How does the institutional context affect the risk of substitution faced by women and men?

Abstract
This paper aims to investigate how the institutional context considered in light of the level of gender equality explains the difference in the risk of substitution faced by men and women. To this end, the probability of automation of European occupation is estimated and it is analysed how it is influenced by the gender of the worker. We found that in contexts where gender equality is higher, female workers face a lower risk compared to contexts with a lower gender equality. However, the protection enjoyed by female workers is reduced in less egalitarian contexts because, due to barriers regarding the participation in formal and non-formal education and training, women are not able to acquire the necessary skills to protect themselves from the risk of substitution.

Keywords: automation of occupations, technological change, unemployment, institutional context, gender

1. Introduction

In recent years, the world of work has undergone radical transformations, in large part driven by automation technologies (i.e., artificial intelligence, big data analytics and robots). Advances in these technologies have in fact occurred exponentially (Skrbiš and Laughland-Booÿ, 2019) and due to their increasing ability to perform work activities they can now potentially replace workers in a growing number of occupations, both low-skill and high-skill (Blanas et al., 2019; Wajcman, 2017). As a result, automation technologies have caused shifts in the occupational structure, the place and the timing of work, and career patterns (Brussevich et al., 2019). In the future automation technologies will continue to transform work and many workers will lose their job (Skrbiš and Laughland-Booÿ, 2019; Spencer, 2018).
While much research has been done concerning the consequences of automation technologies on work including the estimation of the probability of automation of occupations and impact on various occupational groups (e.g., Arntz et al., 2016; Nedelkoska and Quintini, 2018; Pouliakas, 2018), limited attention is paid to how outcomes differ between women and men (Rodriguez-Bustelo et al., 2020). The few existing studies that consider the impact of automation on male and female workers have yielded conflicting results. In Europe men are more at high risk since they usually perform more automatable tasks and occupations with a higher probability of automation (Pouliakas, 2018). Instead in OECD countries, men face a lower risk (Nedelkoska and Quintini, 2018). Previous studies have thus shown that men and women are more or less at risk of substitution depending on the context. However, these analyses do not thoroughly investigate how the institutional context considered in light of the level of gender equality is determinant in explaining the difference in the risk of substitution faced by men and women.
This article addresses this gap by developing a gender perspective on automation, considering how these developments interact with existing social inequalities, gendered barriers and gender segregation patterns in the labour market in different European countries. Specifically, the aim of this paper is to analyse how the institutional context affects the risk of substitution faced by male and female workers.
In this paper, in the first phase the probability of automation of European occupations is estimated by applying the task-based approach. Then, the relationship between the probability of automation and gender is examined considering the institutional context in which male and female workers operate.

2. Literature review

2.1 The impact of automation on female workers

Different opinions have emerged about how automation will impact on the work performed by female and male workers. According to some authors (Delgado Cadena, 2020), automation will affect women more negatively than men. On the contrary, other authors (Pampliega, 2019) state that women will be less affected since they are not present in science and technology sectors, despite some authors (García-Holgado et al., 2019) note that it is precisely the absence in these sectors that represents a disadvantage for women and could massively expel women from the labour market. It has been found that the simple adoption of automation technologies to perform simple routine tasks will have adverse effects on female workers (Delgado Cadena, 2020). In addition, the low presence of women in technology sectors and STEM education programs (Shook and Knickrehm, 2018) will cause the loss of their jobs (Delgado Cadena, 2020).

2.2 The probability of automation of occupations faced by female and male workers

In the literature it has been estimated the probability of automation of occupations and how it has been examined how this probability is affected by socio-demographic characteristics of the worker, including its gender.
To estimate the probability of automation of occupations two main approaches can be applied: according to the occupation-based approach, whole occupations can be automated; according to the task-based approach, work activities instead of entire occupations can be automated. The occupation-based approach has been criticized for various reasons: entire occupations are only rarely eliminated due to automation (Bessen et al., 2020); within an occupation the tasks performed by workers vary considerably (Autor and Handel, 2013) so that workers face different risks of automation depending on the tasks they perform (Arntz et al., 2016).
In the estimation of the probability of automation, it is necessary to consider the following aspect. Despite recent progress in the automation technologies enabling more tasks to be automated than in the past, there are still three *Engineering bottlenecks* that prevent the automation of some non-routine tasks (Frey and Osborne, 2017). These technical limitations are linked to three capabilities: perception and manipulation (i.e., the ability to handle objects and to orient oneself in complex situations), creative intelligence (i.e., the ability to produce new and valuable ideas) and social intelligence (i.e., the ability to respond to a person in an empathetic way) (Arntz et al., 2016; Frey and Osborne, 2017). Since the tasks requiring these skills will not be automatable in the next two decades, the probability of automation of an occupation can be estimated as a function of these capabilities (Frey and Osborne, 2017).
In addition to estimating the probability of automation of occupations, some studies have analysed how this probability is influenced by socio-demographic characteristics of the worker (e.g., age, gender, education) and job-specific factors (e.g., type and size of firm, type of contract, training) (Nedelkoska and Quintini, 2018; Pouliakas, 2018).
Regarding *gender*, conflicting results have emerged. In Europe male workers face a higher risk of substitution since they usually perform more automatable tasks and occupations with a higher probability of automation (Pouliakas, 2018). On the contrary, female workers tend to carry out non-automatable tasks (Pouliakas, 2018). In OECD countries, men face a lower risk of substitution since female workers are more active in occupations with a lower probability of automation but they perform more automatable tasks (Nedelkoska and Quintini, 2018). These mixed results suggest that the relationship between gender and the probability of automation is influenced by the type of occupation and the work activities performed. Moreover, the institutional context seems to affect this relationship.

2.3 The influence of the institutional context

We argue that the different impact of automation technologies on women, including the risk of substitution faced, could be explained considering the gender gaps in the tasks carried out at work, the segregation by gender regarding occupations, and, more generally, the barriers faced by women in accessing a certain occupation (Piasna and Drahokoupil, 2017).
Based on relevant literature, the study aims to analyse how the institutional context affects the risk of substitution faced by male and female workers.

3. Empirical setting

3.1 Data

The database used in this study is the European Skills and Jobs Survey (ESJS) for 2014. It contains information about 49,000 adult workers (24-65 years) employed in different occupations and sectors in the 27 European countries and the United Kingdom. Information regards aspects such as: socio-demographic characteristics of the worker, job characteristics, job-skill requirements, skill mismatches, participation in training, labour market outcomes.

3.2 Method

In this study, for estimating the probability of automation of European occupations, the task-based approach is applied and the methodologies proposed by Frey and Osborne (2017) and by Nedelkoska and Quintini (2018) are followed. First, the probability of automation is estimated. Then, the relationship between this probability and gender is examined.
To estimate the probability of automation, a training set is built by assigning to some occupations a dummy variable equal to 1 if it can be automated and 0 otherwise. Labelled occupations are based on those considered by Frey and Osborne (2017). Some examples are provided in Table 1.

Table 1. Automatable and non-automatable occupations

Automatable occupations	**Non-automatable occupations**

Sales workers	Chief executives, senior officials and legislators
Customer services clerks	Cleaners and helpers
Drivers and mobile plant operators	Health professionals
Food preparation assistants	Legal, social and cultural professionals
General and keyboard clerks	Teaching professionals

Source: our elaboration

Then, the variables of the database that describe the capabilities that cannot be automated – i.e., perception and manipulation, creative intelligence and social intelligence – are selected (Table 2). The selection is provided by Pouliakas (2018).

Table 2. Variables corresponding to the capabilities that cannot be automated

Technical limitations to total automation	Variables
Perception and manipulation	Technical skills
Creative intelligence	Problem solving skills, Learning skills, Learning tasks, Non-routine tasks, Autonomous tasks
Social intelligence	Team working skills, Planning and organisation skills, Foreign language skills, Communication skills, Customer handling skills

Source: our elaboration based on Pouliakas (2018) and ESJS database

Finally, the probability of automation of occupations is estimated using a Gaussian process classifier: a model is built based on the training set and is then applied to estimate the probability of automation of all European occupations. Once the probabilities of automation are estimated, a logistic regression is run with the aim to examine the relationship between this probability and gender, controlling some worker and job characteristics. Specifically, the following model is estimated:

*Probability of automation = f (gender, gender*institutional context,*
socio-demographic characteristics, job-specific factors,
occupational and industry-specific variables)

The institutional context is measured with the Gender Equality Index for the 2017 provided by the European Institute for Gender Equality (EIGE). This index measures gender equality taking into account also aspects such as work and knowledge (which regards educational attainment and training).

3.3 Variable definition

Two sets of variables are used in the analysis. The first one includes the variables used to estimate the probability of automation of occupations (Table 3).

Table 3. Description and sources of variables used for estimating the probability of automation

Variable name	Variable definition	Source
Perception and manipulation		
Technical skills	Categorical variable describing the importance of the skill, with 0 = "Not at all important", 5 = "Moderately important", and 10 = "Essential"	ESJS
Creative intelligence		
Autonomous tasks	Categorical variable describing the frequency of this task, with 1 = "Never", 2 = "Sometimes", 3 = "Usually", and 4 = "Always"	ESJS
Non-routine tasks	Idem	ESJS
Learning tasks	Idem	ESJS
Learning skills	Categorical variable describing the importance of the skill, with 0 = "Not at all important", 5 = "Moderately important", and 10 = "Essential"	ESJS
Problem solving skills	Idem	ESJS
Social intelligence		

Communication skills	Categorical variable describing the importance of the skill, with 0 = "Not at all important", 5 = "Moderately important", and 10 = "Essential"	ESJS
Customer handling skills	Idem	ESJS
Foreign language skills	Idem	ESJS
Planning and organisation skills	Idem	ESJS
Team working skills	Idem	ESJS

Source: ESJS database

The second set of variables regards those used to analyse the relationship between the probability of automation and gender (Table 4).

Table 4. Description and sources of variables used to analyse the impact of socio-demographic characteristics of the worker and job-specific factors

Variable name	Variable definition	Source
Dependent variable		
Probability of automation	Variable describing the probability of automation and taking a value between 0 and 1, estimated in the first phase	Our estimate
Independent variables		
Gender	Dummy variable taking the value 1 if the worker is male, 0 if female	ESJS
Institutional context	Gender Equality Index	EIGE
Control variables		
Socio-demographic characteristics of the worker		
Age	Age of the worker	ESJS
Education	Categorical variable describing the highest level of education or training completed by the worker, with these levels: "No completed education", "Low education", "Medium education", "High education"	ESJS
Vocational qualification	Dummy variable taking the value 1 if the worker has received some learning in the workplace (e.g., through apprenticeships, internships, or other forms of work-based learning) or if the highest qualification was a vocational qualification, 0 otherwise	ESJS
Skills	Worker's level of skills compared to that required for the job (self-assessment)	ESJS
Job-specific factors		
Private company	Dummy variable taking the value 1 if the worker is employed in "A private company or partnership", 0 otherwise	ESJS
Firm size	Categorical variable describing the size of the organization, with these levels: "It varies", "Micro and small firm", "Medium firm", "Large firm"	ESJS
Years in job	Number of years in total the worker has been working for your current employer	ESJS
Weekly hours	Average number of working hours per week	ESJS
Indefinite contract	Dummy variable taking the value 1 if the worker is employed on an "Indefinite/permanent contract", 0 otherwise	ESJS
Training	Dummy variable taking the value 1 if the worker attended training courses (work-based, classroom based and online), 0 otherwise	ESJS
Training reasons	Dummy variable taking the value 1 if the worker attended training courses stay up-to-date with changing skill needs of the job or to perform better at the job, 0 otherwise	ESJS

Commentato [1]: per paper pubblicazione: provare a usare componenti di GEI legate a lavoro e istruzione

Occupation- and industry-specific variables		
Occupational class	Categorical variable describing the occupation of the worker	ESJS
Industry routine level	Categorical variable describing the routine intensity of the industry, with these levels: “Very low routine-intensive”, “Low routine-intensive”, “Medium-low routine-intensive”, “Medium-high routine-intensive, and “High routine-intensive”	ESJS

Source: our elaboration

4 Econometric results

The correlation matrix shows acceptable correlation indexes (Greene, 2003).
The econometric results are presented in Table 5.

Table 5. Econometric results

	Model 1	**Model 2**
Predictors	*Estimates*	*Estimates*
Intercept	0.6268 *** (0.0130)	0.6100 *** (0.0134)
Gender	-0.0119 *** (0.0009)	0.0245 *** (0.0070)
Institutional context	0.0002 *** (0.0001)	0.0005 *** (0.0001)
Gender * Institutional context		-0.0006 *** (0.0001)
Age	0.0001 *** (0.0001)	0.0001 *** (0.0001)
Education: Low education	-0.0071 (0.0093)	-0.0065 (0.0093)
Education: Medium education	-0.0009 (0.0093)	-0.0002 (0.0093)
Education: High education	-0.0050 (0.0093)	-0.0042 (0.0093)
Vocational qualification	-0.0082 *** (0.0012)	-0.0082 *** (0.0012)
Skills	-0.0002 *** (0.0000)	-0.0002 *** (0.0000)
Private company	0.0129 *** (0.0010)	0.0128 *** (0.0010)
Firm size: Micro and small firm	0.0057 (0.0051)	0.0058 (0.0051)
Firm size: Medium firm	-0.0033 (0.0052)	-0.0032 (0.0051)

Firm size: Large firm	-0.0068	-0.0068
	(0.0052)	(0.0052)
Years in job	-0.0002 ***	-0.0002 ***
	(0.0001)	(0.0001)
Weekly hours	-0.0006 ***	-0.0006 ***
	(0.0000)	(0.0000)
Indefinite contract	0.0028 **	0.0028 **
	(0.0012)	(0.0012)
Training	-0.0044 ***	-0.0044 ***
	(0.0013)	(0.0013)
Training reasons	-0.0167 ***	-0.0167 ***
	(0.0012)	(0.0012)
Occupational class: Building, crafts or a related trade person	-0.0162 ***	-0.0159 ***
	(0.0016)	(0.0016)
Occupational class: Clerical support	0.0011	0.0012
	(0.0013)	(0.0013)
Occupational class: Elementary occupations	-0.0073 ***	-0.0070 ***
	(0.0017)	(0.0017)
Occupational class: Manager	-0.0112 ***	-0.0111 ***
	(0.0015)	(0.0015)
Occupational class: Plant and machine operator and assembler	-0.0163 ***	-0.0159 **
	(0.0062)	(0.0062)
Occupational class: Professional	0.0124 **	0.0127 **
	(0.0061)	(0.0061)
Occupational class: Sales, customer or personal service worker	0.0198 ***	0.0198 ***
	(0.0065)	(0.0065)
Occupational class: Skilled agricultural, forestry and fishery worker	-0.0371 ***	-0.0371 ***
	(0.0062)	(0.0062)
Occupational class: Technician or associate professional	0.0026	0.0030
	(0.0063)	(0.0063)
Industry routine level: Low routine-intensive	-0.0318 ***	-0.0319 ***
	(0.0061)	(0.0061)
Industry routine level: Medium-low routine-intensive	0.0211 ***	0.0214 ***
	(0.0061)	(0.0061)
Industry routine level: Medium-high routine-intensive	-0.0237 ***	-0.0233 ***
	(0.0075)	(0.0075)
Industry routine level: High routine-intensive	-0.0141 **	-0.0140 **
	(0.0061)	(0.0061)
Observations	48648	48648

R^2	0.105	0.106

** p<0.1 ** p<0.05 *** p<0.01*

Gender has a negative coefficient in Model 1 (*b* = - 0.0119, p < 0.01), meaning that female workers face a lower risk of substitution compared to male ones. Institutional context has a positive coefficient (*b* = 0.0002, p < 0.01 in Model 1). Model 2 reports the interaction effects of *Gender* and *Institutional context*. *Gender* has a positive coefficient in model 2 (*b* = 0.0245, p < 0.01) and *institutional context* has a positive coefficient (*b* = 0.0005, p < 0.01). The regression results reveal a negative and significant coefficient of the interaction (b = - 0.0006; p < 0.01), implying that in contexts where gender equality is higher, female workers face a lower risk compared to contexts with a lower gender equality.
Instead, the protection enjoyed by female workers is reduced in less egalitarian contexts because due to barriers regarding the participation in formal and non-formal education and training, women are not able to acquire the necessary skills to protect themselves from the risk of substitution. As a consequence of these barriers, women are segregated into occupations that have a higher probability of automation or, when employed in occupations with a lower probability, they perform more routine tasks than in more egalitarian contexts.
Control variables also yield interesting results.

5 Discussion

Society must respond to changes due to automation (Spencer, 2018) by designing targeted policies that minimize the negative consequences of automation technologies on negatively affected workers. Our analysis shows that to guide future labour policies it is important to assess the differential impacts of automation for women and men. In fact, policy makers must prepare both male and female workers for the future. Action should be taken to prevent automation from worsening existing gender inequalities in the labor market. In fact, gender relations in new forms of work and employment interact with the persistent disparities in the workplace associated with gender discrimination (Piasna and Drahokoupil, 2017). As long as technological change leaves social relations of gender unchanged, a continuity and reproduction of gender inequalities is to be expected and policies must avoid this. The employability and the career advancement of women in occupations with a low probability of automation must be promoted. To this aim, supporting programs aimed at female workers must be designed, flexible work arrangements should be offered, and effective labour protection frameworks must be set up. The goal is to assure that women are equally able as men to access occupations that protect them from the risk of substitution. More generally, we need to encourage equal access of women and men to quality jobs and their equal treatment at work.

References

Arntz, M., Gregory, T. and Zierahn, U. (2016), The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis, OECD Social, Employment and Migration Working Papers No. 189, Vol. 189, Paris, available at:https://doi.org/10.1787/5jlz9h56dvq7-en.

Autor, D.H. and Handel, M. (2013), “Putting tasks to the test: Human capital, job tasks, and wages”, Journal of Labor Economics, Vol. 31 No. S1, pp. S59–S96.

Bessen, J., Goos, M., Salomons, A. and van den Berge, W. (2020), Automation: A Guide for Policymakers, Brookings Institution, Washington D.C.

Blanas, S., Gancia, G. and Lee, S.Y. (Tim). (2019), “Who is afraid of machines?”, Economic Policy, Vol. 34 No. 100, pp. 627–690.

Brussevich, M., Dabla-Norris, E., Khalid, S., and IMF e-Library - York University. (2019), Is Technology Widening the Gender Gap?: Automation and the Future of Female Employment, available at: https://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=2138076 (accessed 14 November 2021).

Delgado Cadena, M.V. (2020), “Gender job gaps and challenges in the digital economy: findings from global governance entities”, Cuadernos de Administración, Vol. 36 No. 67, pp. 158–171.

Frey, C.B. and Osborne, M. (2017), “The future of employment: How susceptible are jobs to computerisation?”, Technological Forecasting and Social Change, Vol. 114, pp. 254–280.

García-Holgado, A., Camacho Díaz, A. and García-Peñalvo, F.J. (2019), “La brecha de género en el sector STEM en América Latina: una propuesta europea”, Aprendizaje, Innovación y Cooperación como impulsores del cambio metodológico, presented at the Aprendizaje, Innovación y Cooperación como impulsores del cambio metodológico. Actas del V Congreso Internacional sobre Aprendizaje, Innovación y Cooperación., Servicio de Publicaciones Universidad, Madrid, Spain, pp. 704–709.

Greene, W.H. (2003), Econometric Analysis, Pearson Education India.

Nedelkoska, L. and Quintini, G. (2018), Automation, Skills Use and Training, OECD Social, Employment and Migration Working Papers No. 202, Vol. 202, OECD Publishing, Paris, available at:https://doi.org/10.1787/2e2f4eea-en.

Pampliega, G. (2019), Brecha de Género y Automatización. Efectos de La Revolución Digital En El Mercado Laboral Español, Un mundo complejo, available at: dehttps://epampliega.com/blog/index.php/2019/07/17/brecha-de-genero-y-automatizacion/.

Piasna, A. and Drahokoupil, J. (2017), "Gender inequalities in the new world of work", Transfer: European Review of Labour and Research, Vol. 23 No. 3, pp. 313–332.

Pouliakas, K. (2018), Determinants of Automation Risk in the EU Labour Market: A Skills-Needs Approach, Discussion Paper No. 11829, IZA Institute of Labor Economics, Bonn.

Rodriguez-Bustelo, C., Batista-Foguet, J.M. and Serlavós, R. (2020), "Debating the future of work: the perception and reaction of the Spanish workforce to digitization and automation technologies", Frontiers in Psychology, Vol. 11, p. 1965.

Shook, E. and Knickrehm, M. (2018), "Reworking the Revolution" Are You Ready to Compete as Intelligent Technology Meets Human Ingenuity to Create the Future Workforce?, available at: https://www.accenture.com/_acnmedia/pdf-69/.

Skrbiš, Z. and Laughland-Booÿ, J. (2019), "Technology, change, and uncertainty: maintaining career confidence in the early 21st century", New Technology, Work and Employment, Vol. 34 No. 3, pp. 191–207.

Spencer, D.A. (2018), "Fear and hope in an age of mass automation: debating the future of work", New Technology, Work and Employment, Vol. 33 No. 1, pp. 1–12.

Wajcman, J. (2017), "Automation: Is it really different this time?", The British Journal of Sociology, Vol. 68 No. 1, pp. 119–127.