0.487***	0.199	-0.143
	(0.022)	(0.068)	(0.214)	(0.226)
Growing occupations * Female	-0.053			-0.105*
	(0.063)			(0.064)
Growing occupations * Age		0.006***		0.008***
		(0.002)		(0.002)
Growing occupations * Early childhood education (ref. group)				
Growing occupations * Primary education			0.133	0.118
			(0.246)	(0.246)
Growing occupations * Lower secondary education			0.293	0.287
			(0.220)	(0.220)
Growing occupations * Upper secondary education			0.506**	0.538**
			(0.216)	(0.216)
Growing occupations * Post-secondary non-tertiary education			0.391*	0.452**
			(0.229)	(0.229)
Growing occupations * Tertiary education			1.064***	1.103***
			(0.222)	(0.222)
Controls (sex, age, Belgian and education)	Yes	Yes	Yes	Yes
Years and months fixed effects	Yes	Yes	Yes	Yes
Number of observations	116,944	116,944	116,944	116,944

Note: Growing occupations is a dummy variable distinguishing growing occupations from declining occupations (see the main text for details).

*** $p<0.01$; ** $p<0.05$ and * $p<0.1$

6. Conclusion

Using the European Labor Force Survey (EU-LFS), this chapter studies the effect of the digital revolution on individuals' labor market outcomes. Technological changes are known to restructure the economy, in which some occupations are growing and other are declining, and to replace human labor in certain jobs. We thus considered occupations growth and automation potential as measures of the digital revolution in our analyses and estimated their effects on employment, unemployment, unemployment duration, the probability of being non-employed because of health problems and income deciles. For each of these five different outcomes, we performed three types of analyses: (1) we estimated the direct effect of occupations' growth and automation potential, (2) we examined how the effects have evolved over time and (3) we studied how the effects differ by gender, age and education.

Our results suggest that individuals currently or previously in growing occupations are more likely to be employed compared those currently or previously in declining occupations and the opposite is true for the unemployment probability. Similarly, we find that employment probabilities are larger in occupations with lower automation potential while the unemployment probabilities are larger in these occupations. Our estimated effects suggest that individuals currently or previously in growing occupations have a predicted probability of being employed 8 percent point higher than individuals in declining occupations. Their predicted probability of being unemployed is yet 2.3 percent point lower than those in declining occupations. Occupations' automation potential have, on the contrary, a negative effect on employment probability and a positive effect on unemployment probability: a one percent point increase in the automation potential of occupations lead to a 0.13 points decrease and a 0.05 points increase in the predicted probability of being, respectively, employed and unemployed. Unemployed individuals who were previously in occupations with larger positive growth also are on average in unemployment for a shorter period and those previously in occupations with high automation potential are in unemployment for a longer time. The results for the probability of being non-employed because of health problems are similar: the predicted probability is higher in occupations with larger positive growth and lower in occupations with high automation potential. Finally, we find that workers in occupations that have grown faster in the past have higher income compared to those in occupations that have grown slower or declined. The income of workers in occupations with high automation potential are however lower. Overall, our results thus suggest that workers in occupations that are negatively affected by the digital revolution, in the sense that their labor demand has decreased and that jobs in these occupations are at risk of automation, are worse off because they are more likely to be unemployed, have longer unemployment duration, are more likely to be non-employed because of health problem and have lower income. But, the opposite is true for workers in growing occupations and occupations with low automation potential.

We do not find clear patterns in the evolution of the effects of occupation growth and automation potential over time. While the effect of the dummy for growing occupations on employment and unemployment probabilities disappear over time, there are no clear patterns for the effects of occupations automation potential on these probabilities. Still, the effects of occupations growth rate and automation potential on the probability to be non-employed because of health problems become stronger, especially over the period from 2011-2017.

The results of our interaction analyses suggest that the effect of growing occupations on employment probability differ by gender, age and education and the effects on unemployment probability only differ by gender and age. There are also differences for unemployment duration where highly educated individuals previously in growing educations having shorter unemployment duration compared lower educated individuals in growing occupations. The effect of growing occupation on the income of employed individuals is much stronger for older and better educated workers. Our results are thus mixed and do not suggest that one group benefit more from the digital revolution than another: while better educated individuals in growing occupations have higher wages and lower unemployment duration, women, young and low educated individuals in growing occupations are more likely to be employed.

This study has a number of limitations. The main limitation is that our results and interpretation are built on the strong assumption that the restructuration of the economy results only from technological changes. Yet, other determinants such as international trade and globalization may be playing a role. For example, changes in the economy such as the decline in the manufacturing sector may be the results of the increased import competition from countries like China rather than changes in technologies. The digital evolution has multiple effects and does not just reduce employment because of automation. We thus still believe that our measure better capture the overall effects of the digital revolution than others proxies such as the automation potential or the use of ICT at work which omit the potential creation of new jobs. Another limitation is that our estimates are subject to potential omitted variable bias, so the findings in this report should be interpreted with caution since they do not represent causal effects. Unfortunately, to the best of our knowledge, there are still no good instruments for the digital revolution.

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