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1 Introduction

There is a vast literature showing that the assessment of the effects of tasks on wages, which are defined as the returns to tasks[1], helps to explain wage differences between workers (see for instance Autor and Handel 2013). In particular, Autor et al. (2003) argue that the spread of new technologies impacted the task content and the wages of workers during the last decades. Acemoglu and Restrepo (2020, henceforth AR2020) show that the stock of industrial robots increased fourfold between 1993 and 2007 in the US. This intensive robotization led to a massive displacement of workers, and probably significantly impacted the returns to tasks. To the best of my knowledge, no paper has assessed the impact of robotization on the returns to tasks. This paper fills this gap.

The previous literature focused on the effects of tasks on wages or on the direct effects of robotization on wages. The main contribution of this paper is to take into account the interaction between robotization and tasks to assess the impact of robotization on the returns to tasks. My reduced-form model extends AR2020, which estimates the impact of robotization on wages at the scale of US commuting zones[2] between 1990 and 2007, by including task measures to the analysis. I find that the adoption of one robot per thousand workers increases the changes in the returns to abstract and routine tasks by 0.049 and 0.066 percentage points, respectively, relative to manual tasks. These magnitudes are substantial since they imply that the adoption of one robot per thousand workers increases wages by 1.70% due to the positive impact of robotization on the returns to abstract tasks, and by 3.76% due to the positive effects on the returns to routine tasks. The results are robust to various specifications.

2 Data and Model

Following Autor and Dorn (2013), I measure abstract, routine, and manual tasks using data from the Revised Fourth Edition (1991) of the Dictionary of Occupational Titles[3] (henceforth DOT). The DOT provides data at the occupational level, where each occupation corresponds to a distinct bundle of tasks. For each occupation, I calculate the proportion of time allocated to each of the three types of tasks during a workday. For each task, I divide the original measure by the sum of the measures of the three types of tasks. Task shares are then matched with workers according to their occupation.

Workers are grouped into demographic groups. Demographic groups are defined by gender, age group (14-25, 26-35, 36-45, 46-55, 56-65, and 65+), education group (less than high-school, high-school / GED, some college, college or professional, master or PhD) and race (white, black, Asians, other). Hours worked vary substantially across demographic groups. To identify the effects of tasks, I thus work on the task shares of each demographic group[4]. They are calculated as the means of the task shares of the corresponding work-

[1]This is because the compensation a worker earns for a specific task corresponds to the returns to the human capital accumulated for the production of this task.

[2]Commuting zones are proxies of labor markets (Tolbert and Sizer 1996). There are 722 continental commuting zones (without Alaska and Hawaii).

[3]See a description of tasks in Appendix A.

[4]I thank the associate editor for this suggestion.

ers, weighted by their respective sample weights. This approach ensures that task shares are independent of the workday length. I calculate the real hourly wages of demographic groups for 1990 and 2007 using data from the 1990 decennial census and the 2006-2007-2008 American Community Survey (henceforth ACS).

The proxy of robotization is the exposure to robots of AR2020, which is constructed with data on the US industrial stocks of robots. I instrument it by a European equivalent, as robotization advanced more rapidly in European countries compared to the US prior to 2007[5]. The underlying assumption is that the adoption of robots by technologically advanced European countries, particularly Germany, affects the behavior of US firms but does not directly influence wages.

I examine the effects of robotization on the relationships between tasks and wages by interacting quantitative measures of task shares and exposure to robots in the reduced-form model[6]:

$$d \ln w_{g,c} = \beta_0 + \beta_1 e_c + \sum_{n \in \mathcal{T}} \beta_{2,n} s_{n,g,c} + \sum_{n \in \mathcal{T}} \beta_{3,n} s_{n,g,c} e_c + \mathrm{B} \cdot \mathrm{controls}_c + \phi_g + \epsilon_{g,c} \tag{1}$$

where $\mathcal{T}$ is the set of tasks entering the regression, with manual tasks as the reference category; $d \ln w_{g,c}$ is the change in the hourly wage of the demographic group g in the commuting zone c; β_0 is the intercept; β_1 captures the effect of robotization on the change in wage that is uncorrelated with the effects of abstract and routine tasks; e_c is exposure to robots; $\beta_{2,n}$ corresponds to the change in the returns to task n relative to manual tasks, uncorrelated with the effects of robotization; $s_{n,g,c}$ is the share of task n for workers in the demographic group g in the commuting zone c; $\beta_{3,n}$ captures the impact of robotization on the change in the returns to task n relative to the impact on manual tasks. Specifically, if $\beta_{3,n}$ is positive, robotization has a larger impact on the returns to task n compared to the impact on manual tasks, suggesting that robotization favors task n over manual tasks. B is a vector of coefficients associated with controls for commuting zones; ϕ_g captures the fixed effect of the demographic group g, which includes the effects of gender, age, education, and race; and $\epsilon_{g,c}$ is the error term.

3 Results

Table 1 presents the IV estimates of Equation (1)[7]. The baseline specification in Column 1 includes the instrumented US exposure to robots, the census divisions fixed effects and the demographic groups fixed effects. The estimates suggest that one more robot per thousand workers decreases wages by 1.12%. The specification in Column 2 adds task shares. The coefficient corresponding to exposure to robots remains significant and is similar to the baseline estimate. This suggests that exposure to robots and task shares are not significantly correlated. The coefficients corresponding to abstract and routine tasks are negative and

[5]See AR2020 for further details on the construction of exposure to robots and the instrument.

[6]See Appendix B for a related theoretical framework.

[7]Table C.1 in Appendix C presents the analogous OLS estimates. In Column 1, the magnitude of the coefficient corresponding to exposure to robots is lower than the IV estimate. This suggests that OLS estimates underestimate the effects of robotization on wages. The estimates for tasks are not significantly different from the IV estimates.

significant. When I control for interactions between tasks and exposure to robots (Column 3), the coefficient corresponding to exposure to robots increases significantly in magnitude. The coefficients corresponding to tasks remain negative and significant. The coefficients corresponding to interactions between tasks and exposure to robots are positive and significant.

Table 1: Robotization and Returns to Tasks

	(1)	(2)	(3)	(4)	(5)
US Exp. to Robots	-1.120^{***}	-1.107^{***}	-7.364^{***}	-6.916^{***}	-6.362^{***}
	(0.241)	(0.241)	(2.339)	(2.279)	(2.217)
Abstract Tasks		-0.462^{***}	-0.537^{***}	-0.318^{***}	-0.324^{***}
		(0.082)	(0.087)	(0.058)	(0.053)
Routine Tasks		-0.335^{***}	-0.438^{***}	-0.316^{***}	-0.313^{***}
		(0.072)	(0.078)	(0.061)	(0.056)
Abstract Tasks × US Exp. to Robots			0.056^{***}	0.052^{***}	0.049^{***}
			(0.017)	(0.016)	(0.016)
Routine Tasks × US Exp. to Robots			0.075^{***}	0.074^{**}	0.066^{**}
			(0.029)	(0.029)	(0.027)
Num. obs.	66376	66376	66376	66376	66376
R^2	0.328	0.331	0.331	0.341	0.346
			Covariates		
Divisions and Groups Fixed Effects	✓	✓	✓	✓	✓
Commuting Zone Demographic Controls				✓	✓
Other Commuting Zone Controls					✓

Notes: This table presents IV estimates of the impact of robotization on the changes in log wages. Standard errors that are robust against heteroskedasticity and clustered by commuting zones are given in parentheses. Commuting zones are geographic units that define local labor markets. There are 722 commuting zones in the continental US. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

Following AR2020, I add controls specific to commuting zones. Specifically, the specification in Column 4 adds: the log of the population, the shares of females, whites, blacks, Hispanics, and Asians, the shares of workers who did not attain college, who obtained a college or a professional degree, and who obtained a master or a PhD degree, and the share of the population that is more than 65 years old. The specification in Column 5 adds other controls specific to commuting zones: the share of workers in routine-intensive occupations, the share of employment in manufacturing, the share of female workers in manufacturing, the share of employment in light manufacturing (textile and paper-publishing-printing industries), and the exposure to Chinese imports of Autor et al. (2021). The estimates are robust to these additional specifications. They are not significantly different from those of Column 3. According to the theoretical framework in Appendix B, the coefficient corresponding to exposure to robots in Column 5 suggests that the effect of exposure to robots on wages uncorrelated with abstract and routine tasks is negative. This effect includes the impact of robotization on the returns to manual tasks. Its magnitude is discussed in the next section. The results in Column 5 also indicate that the adoption of one robot per thousand workers increases the changes in the returns to abstract and routine tasks by 0.049 and 0.066 percentage points, respectively, relative to manual tasks. The estimates of the coefficients corresponding to task shares suggest that, relative to manual tasks, the returns to abstract and routine tasks decrease respectively by 0.324 and 0.313 percentage points due to unobserved phenomena.

Appendix C provides additional specifications and robustness checks. Tables C.2 and C.3 control for hours worked and different types of capital, respectively. The estimates are robust to these specifications, suggesting that the effects of tasks are not affected by differences in workday length across sub-samples, and the effects of robotization are distinct from those of standard capital. Table C.4 explores the effects of outliers, which are the top 1% of commuting zones with the highest exposure to robots. The estimates are robust, except for the coefficients corresponding to the interaction between abstract tasks and exposure to robots, suggesting that the average effect of robotization on the returns to abstract tasks is driven by outliers. Finally, Tables C.5 and C.6 present results by occupation group and education level, respectively. These specifications show that the positive effects of robotization on the returns to tasks are mostly concentrated among middle-skill workers, specifically those in routine occupations and with intermediate education levels.

4 Discussion

The impact of exposure to robots on wages is close to -1.022 in the most parsimonious specification (Column 1), which is the estimate of AR2020, the difference being due to the number of observations. This estimate remains similar in Column 2 but increases sixfold in magnitude in Column 5. The results suggest that the estimates in Columns 1 and 2 include the positive effects of exposure to robots on the returns to abstract and routine tasks, which reduce the magnitude of the impact. Specifically, we can decompose the effect of exposure to robots on wages as follows:

$$\frac{\partial \ln w_{g,c}}{\partial e_c} = \beta_1 + \sum_{n \in \mathcal{T}} \beta_{3,n} s_{n,g,c} \tag{2}$$

The total impact of exposure to robots on wages, on the left-hand side, is given by the specifications for which exposure to robots does not interact with tasks. The first term on the right-hand side captures the effect of exposure to robots uncorrelated with abstract and routine tasks. In particular, this term includes the effect of exposure to robots on the returns to manual tasks, as shown in Appendix B. The second term corresponds to the effects of exposure to robots interacting with abstract and routine tasks. The total impact ranges from -1.120 in Column 1 to -1.022 in AR2020. The value of the second term, calculated using the average task shares, is 5.46, with 1.70 point corresponding to the effect of exposure to robots on wages correlated with abstract tasks, and 3.76 points to the effect correlated with routine tasks[8]. Approximately -6.4 percentage points remain for the effect of exposure

[8] In 1990, the average shares of abstract and routine tasks were 34.62 and 56.93 percentage points, respectively. Multiplying the average task shares by their corresponding coefficients for interaction with exposure to robots in Column 5, i.e. 0.049 for abstract tasks and 0.066 for routine tasks, yields 1.70 and 3.76, respectively.

to robots uncorrelated with abstract and routine tasks. The value of -6.362 in Column 5 is in line with this decomposition.

To the best of my knowledge, only Deming (2017) provides analogous estimates for tasks. This author uses longitudinal data and finds that the returns to math tasks declined between two successive cohorts of workers, which is in line with the estimated coefficient for abstract tasks. The main findings, which are the impacts of robotization on the returns to tasks might appear surprising since robotization displaces workers on routine tasks only but they are in line with recent evidence suggesting that the firms that adopt robots, which are intensive in abstract and routine tasks, do not decrease their wages and increase their employment (e.g. Acemoglu et al. 2020).

References

Acemoglu, D., C. Lelarge, and P. Restrepo (2020). “Competing with Robots: Firm-Level Evidence from France”. In: *AEA Papers and Proceedings* 110, pp. 383–388.

Acemoglu, D. and P. Restrepo (2020). “Robots and Jobs: Evidence from US Labor Markets”. In: *Journal of Political Economy* 128.6, pp. 2188–2244.

Autor, D. and D. Dorn (2013). “The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market”. In: *American Economic Review* 103.5, pp. 1553–1597.

Autor, D., D. Dorn, and G. H. Hanson (2021). “On the Persistence of the China Shock”. In: IZA Discussion Papers 14804.

Autor, D. and M. Handel (2013). “Putting Tasks to the Test: Human Capital, Job Tasks, and Wages”. In: *Journal of Labor Economics* 31.2, S59–S96.

Autor, D., L. F. Katz, and M. Kearney (2006). “The Polarization of the U.S. Labor Market”. In: *American Economic Review* 96.2, pp. 189–194.

Autor, D., F. Levy, and R. J. Murnane (2003). “The Skill Content of Recent Technological Change: An Empirical Exploration”. In: *The Quarterly Journal of Economics* 118.4, pp. 1279–1333.

Deming, D. (2017). “The Growing Importance of Social Skills in the Labor Market”. In: *The Quarterly Journal of Economics* 132.4, pp. 1593–1640.

Tolbert, C. M. and M. Sizer (1996). “U.S. Commuting Zones and Labor Market Areas: A 1990 Update”. In: United States Department of Agriculture, Economic Research Service Staff Reports 278812.