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COVID-19 and automation: Evidence from European countries

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Abstract

We add new empirical evidence on the link between COVID-19, job losses and automation. This is the first analysis using European data covering the period up to August 2022. We first show that during the second and third year of the pandemic, workers in automatable occupations were more likely to lose their job. However, this effect disappears after accounting for the fact that workers at high risk of automation were more likely to lose their job even before COVID-19. Our results differ from those of other empirical studies and indicate that the declared intentions of firms to automate production due to COVID-19 may not have materialized, as we find no acceleration in job losses of automatable workers.

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1 Introduction

Coombs (2020), Seric and Winkler (2020) and Wallace-Stephens and Morgante (2020) argued that automation will accelerate following the COVID-19 pandemic. Surveys and empirical work seem to support these predictions. Sedik and Yoo (2021) show that pandemic events accelerate robot adoption, and the results of a survey conducted in mid-2020 on 441 executives from 29 countries confirm this, indicating that two-thirds of surveyed organisations have used automation in their COVID-19 response (Watson et al., 2020). Another survey from July 2020 shows that 68% of 800 business executives from nine mostly developed countries indicated they have plans to increase adoption of automation and AI due to COVID-19 outbreak (Lund et al., 2021). Ding et al. (2020) explore early trends and document that in the US the pandemic displaced more workers in automatable occupations. Egana-delSol et al. (2022) and Bonilla et al. (2022) bring evidence from developing countries. The Chilean data show that in the first year of the pandemic, occupations with a higher risk of automation experienced the most significant employment declines, and the results of Bonilla et al. (2022) for the period from January 2020 to August 2021 suggest that both vacancies and salaried employment in Colombia fell more in highly automatable occupations. Bellatin and Galassi (2022) analyze Canadian data and a slightly longer time period and show that a decline in the proportion of online vacancies for occupations at high risk of automation in the second half of 2020 was only temporary, as it climbed back to normal levels in 2021.

2 Data and estimation

We use European Social Survey (ESS) data collected for 22 European countries from September 2020 to August 2022 and published in July 2023 (ESS Round 10, edition 3.1). Since it is released biannually, for the first time it includes questions about the impact of COVID-19. Crucial for our analysis is that it contains occupational information (current/last main job) coded at the 4-digit ISCO-08 level. Through this variable, we assign to individuals their automation risk and the degree of teleworkability of their job. In both cases we use measures that are standard in the literature: Frey and Osborne (2017), Dengler and Matthes (2018) and Mihaylov and Tijdens (2019) for occupation-level automation risks, and Dingel and Neiman (2020) for the degree of teleworkability.

To investigate the impact of COVID-19 on the pace of automation, the following models with two different independent variables, $Jloss_{ijc}$ and $Unemp_{ijc}$, are estimated. In Equation 1, $Jloss_{ijc}$ corresponds to job loss and $Unemp_{ijc}$ represents unemployment status of individual i in industry j and country c. $Jloss_{ijc}$ takes value 1 if the respondent experienced job loss between the start of the pandemic and the day of the interview, 0 otherwise. $Unemp_{ijc}$ is 1 if he/she was unemployed at time of the interview and 0 if in paid work (here we restrict the analysis to those who had a job at the start of the pandemic). The difference between the two is that one was directly asked in the interview ($Jloss_{ijc}$), while the other is our own measure constructed from two variables. The advantage of using our own measure is a slightly larger sample size. Technical details are in Table A4.

$$\{Jloss_{ijc}, Unemp_{ijc}\} = \alpha + \lambda Aut_{ijc} + \tau Tel_{ijc} + \boldsymbol{X_{ijc}\beta} + \gamma_j + \phi_c + \varepsilon_{ijc}. \tag{1}$$

Aut_{ijc} is also a dummy variable and equals 1 if his/her job is/was at high risk of automation (probability of automation higher than 70%, a standard threshold in the literature). Tel_{ijc} measures the possibility of working from home. Matrix $\boldsymbol{X_{ijc}}$ includes several respondent characteristics, namely gender, age and education (years of full-time education completed), and γ_j and ϕ_c are industry and country fixed effects, respectively. Since the implementation of some automation technologies may take some time, seemingly automation-related job losses in 2020 may not have been the result of actual/permanent labor displacement. Observations from 2020 are therefore omitted from the baseline analysis.

Even before the pandemic, workers at high risk of automation may have been more likely to lose their job. The ESS round 10 data were thus combined with the data from the previous round of the survey. The ESS Round 9 (edition 3.1) data were collected from August 2018 to January 2020. This data set allows us to compare the differences in unemployment status before and after the COVID-19 pandemic in a difference-in-differences (DiD) research design. Due to the short pre-treatment period, the parallel trend assumption is assumed because it cannot be tested or controlled for. The following model is estimated:

$$Unem_{ijct} = \alpha + \lambda Aut_{ijc} + Post_t + \delta Aut_{ijc} \times Post_t + \tau Tel_{ijct} + \boldsymbol{X_{ijct}\beta} + \gamma_j + \phi_c + \varepsilon_{ijct}, \tag{2}$$

where the parameter δ is of key interest. λ shows the difference between automatable and non-automatable workers before the pandemic, $Post_t$ dummy variable captures the difference in the probability of being unemployed for non-automatable workers after the pandemic, and δ shows the difference in the probability of being unemployed for automatable workers after COVID-19 compared to the differences before the pandemic. Matrix $\boldsymbol{X_{ijct}}$ refers to respondent characteristics (gender, age and education) in the time period t. Equations (1) and (2) are estimated using logit estimation and odds ratios are reported in the results.

3 Results

Tables 1 and 2 show that during the second and third year of the pandemic, workers in automatable occupations were more likely to lose their job. In the first case, it is documented that they were at least 46% more likely to lose their job than to be unaffected or "just" (i) furloughed, (ii) forced to take unpaid leave/holiday, (iii) experience a reduction in income or (iv) experience a reduction in working hours (or a combination thereof). Table 2 uses a different strategy and provides similar results in terms of unemployment. It shows that among those who had a job at the start of the pandemic, those in automatable jobs were at least 56% more likely to be unemployed at the time of the interview.

Table 1: Estimation of the probability of job loss in 2021 and 2022

	(1)	(2)	(3)	(4)	(5)	(6)
	High risk vs. medium/low risk occupations			High risk vs. low risk occupations		
Automatable	1.950***	1.808***	1.461**	2.808***	2.495***	2.256***
	(0.257)	(0.246)	(0.236)	(0.553)	(0.519)	(0.532)
Teleworkability		0.678**	0.666*		0.696*	0.709
		(0.120)	(0.144)		(0.147)	(0.189)
Male	0.923	0.891	1.101	1.053	1.014	1.218
	(0.117)	(0.114)	(0.160)	(0.155)	(0.151)	(0.206)
Age	0.980***	0.981***	0.987**	0.978***	0.979***	0.987**
	(0.00506)	(0.00507)	(0.00531)	(0.00587)	(0.00589)	(0.00623)
Education	0.912***	0.926***	0.936***	0.920***	0.932***	0.952*
	(0.0186)	(0.0201)	(0.0213)	(0.0230)	(0.0243)	(0.0257)
Industry dummies	No	No	Yes	No	No	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,675	14,675	12,465	10,705	10,705	8,748

Source: Authors' elaboration based on the estimates of Frey and Osborne (2017) and Dingel and Neiman (2020) and microdata from the ESS round 10.
Note: Odds ratios are reported. For further details see Table A4.

Automation and teleworking technologies affect different occupations. Controlling for the possibility of teleworking does not change the impact of the risk of automation on job losses or unemployment. As expected, higher teleworkability is associated with a lower probability of job loss.

Table 2: Estimation of the probability of being unemployed in 2021 and 2022 for those who had a job at the start of the pandemic

	(1)	(2)	(3)	(4)	(5)	(6)
	High risk vs. medium/low risk occupations			High risk vs. low risk occupations		
Automatable	1.746***	1.575***	1.561***	2.428***	2.103***	2.182***
	(0.115)	(0.107)	(0.124)	(0.231)	(0.213)	(0.249)
Teleworkability		0.581***	0.689***		0.649***	0.769**
		(0.0519)	(0.0730)		(0.0696)	(0.0990)
Male	0.771***	0.739***	0.845**	0.879*	0.843**	0.938
	(0.0499)	(0.0481)	(0.0637)	(0.0672)	(0.0649)	(0.0828)
Age	0.983***	0.984***	0.988***	0.985***	0.986***	0.990***
	(0.00249)	(0.00250)	(0.00261)	(0.00294)	(0.00295)	(0.00310)
Education	0.894***	0.913***	0.924***	0.903***	0.916***	0.929***
	(0.00918)	(0.00991)	(0.0106)	(0.0115)	(0.0121)	(0.0129)
Industry dummies	No	No	Yes	No	No	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,296	17,296	16,642	12,578	12,578	12,027

Source: Authors' elaboration based on the estimates of Frey and Osborne (2017) and Dingel and Neiman (2020) and microdata from the ESS round 10.
Note: Odds ratios are reported. For further details see Table A4.

To account for fact that workers at high risk of automation may have been more likely to lose their job even before COVID-19, we employ a DiD research design that controls for pre-COVID-19 differences. Previous ESS waves were conducted before the pandemic, so they did not include questions about the impact of COVID-19. However, our DiD estimation can be based on employment status information. This empirical strategy does not document accelerated automation in the COVID-19 era (Table 3).

Table 3: Has COVID-19 accelerated automation? DiD estimation of the probability of being unemployed after the COVID-19 outbreak (high risk vs. low risk occupations)

	(1)	(2)	(3)	(4)	(5)	(6)
	FO		DM		MT	
Automatable	2.130***	2.227***	1.036	1.157	1.187*	1.334***
	(0.235)	(0.265)	(0.117)	(0.152)	(0.119)	(0.148)
Post COVID-19	0.864	0.906	0.838**	0.856*	0.821***	0.846**
	(0.113)	(0.122)	(0.0651)	(0.0686)	(0.0579)	(0.0612)
Autom*Post COVID-19	1.015	0.975	0.906	0.877	0.938	0.895
	(0.151)	(0.148)	(0.148)	(0.148)	(0.137)	(0.134)
Teleworkability	0.656***	0.772**	0.528***	0.608***	0.550***	0.660***
	(0.0586)	(0.0813)	(0.0458)	(0.0651)	(0.0443)	(0.0645)
Male	0.903	0.925	0.827***	0.801***	0.783***	0.795***
	(0.0578)	(0.0675)	(0.0551)	(0.0633)	(0.0475)	(0.0567)
Age	0.982***	0.986***	0.979***	0.983***	0.977***	0.980***
	(0.00244)	(0.00254)	(0.00257)	(0.00269)	(0.00231)	(0.00241)
Education	0.935***	0.945***	0.909***	0.934***	0.897***	0.918***
	(0.0100)	(0.0106)	(0.00938)	(0.0106)	(0.00848)	(0.00940)
Industry dummies	No	Yes	No	Yes	No	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,601	22,828	22,093	21,239	27,045	26,154

Source: Authors' elaboration based on the estimates of Frey and Osborne (2017), Dengler and Matthes (2018), Mihaylov and Tijdens (2019) and Dingel and Neiman (2020) and microdata from the ESS rounds 9 and 10.
Note: Odds ratios are reported. For further details see Table A4.

The coefficients in the first row indeed show that workers at high risk of automation were more likely to be unemployed even before COVID-19. The key parameter of interest here is the interaction term between automatability and post COVID-19 dummy. A statistically significant estimate with a value above 1 would indicate an increased probability of unemployment for highly automatable occupations in the post-COVID-19 period compared to non-automatable occupations. However, we provide robust empirical results showing that there has been no such increase, suggesting no acceleration of automation. It is shown that differences in unemployment probabilities between high and low risk occupations did not increase after the COVID-19 outbreak (columns 1 and 2). The use of other measures of occupation-level automation exposure (Dengler and Matthes, 2018; Mihaylov and Tijdens, 2019) does not change our conclusion about non-accelerated automation (columns 3–6). The results are the same (no acceleration of automation) when running the regressions for EU member states only (Table A1). Tables A2 and A3 provide two additional robustness checks of our results. In Table A2, we interact teleworkability with post COVID-19 dummy and document that the pandemic did not differentially affect teleworkers and non-teleworkers. This finding highlights the importance of analysing longer time periods when assessing COVID-19 impacts, as it shows that the effect found by Beland et al. (2020) and Gallacher and Hossain (2020) was indeed only short-term. Equally important is that the evidence of not accelerated automation is robust to this modification of our baseline model. In Table A3, observations from 2020 are included in the estimation (unlike in Table 3) and the results remain the same.

4 Conclusion

We add new empirical evidence on the link between COVID-19, job losses and automation using European Social Survey data. The novelty of this paper lies in the countries analysed, the longer time period studied and the research design. It is the first analysis using European data covering the period up to August 2022. We first show that during the second and third year of the pandemic, workers in automatable occupations were more likely to lose their job. However, this effect disappears after accounting for the fact that workers at high risk of automation were more likely to lose their job even before COVID-19. We use a DiD research design for this purpose. Our results differ from those of other empirical studies and indicate that the declared intentions of firms to automate production due to COVID-19 may not have materialized, as we find no acceleration in job losses of automatable workers.

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Appendix

Table A1: DiD estimation of the probability of being unemployed after the COVID-19 outbreak (16 EU countries)

	(1)	(2)	(3)	(4)	(5)	(6)
	High risk vs. medium/low risk occupations			High risk vs. low risk occupations		
Automatable	1.411***	1.294***	1.250**	2.323***	2.068***	2.143***
	(0.111)	(0.103)	(0.109)	(0.273)	(0.249)	(0.275)
Post COVID-19	0.767***	0.776***	0.777***	0.832	0.849	0.862
	(0.0653)	(0.0662)	(0.0676)	(0.122)	(0.125)	(0.128)
Autom*Post COVID-19	1.205	1.193	1.175	1.071	1.050	1.025
	(0.138)	(0.136)	(0.137)	(0.176)	(0.173)	(0.172)
Teleworkability		0.574***	0.690***		0.648***	0.788**
		(0.0462)	(0.0647)		(0.0633)	(0.0906)
Male	0.831***	0.796***	0.850**	0.914	0.869**	0.890
	(0.0477)	(0.0459)	(0.0569)	(0.0632)	(0.0608)	(0.0712)
Age	0.980***	0.981***	0.984***	0.982***	0.984***	0.987***
	(0.00222)	(0.00223)	(0.00230)	(0.00267)	(0.00269)	(0.00278)
Education	0.899***	0.918***	0.931***	0.920***	0.933***	0.946***
	(0.00814)	(0.00881)	(0.00936)	(0.0105)	(0.0110)	(0.0116)
Industry dummies	No	No	Yes	No	No	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,122	27,122	26,361	19,553	19,553	18,888

Source: Authors' elaboration based on the estimates of Frey and Osborne (2017) and Dingel and Neiman (2020) and microdata from the ESS rounds 9 and 10.
Note: Odds ratios are reported. For further details see Table A4.

Table A2: DiD estimation of the probability of being unemployed after the COVID-19 outbreak with teleworkability interactions

	(1)	(2)	(3)	(4)
	High risk vs. medium/low risk occupations		High risk vs. low risk occupations	
Automatable	1.314***	1.309***	2.227***	2.237***
	(0.108)	(0.109)	(0.265)	(0.277)
Post COVID-19	0.773***	0.761***	0.906	0.918
	(0.0631)	(0.0762)	(0.122)	(0.156)
Autom*Post COVID-19	1.188	1.199	0.975	0.966
	(0.129)	(0.136)	(0.148)	(0.162)
Teleworkability	0.692***	0.679***	0.772**	0.781*
	(0.0597)	(0.0749)	(0.0813)	(0.107)
Telework*Post COVID-19		1.040		0.977
		(0.150)		(0.174)
Male	0.871**	0.871**	0.925	0.925
	(0.0538)	(0.0538)	(0.0675)	(0.0675)
Age	0.983***	0.983***	0.986***	0.986***
	(0.00213)	(0.00213)	(0.00254)	(0.00254)
Education	0.934***	0.934***	0.945***	0.945***
	(0.00865)	(0.00865)	(0.0106)	(0.0106)
Industry dummies	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes
Observations	31,445	31,445	22,828	22,828

Source: Authors' elaboration based on the estimates of Frey and Osborne (2017) and Dingel and Neiman (2020) and microdata from the ESS rounds 9 and 10.
Note: Odds ratios are reported. For further details see Table A4.

Table A3: DiD estimation of the probability of being unemployed after the COVID-19 outbreak (observations from 2020 included in the estimation)

	(1)	(2)	(3)	(4)	(5)	(6)
	High risk vs. medium/low risk occupations			High risk vs. low risk occupations		
Automatable	1.489***	1.368***	1.322***	2.407***	2.155***	2.268***
	(0.109)	(0.102)	(0.108)	(0.258)	(0.237)	(0.269)
Post COVID-19	0.768***	0.779***	0.789***	0.882	0.898	0.941
	(0.0606)	(0.0616)	(0.0637)	(0.114)	(0.116)	(0.125)
Autom*Post COVID-19	1.197*	1.184	1.171	0.999	0.983	0.943
	(0.126)	(0.125)	(0.126)	(0.146)	(0.144)	(0.141)
Teleworkability		0.602***	0.709***		0.676***	0.799**
		(0.0442)	(0.0604)		(0.0597)	(0.0831)
Male	0.864***	0.831***	0.873**	0.954	0.915	0.932
	(0.0456)	(0.0440)	(0.0535)	(0.0599)	(0.0581)	(0.0673)
Age	0.979***	0.980***	0.983***	0.981***	0.982***	0.986***
	(0.00203)	(0.00204)	(0.00211)	(0.00240)	(0.00242)	(0.00251)
Education	0.905***	0.922***	0.933***	0.923***	0.934***	0.944***
	(0.00751)	(0.00809)	(0.00858)	(0.00950)	(0.00996)	(0.0105)
Industry dummies	No	No	Yes	No	No	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,780	32,780	31,901	23,944	23,944	23,168

Source: Authors' elaboration based on the estimates of Frey and Osborne (2017) and Dingel and Neiman (2020) and microdata from the ESS rounds 9 and 10.

Note: The post-COVID period starts in September 2020 and lasts until August 2022, and the pre-COVID period ends in January 2020 (starting in 2018). Odds ratios are reported. For further details see Table A4.

Table A4: Technical notes

Table 1	The dependent variable equals 1 if the respondent marked "Things happened since start of COVID-19: was made redundant/lost job" and at the time of the interview was still unemployed, and 0 if he/she did not mark the statement (but may have experienced one or more of the following things: furlough; unpaid leave/holiday; reduction in income; reduction in working hours) and had a paid work at the time of the interview. Those who lost their job but were no longer unemployed are dropped from the sample because we only know their current/new job and not the one they lost.
Table 2	The dependent variable equals 1 if the respondent was unemployed at the time of the interview and 0 if he/she had a paid work. To be sure to capture the COVID-19 impact, we restrict the analysis to those who did not mark "Things happened since start of COVID-19: not in work since start of COVID-19" (i.e., had a job at the start of the pandemic).
Table 3	The dependent variable equals 1 if the respondent was unemployed at the time of the interview and 0 if he/she had a paid work. The post-COVID period is 2021–2022 and the pre-COVID period is 2018–2019. For the post-COVID period, we only keep those who did not mark "Things happened since start of COVID-19: not in work since start of COVID-19" (i.e., had a job at the start of the pandemic).