When robots do (not) enhance job quality: The role of innovation regimes

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When robots do (not) enhance job quality: The role of innovation regimes

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Abstract:

Under a 'high cumulativeness' innovation regime, robot adoption results in better job quality as workers have some negotiation power. The *opposite* holds for robot adoption in low-cumulativeness regimes. In the latter, robot adoption leads to more dead-end 'Taylorist' jobs. Our results emerge from multi-level estimates of two countries (Italy and Germany). We conclude that previous studies tended to find weak effects of robot adoption as they did not control for innovation regimes. High rates of temporary jobs have a negative impact on the productive use of robots in innovation regimes with a high cumulativeness of knowledge, and less so in low-cumulativeness regimes.

JEL-codes : J3, J5, M5, O3

Key words: robot adoption, quality of work, innovation regimes, knowledge cumulativeness

1 Introduction

In recent years, we saw a resurgence of interest in robotization and artificial intelligence (Vivarelli 2014; Acemoglu and Restrepo 2019, 2020) with an interest in employment effects. Some authors, focusing on vulnerability of jobs to automation, warn that 47 percent of all workers in the US and around 54% in Europe might be at risk of becoming redundant during the next one or two decades (Frey and Osborne, 2017). Others pursue a task-based approach and argue that, within an occupation, many workers specialize in tasks, such as cognitive and manual non-routine tasks, that cannot be performed by machines (Brynjolfsson et al. 2018). Adopting this approach, only 9% of jobs in 21 OECD countries are at risk as a sizable share of tasks cannot be automated easily (see also Arntz et al. 2016). Also, Bessen et al (2019) find only quite moderate employment losses through automation that do not support the Frey & Osborn (2017) warning.

In theory, robotization could substitute workers in a range of specific tasks and reduce employment (displacement effect). Robot adoption, however, generates productivity effects and prompts compensation mechanisms, through price reductions, input-output linkages and final demand effects, that may even expand employment and counterbalance initial job destruction through a reinstatement effect (Acemoglu and Restrepo, 2019).

In the US, Acemoglu and Restrepo (2020) found a displacement effect, with robots turning out detrimental for employment and wages. By contrast, Graetz and Michael (2018), focusing on a country-industry panel of 238 units (across 17 OECD countries), between 1993 and 2007, found important productivity effects, without a significant reduction of workers or hours worked. Dauth et al. (2018) studied the German case and estimated inter-industry shifts of employment, from manufacturing to business services. Interestingly, they also studied the impact of robot exposure at the worker level and did not find negative effects of robots on the *incumbent* workers in terms of lay-offs. Instead, robot exposure induces firms to create fewer *new* jobs for young people. Dottori (2020) examines Italian data, both at the local labour market level and at the individual worker level, for the period 1991-2016. He finds weak employment effects of robots. Furthermore, he finds that workers in sectors with a high robot exposure have longer job tenures, and, given that they stay in the same firm, they earn higher wages. Other studies (e.g., Dixon et al. 2020; Acemoglu et al. 2020; or Koch et al. 2019) find some employment gains in robot-adopting firms, which, however, are at the cost of non-adopting firms through redistribution of market shares. Altogether, a cautious conclusion from today's literature could be that, at macro-level, robot adoption may slightly reduce employment.

This paper does not explore employment gains or losses, but analyses the impact of robot adoption on the *quality* of jobs. We investigate whether robot adoption enhances hiring of permanent (other than temporary) workers. Temporary contracts are often associated with low pay, low job quality, little training (Booth et al. 2002) and hence poor career prospects. We investigate, in a second step, the correlation between temporary contracts and low-quality jobs by means of a wage equation: is robot adoption associated with wage gains or wage penalties for certain categories of workers?

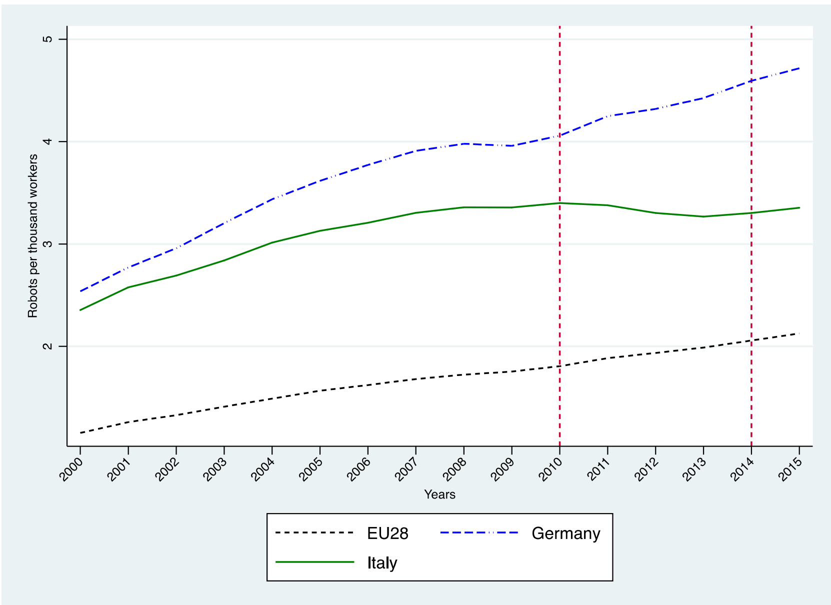
We expect that the diffusion of robot technology will increase shares of permanent jobs, assuming that robots raise the quality and the knowledge content of work, requiring training and job re-design. Robots substitute manual routine tasks, but require complementary non-routine, cognitive tasks (Acemoglu and Restrepo, 2019). Hence, they may reduce shares of fixed-term contracts, that usually do not offer incentives for skill development and processes of human capital accumulation (Bosio, 2014; Damiani et al. 2016). We first focus on the moderating role of industry-level robot exposure on the relationship between age and temporary contracts. Second, we explore if industry-level robot exposure plays a role in attenuating the wage penalty borne by temporary workers.

Our analysis is further refined by controlling for heterogeneity between industries, drawing from neo-Schumpeterian literature. Breschi et al. (2000) suggested a division of industries by the type of knowledge required for innovation. Some industries (including start-up industries, but also low-technology manufacturing and services) rely primarily on *generally available* knowledge; in the literature, such industries are sometimes referred to as 'Schumpeter-I' industries. Other industries (sometimes called 'Schumpeter-II' industries) rely heavily on a firm-specific and historically grown knowledge base. The latter stems from experience in handling technologies; such knowledge from experience tends to be ill-documented and 'tacit' and therefore is mainly 'embodied' in people (Kleinknecht et al. 2020).

Grouping industries in Schumpeter-I versus Schumpeter-II industries, we make use of work by Peneder (2010). Drawing from European *Community Innovation Survey* (*CIS*) data, Peneder provided a 'taxonomy' of industries with a high versus low 'cumulativeness' of knowledge. We hypothesize that in industries with a high 'cumulativeness' of knowledge, workers have a degree of negotiation power as they possess crucial knowledge; they therefore can more easily get permanent contracts, as well as higher wages, as productivity rises. The opposite may hold for industries that are not so dependent on worker-embodied knowledge from experience, i.e., in industries with a low cumulativeness of knowledge according to Peneder (2010).

We make a comparative study of Italy and Germany. The two countries show similarities in their labour market institutions (OECD, 2017, p.125: 165), and they both have a strong manufacturing sector. Both countries are characterized by the highest incidence of robotization in the European Union, although with trends evolving at different paces in recent years. Figure 1 shows that, around 2000/2001, robot density in Italy, measured as numbers of robots per thousand workers, was far above the EU average and pretty close to the German level. Short after the turn of the century, however, we see a widening gap between Italy and Germany. After the crisis of 2008/10, robot use stagnates in Italy, but is still growing in Germany. This is consistent with the stagnation of Italian labour productivity growth since the turn of the century, which Lucidi & Kleinknecht (2010) ascribe, among others, to labour market reforms in the 1990s, showing that firms that made most use of the new flexibility options exhibited the lowest wage and labour productivity growth.

Figure 2: Robot density in Italy, Germany and EU28



Source: IFR and EUKLEMS

We use worker-level data from the *Structure of Earnings Survey (SES)* collected by *Eurostat*, combined with industry-level data from the *International Federation of Robotics (IFR)* for robot exposure, and add, as a control, *EUKLEMS* data on ICT capital stock. We estimate Probits on the choice between temporary versus permanent jobs in Italian and German industries in 2010 and 2014. We consider permanent jobs as a proxy for better job quality and temporary jobs as indicating a rather 'Taylorist' work regime. We also test the moderating role of robot exposure on the seniority/temporary job relationship and replicate this analysis taking into account different degrees of 'cumulativeness' of knowledge of sectors. Finally, maintaining the distinction by cumulativeness of knowledge, we estimate Mincer-type wage equations on the impact of robot adoption on wages earned. Our estimates take into account the multi-level character of data and the potential endogeneity of robot exposure.

The paper proceeds as follows. Section 2 motivates our research and discusses related literature. Section 3 introduces the data and descriptive statistics. Section 4 covers the econometric approach, the main results and some robustness checks. Section 5 concludes.

2 Motivation and Background

2.1 Automation, temporary jobs and related literature

As argued by Autor (2015), automation may amplify the comparative advantage of employees occupied in tasks requiring solving skills, creativity and adaptability. For these employees, automation positively affects the demand for their labour because it raises 'the value of the tasks that workers uniquely supply' (Autor, 2015, p. 5). In other words, 'jobs involving analysis, decision making, abstract thinking, learning, innovation, and creativity are often complemented by new technology' (Gibbs 2017, p. 3). The latter tasks require rules that cannot be easily codified, simply because in such cases 'We know more than we can tell', as observed by Polanyi (1966). For a large number of jobs, professionals *know* how to perform a task but cannot *tell* a machine the required procedures. Hence, the extent of machine substitution for human inputs should not be overstated and strong complementarities that augment demand for skilled labour should not be ignored (Autor 2014, p. 130).

On the other hand, the new factor-augmenting technologies may increase the productivity of both high *and* low skill workers (the latter being more frequently on temporary contracts) and thus they are not 'explicitly skill-replacing technologies' (Acemoglu and Autor, 2012, p.434). Illustration through a practical example may be useful. Consider the case of building construction, a sector for which the impact of robotization in terms of worker substitution has been overstated. In spite of automation in construction due to robotization of cranes, excavators, arc welders and pneumatic nail guns, construction workers still perform a number of tasks: 'Construction workers supply tasks such as control, guidance and judgment that have no current machine substitutes and which therefore become more valuable as machinery augments their reach … To a first approximation, automation has therefore complemented construction workers—and it has done so in part by substituting for a subset of their job tasks.' (Autor, 2014, p. 137).

We address in this paper a different aspect: what is the influence of robots on the use of temporary contracts and on wages? Flexible contracts can be 'dead ends' as they discourage firm-sponsored training (Booth et al. 2002). We expect that, in industries more exposed to robotization, temporary jobs hinder the process of closing the gap between workers' skills and their new job tasks. Successful use of robots may therefore require hiring more people on permanent jobs.

There are at least three additional factors, measured at industry level, that can influence job design. The first one is ICT. Dauth et al. (2018) hypothesise ICT as a distinct form of innovation that, similar to robots, may complement some type of occupations, while making redundant some others, thus affecting workers in different ways. Remarkably, their estimates do not suggest a significant impact of ICT on total employment.

Michaels et al. (2014) show that ICT affects the composition of the labour force by increasing demand for highly educated workers, at the expense of workers with medium levels of education, and with small effects on low-educated workers. Chiacchio et al. (2018) argue that, differently from robot exposure, ICT positively affects employment, which they ascribe to the expansion of on-line marketing and trade. Degryse (2016: 23) argues that the so-called gig-economy may increase the fraction of extremely flexible and precarious jobs, such as those emerging in the digital platforms for food delivery, city mobility (Uber drivers) or casual odd-jobbing (repairs, home improvement, pet care, etc.).

A second industry-level factor is the degree of productivity dispersion. Recently, Foster et al. (2018) observed that creative destruction causes skewness in growth rate distributions. They underline that productivity dispersion is more pronounced in high-tech sectors (Foster et al. 2018). We therefore expect that, in the context of rapid innovation, technological laggards try to avoid their exit from the market by adopting flexible contracts that reduce their labour costs. For this reason, we expect productivity dispersion to be positively associated with the adoption of temporary contracts.

A third industry-level factor is an industry's dominant innovation regime. As indicated above, we rely on Peneder (2010) who classified industries by the degree to which innovation relies on a higher or lower 'cumulativeness' of knowledge, i.e., the degree to which innovative competences depend on firm-specific (and worker-embodied) knowledge from experience that has been accumulated over longer periods. We expect that in industries with a low cumulativeness of knowledge, relying mainly on generally available knowledge, flexible contracts will not be so harmful. By contrast, in industries with a high cumulativeness of knowledge, flexible contracts (and a higher labour turnover) are harmful as they hinder the long-run accumulation of (tacit) knowledge that tends to be 'embodied' in people (Kleinknecht 2020).

3. Data sources, variables and descriptive statistics

Three different databases have been merged for our empirical analysis:

First, data about individual characteristics of workers (type of contract, sex, age, wage, tenure, educational attainment, occupation) and about companies in which they are employed (firm size, economic activity, private versus state-owned firms) come from the *Structure of Earnings Survey (SES).* This is a four-yearly survey, conducted by national statistical offices and coordinated by Eurostat. The *SES* collects data from enterprises with at least 10 employees. Data cover Italy and Germany for two years, 2010 and 2014.

Second, information on robot adoption comes from the *International Federation of Robotics (IFR)*, which covers the stock of industrial robots installed at the industry/country level over the period from 1994 to 2015. The IFR database on robots covers almost all manufacturing industries, but service sector coverage is poor. Outside of well-defined manufacturing industries we have consistent data for four other industries, that is, Mining and Quarrying, Public Utilities, Construction and R&D and Education activities (IFR, 2016)[1].

[1] Following Graetz and Michaels (2018), we do not use the IFR categories 'all other manufacturing', 'all other non-manufacturing', and 'unspecified'. This is because the bulk of robots from the latter three industries is included in 'Unspecified' and the risk of misallocation of these robots among industries is high. In doing so we lose on average 11% of robots for Germany and 15% of robots for Italy. Instead, we use weights based on the respective share of employees to split robots in the R&D and in the Education sectors. The motivation is that Peneder's taxonomy does not include Education, but covers R&D as an industry with high knowledge cumulativeness (see Table 1).

Third, from the *EU-KLEMS* database we obtain industry level data on ICT capital stock and on numbers of employees, necessary to normalize ICT equipment and robots at the industry-country level. In order to map IFR into SES and EUKLEMS industries we used correspondence tables (ISIC Rev.4 / NACE Rev.2) that led us to aggregate the three databases into 14 industries (see Table 1).

Our dependent variable is binary, indicating if a worker has a temporary or a permanent contract (1 and 0, respectively). For a better contrast between permanent and temporary jobs, we omitted workers with apprenticeship contracts.

Furthermore, we have a binary explanatory variable at individual level for two age groups, i.e., older (30-64 years) versus younger workers (15-29 years). According to the ILO (2013) the passage of a young person to the first stable or satisfactory job, tends to occur at the age of 25-29 years. We therefore expect a negative sign for our binary variable *workers_30-64*, as seniority is expected to reduce the probability of being on a temporary job. Additional variables control for those individual characteristics that also affect the temporary worker status, such as gender, educational attainment, occupation and tenure (i.e., the years a worker is employed in the same company).

Industry-level robot exposure is our second key explanatory variable. We follow Acemoglu and Restrepo (2020) and Dauth et al. (2017), by measuring the cumulated growth rates over ten years in robot adoption per thousand workers (employed at the initial period in a given industry).

More precisely, we calculate this variable as follows:

$$Robot\_exposure_{c,j,t1} = \frac{robots_{c,j,t1} - robots_{c,j,t0}}{Employees_{c,j,1999}} \qquad (1)$$

where c=Germany, Italy; j= 14 industries as reported in Table 1; t_1= 2010, 2014; t_0 = 2000; 2004.

Following Acemoglu and Restrepo (2020), we normalize the numerator of (1) by taking the employees observed in each country/industry *before* the base period, that is 2000 in our case. This avoids that we normalize by employment affected by robot exposure over years under scrutiny[2]. Likewise, we disentangle robot exposure from other industry level factors such as ICT. We test whether ICT adoption affects the propensity to employ temporary workers independently of robot introduction.

We expect ICT density to have ambiguous effects. As already mentioned, ICT may increase the share of temporary and precarious jobs, at least among the younger labour force in the platform economy; in other cases, however, ITC requires 'learning by doing', professional training and career preparation. We follow Dauth et al. (2018) by introducing *ICT-exposure* at the industry level:

$$ICT\_exposure_{c,j,t1} = \frac{ICT_{c,j,t1} - ICT_{c,j,t0}}{Employees_{c,j,1999}} \quad (2)$$

where ICT is the real fixed capital stock in information and communication equipment (millions of euros, 2010 prices) and the same subscripts as in equation (1) apply.

Furthermore, we control for within-industry productivity dispersion. A high productivity dispersion marks the presence of firms with low efficiency, besides top performers. We expect low-efficiency firms to employ high rates of temporary workers as a defensive strategy. We follow Foster et al. (2018) and introduce the interquantile ratio of average wages paid by firms at region-industry level as a proxy for productivity dispersion.

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[2] Differently from Acemoglu and Restrepo (2020), our dependent variable is not the cumulated days of employment over years, but the probability to have a temporary job in 2010 and 2014 respectively. Thus, we assume that 10 years of robot exposure, and not 20 years, is a sufficient time to shape the propensity of firms located in a given industry to employ temporary workers.

$$Product\_disp_{c,j,r,t1} = \frac{PC75_{c,j,r,t1}}{PC25_{c,j,r,t1}} \qquad (3)$$

where $PC75$ and $PC25$ are the 75th and 25th percentiles of average wages paid at the firm level; c=Germany, Italy; j= industries; r= NUTS1 regions; t1= 2010, 2014. The construction of $Product\_disp$ relies on the aggregation of individual wages contained in the SES database. Data on firms, NUTS1 regions and industries allow us to exploit more variability for this indicator by taking into account both the industrial and the regional dimensions. Introducing the regional dimension leads us to better specify $Product\_disp$ as a control variable; this is particularly important for Italy, where asymmetries in size and productivity among companies play a key role in Southern regions (Sabatino, 2016, p.11). On the other hand, creating a control variable at the industry-region level alleviates multicollinearity problems in regressions where we introduce two industry-level variables (*robots*- and *ICT-exposure*).

We cannot exclude unobserved properties of industries (or specific demand shocks) to simultaneously influence robot use and the propensity to employ temporary workers. Thus, we use an instrumental variable strategy as suggested by Acemoglu and Restrepo (2020) and Dauth et al. (2017) and consider *robot_exposure* for France, the UK, Sweden and Finland as instruments for the corresponding robot variables for Germany and Italy. The underlying assumption is that common technological shocks shape the introduction of industrial robots in these four countries as well as of Germany and Italy, but cannot be influenced by specific labour market structures that affect temporary employment in the latter.

We also use industry-level information about a high versus a low degree of *cumulativeness of knowledge,* which we borrow from Peneder (2010). In industries with a high degree of *knowledge cumulativeness* innovative competences depend on the stock of knowledge from experience a firm has accumulated in the past. Peneder (2010) measures cumulativeness of knowledge by counting numbers of information sources that innovating firms reported as 'important' or 'crucial' to their innovative projects. Innovative leaders are considered highly cumulative if their *internal* sources of innovative ideas are more (or at least as) important than external sources, while innovative followers are highly cumulative if they rely more on external sources. The opposite cases (i.e., innovative leaders relying strongly on external sources or followers relying strongly on internal sources) fall into the category of 'low cumulativeness'. An account of industries falling into either category can be found in the bottom of Table 1. A discussion of the classification procedure is given in Peneder (2010, p. 327).

In the following, we assume that an innovating firm's use of its internal knowledge base relies on personnel with long job tenures who are able to accumulate often weakly documented and worker-embodied knowledge. Obviously, the latter requires *stable* employment relations with low rates of job turnover. We therefore hypothesize that industries that introduce robots have incentives for offering permanent rather than temporary jobs; and this incentive will be strongest in industries that rely most on accumulated knowledge. Applying Peneder's taxonomy (2010, p. 331) we group industries for which robot data are available in high & medium versus low cumulativeness industries and estimate separate equations for each group, omitting a few industries which are not covered by Peneder (2010). Finally, when exploring the role of robot exposure for wages of temporary versus permanent workers, we transform hourly wages in the SES database into real wages (Euros 2015 purchasing power parities).

Table 1 shows summary statistics averaged over 14 industries reported at the bottom. In Germany, the percentage of temporary jobs among youngsters is higher than in Italy, even though in Italy the share of flexible employment doubled between 2010 and 2014. As for senior workers, the opposite holds; i.e., Italy has higher shares of temporary senior workers, approaching ten percent in 2014.

Table 1: Summary statistics for variables used in the empirical analysis

	Workers in 2010				Workers in 2014			
Variables	Italy *Young*	Germany *Young*	Italy *Senior*	Germany *Senior*	Italy *Young*	Germany *Young*	Italy *Senior*	Germany *Senior*
SES dummy/categorical variables (individual-level)								
Temporary Workers	14.17	23.14	6.31	4.48	28.22	37.18	9.10	7.47
Public ownership	8.82	45.92	21.60	29.83	13.48	31.19	42.22	39.44
Women	33.09	38.02	34.06	34.49	39.16	37.63	41.48	38.96
Prim_Education	32.78	22.09	34.30	14.05	24.36	17.43	31.40	9.33
Sec_Education	55.88	63.90	47.80	64.44	50.69	59.16	48.50	56.64
Tert_Education	11.34	14.00	17.90	21.51	24.95	23.40	20.10	34.03
Managers	0.07	0.53	0.91	4.14	0.24	0.28	2.14	3.53
Professionals	11.08	9.65	17.57	16.00	14.64	17.23	23.61	24.74
Technicians	15.90	9.16	15.61	19.13	22.79	20.19	22.52	17.82
Clerical Supp_Workers	22.05	35.45	21.05	12.70	26.15	15.71	25.66	15.32
Serv.& Sales Workers	2.60	3.11	1.78	3.34	6.15	4.73	2.77	4.12
Skilled Agric_Workers	0.22	0.18	0.39	0.26	0.06	0.10	0.05	0.09
Craft Workers	22.78	21.15	17.83	19.37	16.13	23.95	10.37	15.25
Machine Operators	17.14	10.02	16.18	14.47	6.58	9.59	6.88	10.38
Elementary Occupations	8.16	10.74	8.67	10.59	7.27	8.23	5.99	8.74
Small Firms	38.31	14.46	23.19	17.42	41.54	21.79	28.76	20.68
Medium_Sized Firms	26.55	24.22	32.03	29.91	25.69	24.57	25.80	21.97
Large Firms	35.14	61.32	44.78	52.67	32.77	53.64	45.45	57.35
SES continuous variables (individual- and region-industry level)								
Tenure	3.32	3.19	12.12	14.84	2.31	3.51	9.99	16.89
Product_disp	1.39	1.61	1.39	1.61	1.50	1.61	1.50	1.61
Wages (temp. workers)	13.23	13.23	16.02	16.20	11.07	13.89	14.91	16.52
Wages (perm. workers)	13.30	13.45	16.52	21.19	11.38	15.74	17.42	21.54
Monthly hours worked	164.95	129.83	159.11	147.71	169.21	150.18	159.86	152.08
IFR continuous variables (industry-level)								
Robot_exposure	2.95	3.78	2.95	3.78	2.09	4.15	2.09	4.15
EUKLEMS continuous variables (industry-level)								
ICT_exposure	1.69	0.60	1.69	0.60	1.97	1.13	1.97	1.13
Industries with								
High & Med_Cumulativeness	**57.19**	**44.95**	**51.32**	**54.88**	**52.06**	**46.31**	**44.3**	**51.81**
Petroleum, Chem. & Pharma	5.59	4.22	6.81	5.92	5.09	3.80	5.88	5.59
Rubber, Plastic & Non- Metallic	5.60	3.65	6.38	5.02	5.10	3.32	5.51	4.74
Metal Products	8.42	4.13	6.82	4.93	7.66	5.79	5.89	4.65
Machinery	8.02	4.46	6.63	5.10	7.30	4.84	5.72	4.81
Motor vehicles & Transport Eqmt.	5.66	5.36	6.56	7.55	5.15	5.44	5.66	7.13
Electrical Eqmt & Computers	10.62	7.93	8.04	10.12	9.67	6.29	6.94	9.55
R&D	13.28	15.20	10.08	16.24	12.09	16.83	8.70	15.33
Low _Cumulativeness	**18.95**	**10.78**	**16.44**	**14.73**	**16.34**	**13.74**	**12.47**	**13.88**
Mining & Quarring	0.00	0.70	0.00	1.27	3.54	0.82	3.41	1.17
Food Industry	6.35	3.94	5.41	4.93	5.12	6.12	3.50	5.39
Textile & Garments	6.69	2.11	6.31	3.44	4.69	2.83	3.02	3.35
Wood &Printing	5.91	4.03	4.72	5.09	2.99	3.97	2.54	3.97
Other	**23.85**	**44.26**	**32.26**	**30.39**	**31.6**	**39.95**	**43.23**	**34.3**
Utilities	7.51	4.35	9.87	6.82	9.95	3.87	13.23	7.70
Construction	7.96	5.07	6.06	6.00	10.55	10.75	8.12	6.77
Education	8.38	34.84	16.33	17.57	11.10	25.33	21.88	19.83

Source: SES_2010 and 2014, Eurostat; IFR and EUKLEMS. Note: All values are percentages with exception for Tenure (the length of service in the same enterprise is measured in years), Robot-exposure (Δrobots x thousand workers); ICT-exposure (ΔICT capital stock x thousand workers); Product_disp (ratio $75^{th}/25^{th}$ percentiles); wages (real hourly wages in 2015 Euros PPP) and number of monthly hours worked.

Robot_exposure reflects the robot density pattern of Figure 1, even though the former is measured in a slightly different way. In Germany between 2000 and 2010, on average, an additional 3.78 robots per thousand workers were newly installed as opposed to 2.95 in Italy. The ten-years *robot_ exposure* advanced at a different pace between 2004 and 2014, as it increased in Germany and weakened in Italy (4.15 versus 2.05 robots per thousand workers, respectively). Taking the *variation* of robots over years, rather than the *stock* of robots, has the advantage of alleviating the large skewness of their distribution across industries (Fernández-Macías et al., 2020).

ICT_exposure was, on average, higher in Italy than in Germany: in 2014 the real fixed capital stock increased by 1.97 million euros per thousand workers over the past ten years while in Germany the corresponding figure is 1.13. This reflects the efforts made by Italy, after the 2008 crisis, in catching up with the EU leader countries in ICT investment and it is coherent with statistics reported by other sources. For example, in 2017 the Italian ICT investment share in GDP was above the corresponding German share (OECD, 2019).

A remarkable disparity between Italy and Germany relates to education. Table 1 shows in 2010 a higher share of Italian senior workers with only a primary education level (34.3% compared to 14% in Germany); also, shares with higher education levels, both secondary and tertiary in Italy are lower than in Germany (47.8% and 17.9% and 64% and 21.5%).

The distribution of workers by firm size reflects structural characteristics. In Italy, more than half of all workers are employed in small and medium-sized companies whereas in Germany we find the majority of employees in large and medium sized enterprises. As expected, wages earned by temporary workers are always lower than those of permanent workers and the wage penalty aggravates for older (temporary) workers especially in 2014.

Finally, at the bottom of Table 1, 14 industries are clustered according to Peneder's taxonomy of knowledge cumulativeness, i.e., according to high and medium versus low cumulativeness. High and medium cumulativeness includes R&D services besides a number of manufacturing industries. More than half of the workers in our sample are employed in these industries.

4. Econometric approach

We estimate the probability of being employed on a temporary contract applying a static probit model to Italy and Germany separately. We first explore how seniority and robot_exposure, independently of each other, affect the probability of having a temporary job:

$$P\left(TJ_{i,j,t}=1\middle|\boldsymbol{X_{i,j,t}}\right)=\Phi\left[\boldsymbol{X'_{i,j,t}}\,\boldsymbol{\beta}\right]=\Phi\left[\beta_0+\ \beta_1(Work\_30-64)_{i,j,t}+\beta_2(Rob\_exp)_{j,t}+\beta_3(ICT\_exp)_{j,t}+\beta_4(Prod\_disp)_{j,r,t}+\boldsymbol{\beta_5}(\boldsymbol{WC})_{i,j,t}+\eta_j+Year\_2014\right] \quad (4)$$

where i= workers; j=industries; r= NUTS1 regions (the latter only refers to $Prod\_disp$) and t=2010 and 2014. Despite observations over two years, we do not have repeated observations for the *same* workers, hence we deal with pooled cross sections and not panel data. The probability of a worker having a temporary contract is a function of seniority ($Work\_30-64$) and the industry-level *robot_exposure*. This probability also depends on a vector *WC* of individual-level worker characteristics, such as gender, education, occupation, tenure, size and state (vs. private) ownership of the firm in which the individual is employed. $ICT\_exposure$ and productivity dispersion ($Prod\_disp$) are potential confounding factors that affect the industry-level impact of *Robot_exposure*. It is worth noting that productivity dispersion also shows greater variability at industry-region (NUTS1) level, as discussed in the previous section. $Year\_2014$ is a time dummy controlling for common shocks occurred in 2014 and η_j are industry dummies.

In the second model we introduce an interaction term to analyse whether *robot_exposure* moderates the relationship between seniority and temporary jobs:

$$P\left(TJ_{i,j,t}=1\middle|\boldsymbol{X_{i,j,t}}\right)=\Phi\left[\beta_0+\ \beta_1(Work\_30-64)_{i,j,t}+\beta_2(Rob\_exp*\ Work\_30-64)_{i,j,t}+\beta_3(ICT\_exp)_{j,t}+\beta_4(Prod\_disp)_{j,r,t}+\boldsymbol{\beta_5}(\boldsymbol{WC})_{i,j,t}+\eta_j+Year\_2014\right] \quad (5)$$

Because of the multilevel character of the data, we use industry dummies η_j with caution as they encapsulate industry-level variance also captured by Rob_exp and ICT_exp. This implies that we introduce industry dummies only in specifications where *individual*-level regressors are used. In other words, in order to avoid multicollinearity problems, we omit them if we introduce Rob_exp and ICT_exp. Likewise, in model (5) we follow the recommendations of Bryan and Jenkins (2016) and Snijders and Bosker (1999) and omit the main effect of Rob_exp when we control for industry dummies, or omit the latter if we introduce Rob_exp and ICT_exp.

As discussed in the previous section, if *robot_exposure* is endogenous the coefficient of interest β_2 could be biased. For this reason, we perform an instrumental variable probit regression (IV-probit) based on the conditional maximum likelihood estimation. The reduced form is an OLS regression of the endogenous variable on excluded and included instruments as follows:

$$(Rob\_exp * \ Work\_30 - 64)_{i,j,t} = \beta_0 + \boldsymbol{\beta_1} \textstyle\sum_{n=1}^{4}(Rob\_exp\_for)_{i,n,j,t} + \beta_3(ICT\_exp)_{j,t} + \beta_4(Prod\_disp)_{j,r,t} + \boldsymbol{\beta_5}(\boldsymbol{WC})_{i,j,t} + \eta_j + Year_{2014} + \ v_{i,j,t} \quad (6)$$

where Rob_exp_for are the four instruments already mentioned above, that is, *robot_exposure* of the UK, France, Finland and Sweden. The remainder includes the exogenous variables of the structural equation 5. In doing so, we follow Wooldridge (2010, p. 592-593) and assume that instruments that are good for *robot_exposure*, are also good for the interaction term $Rob\_exp * \ Work\_30 - 64$. This procedure allows us to perform a robustness check on the exogeneity of the latter. The exogeneity test is based on the null hypothesis $\rho = 0$, where ρ is the correlation between error terms from the latent variable version of structural equation 5 and error terms $v_{i,j,t}$ from the reduced form, i.e., equation 6 (Wooldridge 2010; Cameron and Trivedi, 2009).

As is well known, the coefficients of equations (4) and (5) are not so informative if we are interested in the magnitude of the partial effects of explanatory variables on the probability to have a temporary job. This is because the marginal effect depends on **X,** through $\Phi[\boldsymbol{X}' \boldsymbol{\beta}]$ (see equation 4)**.** Therefore, in all results reported in the next section, we summarize the estimated marginal effects by taking the average value of the marginal effects across all the observations in our sample. In other words, we report all Probit estimated coefficients as average *partial* effects (see Wooldridge, 2010 and Cameron and Trivedi, 2009 for details). The latter give us more complete information than calculating the marginal effects at given values of explanatory variables (i.e., given numbers of years for tenure, given educational attainment, etc.). This especially holds if we study the effect of a single explanatory variable on the response variable.

Finally, we run a Mincer wage equation to show if, after controlling for various characteristics of employees, the wage penalty borne by temporary workers persists. By interacting the temporary worker dummy and *robot_exposure* we also test if robotization may influence this wage gap:

$$wage_{i,j,t} = \beta_0 + \ \beta_1(temp)_{i,j,t} + \beta_2(Rob\_exp * \ temp)_{i,j,t} + \beta_3(ICT\_exp)_{j,t} + \beta_4(hours\ worked)_{j,r,t} + \boldsymbol{\beta_5}(\boldsymbol{WC})_{i,j,t} + \eta_j + Year_{2014} + \varepsilon_{i,j,t} \quad (7)$$

where $temp$ is a dummy for temporary workers and $Rob\_exp * \ temp$ is the interaction term; $hours\ worked$ is the number of monthly hours worked, which controls for the business cycle; the remainder of terms in the right-hand side of equation 7 are identical to those previously discussed.

Equation 7 is a simple OLS regression that serves as corroborative analysis for results we get from equation 6. As we are aware of the econometric problems affecting the analysis of temporary workers and wages (Picchio, 2006; Bosio, 2014), we emphasize the explorative and descriptive character of the wage equations without making strong causal claims.

5. Results for robots, temporary jobs and wages

All tables that summarize results from Probit estimates cover *average marginal* effects, reporting effects separately for Italy and Germany. The OLS wage equation also reports separate effects for the two countries.

5.1 The baseline model for temporary jobs

Our baseline model in Table 2 shows the role of individual characteristics, such as seniority, tenure (i.e., years in the same firm), education, occupation and gender for the adoption of temporary contracts (columns 1-4). These baseline specifications are then augmented with industry level data, i.e., robot and ICT_ exposure, and productivity dispersion (columns 5-10). The goodness of fit, especially the percentage of correctly specified observations, increases if we add individual and industry level controls. For instance, in column 9 (Italy) the percentage of correctly predicted observations is 96.1, that is, the model correctly predicts temporary workers 58.2 percent of the time and permanent workers 96.2 percent of the time. For Germany (column 10) the percentage of correctly predicted observations is 91.7, of which correct predictions for temporary workers are 72.5 percent, whereas those for permanent workers are 92.4 percent.

As expected, *age 30_64* as a stand-alone term (columns 1 and 2) reduces the probability of being a temporary worker by 0.08 in Italy and about 0.12 in Germany. If we add individual characteristics as controls (gender, education, tenure, state ownership of firms, occupation and firm size) the role of ageing is confirmed only for Italy (column 3), and becomes insignificant for Germany (column 4).

Concerning the second key explanatory variable, *Robot_exposure,* we obtain negative and significant average marginal effects but of small magnitude (-0.001) for Italy and Germany (columns 5 and 6, respectively). For Italy this weak effect loses statistical significance when we add *ICT_exposure* and productivity dispersion (columns 7 and 9). By contrast, in Germany, in the full specification, the result for *robot_exposure* is confirmed and we obtain that it significantly reduces the probability to be a temporary worker by -0.002 (column 10).

It is reassuring to see that other results for individual level and industry level controls are coherent with the key findings for temporary employment offered by EU-Labour Force Survey data (for an overview see Eurofound 2015). For example, *Tenure* shows that one more year of work in the same firm reduces the probability of having a temporary job by -0.088 in Germany and by -0.033 in Italy. In Germany temporary contracts are more frequently than in Italy stepping stones towards permanent contracts, which is also signalled by Eurofound (2015, Fig.17, p.32) and in line with other studies (Loh, 1994; Bosio, 2014).

Our gender dummy indicates that females more often have temporary contracts in Italy; but for Germany, the effect is weaker. This result is in line with evidence for most OECD countries, where the percentage of females among fixed-term workers is above the share of males, although gender differences are not very pronounced (OECD, 2014, p.154).

The positive and significant coefficient for the public sector comes from the education sector, which has high shares of temporary workers; this is, again, consistent with statistics from EU-Labour Force Survey data (Eurofound, 2015, p. 24). As for *Education,* we find that tertiary education is positively associated to higher probabilities of temporary contracts in Germany, but not in Italy.

As expected, low and medium skilled occupations, such as elementary occupations, machine operators, craft workers, sales and service workers, show a higher probability for recruitment as temporary jobs compared to managers (our reference group). Finally, the result that medium-sized companies use more flexible labour is also coherent with findings in Eurofound (2015, p. 23-24).

Models (9) and (10) of Table 2 include ICT capital stock as a control, finding that coefficients for *robot_exposure* do not significantly change. One should also note that ICT is weakly significant (at the 10 percent level) only in the Italian case, and insignificant in Germany, in line with the findings by Dauth et al. (2017).

Finally, for both countries, we obtain a positive and significant effect of the proxy of productivity dispersion. This is in line with our conjecture that higher variability signals the presence of laggard companies in a given region and industry, which use high numbers of temporary contracts for cost-cutting as a defence against innovative market leaders.

Table 2: Probability to get a temporary job: senior vs younger workers and effect of sectoral robot exposure (Baseline Probit Model, Average Marginal Effects)

	Dependent variable: Probability of a temporary job									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Independ. variables:	Italy	Germany	Italy	Germany	Italy	Germany	Italy	Germany	Italy	Germany
Workers_30-64	-0.080***	-0.116***	-0.026***	-0.009	-0.025***	-0.020	-0.025***	-0.011	-0.025***	-0.011
		(0.011)	(0.005)	(0.033)	(0.007)	(0.032)	(0.007)	(0.034)	(0.007)	(0.034)
Robot_exposure					-0.001**	-0.001**	-0.001	-0.001***	-0.001	-0.002***
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Product_disp							0.056***	0.212***	0.055***	0.210***
							(0.015)	(0.060)	(0.015)	(0.058)
ICT_exposure									-0.001*	0.006
									(0.001)	(0.004)
Governmt-owned firms			0.037***	0.085***	0.050***	0.138***	0.048***	0.111***	0.048***	0.106***
			(0.009)	(0.019)	(0.017)	(0.025)	(0.015)	(0.018)	(0.015)	(0.019)
Year_2014			0.004	0.039***	0.003	0.045***	0.002	0.060***	0.003	0.058***
			(0.008)	(0.015)	(0.007)	(0.011)	(0.004)	(0.011)	(0.004)	(0.010)
Tenure (years in same firm)			-0.032***	-0.088***	-0.033***	-0.082***	-0.033***	-0.085***	-0.033***	-0.085***
			(0.001)	(0.008)	(0.005)	(0.014)	(0.004)	(0.011)	(0.004)	(0.011)
Women			0.005**	0.004	0.012***	0.015***	0.011***	0.008	0.011***	0.008
			(0.002)	(0.004)	(0.002)	(0.005)	(0.001)	(0.005)	(0.002)	(0.005)
Education										
Secondary Education			-0.005	-0.026*	-0.004	-0.036*	-0.005	-0.028*	-0.005	-0.028*
			(0.004)	(0.016)	(0.004)	(0.019)	(0.005)	(0.015)	(0.005)	(0.015)
Tertiary Education			-0.005	0.015***	-0.001	0.008*	-0.002	0.015***	-0.002	0.015***
			(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
Occupation										
Professionals			0.017	0.029***	0.030***	0.038***	0.030**	0.037***	0.030**	0.036***
			(0.012)	(0.002)	(0.011)	(0.004)	(0.012)	(0.003)	(0.012)	(0.003)
Technicians			0.012*	0.012	0.005	0.003	0.008	0.017	0.008	0.017
			(0.007)	(0.012)	(0.008)	(0.011)	(0.007)	(0.015)	(0.007)	(0.015)
Clerical Sup. Workers			0.017	-0.000	0.016	0.004	0.018	0.002	0.017	0.002
			(0.012)	(0.004)	(0.016)	(0.003)	(0.015)	(0.003)	(0.015)	(0.003)
Service and sales workers			0.022**	0.007	0.022*	0.017**	0.022**	0.011*	0.022**	0.012**
			(0.009)	(0.006)	(0.012)	(0.007)	(0.010)	(0.006)	(0.010)	(0.005)
Skilled Agric_Workers			0.020***	0.013	0.014*	-0.015	0.022**	0.007	0.022**	0.007
			(0.008)	(0.015)	(0.008)	(0.012)	(0.009)	(0.016)	(0.009)	(0.016)
Craft Workers			0.013*	0.045***	0.007	0.014*	0.011*	0.035**	0.012*	0.038**
			(0.007)	(0.017)	(0.007)	(0.007)	(0.006)	(0.015)	(0.006)	(0.017)
Machine Operators			0.019***	0.047***	0.009	0.025***	0.015**	0.040***	0.015**	0.045***
			(0.007)	(0.012)	(0.006)	(0.008)	(0.006)	(0.010)	(0.006)	(0.012)
Elementary Occupations			0.017***	0.055***	0.012*	0.045***	0.019***	0.058***	0.019***	0.058***
			(0.004)	(0.012)	(0.007)	(0.011)	(0.006)	(0.013)	(0.006)	(0.013)
Firm Size										
Medium Sized Firms			0.011***	0.034***	0.014***	0.028***	0.010***	0.032***	0.011***	0.033***
			(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Large Firms			-0.012	0.059***	-0.016**	0.069***	-0.016*	0.063***	-0.015*	0.063***
			(0.008)	(0.007)	(0.008)	(0.010)	(0.009)	(0.008)	(0.009)	(0.008)
Sectoral Dummies	Yes	Yes	Yes	Yes	No	No	No	No	No	no
Observations	189,113	917,580	177,495	857,038	177,495	857,038	177,495	857,038	177,495	857,038
Pseudo_R2	0.102	0.124	0.241	0.308	0.219	0.287	0.228	0.302	0.229	0.304
% correctly classified	93.43	88.47	96.09	91.90	96.08	91.75	96.06	91.72	96.06	91.73

Note: Sector-level cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Pseudo_R2* and *% correctly classified* observations measure the goodness of fit for the raw coefficient estimates. Robot and *ICT-exposure* are sector-level variables calculated as cumulative change of sector level number of industrial robots and ICT capital (2000-2010 and 2004-2014) on sector-level employees in 1999. Product_disp is a proxy for productivity dispersion at sector-region level, that is, the interquartile ratio of firm level average wages. The dependent variable and all other regressors are worker level variables. Primary Education is the omitted variable for education; managers, senior officials and legislators is the omitted variable for occupations, small firms is the omitted variable for firm size.

5.2 The impact of high versus low cumulativeness of knowledge

In Table 3, we report additional estimates of the probability of getting a temporary contract that are obtained by introducing the interaction term *Rob x Workers_30-64* and controlling for endogeneity by means of IV-Probit estimates, as explained above. In order to save space, we do not document coefficients of all individual control variables as in the previous table, which look very similar. We neither document the Probit version of equation 5 (without IVs) since the estimated coefficients, especially those referring to the whole sample (columns 1 and 2), are also very similar to those reported in Table 3 (results are available on request). The low correlation between residuals of structural and reduced form (ρ) and the Wald test reported at the bottom of Table 3 signals that we cannot reject the null hypothesis of its exogeneity in three out of six cases (columns 1, 2 and 4).

Further, this result is not conditioned by a possibly low quality of instruments chosen for *Rob x Workers_30-64.* The first stage of the IV estimates (as reported in Table A.1, Appendix) shows that, in any specification, at least two instruments are always positively correlated to our suspected endogenous variable and values estimated for the Kleinbergen-Paap Wald F statistic tell us that they are relevant. As explained in section 4, we neither use the main effect for *Robot_exposure* nor introduce industry dummies in Table 3 because other industry level controls (*ICT_exposure*) already capture variance at the industry level.

For the *total* sample, we obtain in Table 3 a negative but weakly significant average marginal effect for the interaction term only for Germany, while for Italy we only find a confirmation of the main effect of seniority. The fact that no difference is detected for seniority in Germany (Workers_30_64 is insignificant) means that even for this country we cannot find a moderating effect of *Robot_exposure* on seniority. Indeed, the significant coefficient of *Rob x Workers_30-64* obtained in the specification for Germany (probability of temporary jobs reduced by -0.003, column 2) and the insignificant effect for Workers_30_64, confirm an overall weak effect of the industry level *Robot_exposure* regardless of seniority and similar to what we found in Table 2.

Using the IV-Probit for results in Table 3 is important, however, since, after splitting the sample by degrees of cumulativeness, the exogeneity of *Rob x Workers_30-64* is questioned in three out of six specifications (columns 3, 5 and 6). As compared to Table 2, the coefficients in Table 3 change decisively once we take into account the dominant innovation regime. In models 3-6, we estimate our model separately for industries with a high and medium versus a low cumulativeness of knowledge according to Peneder's (2010) taxonomy. In the former industries in which innovative competences are dependent on historical accumulation of knowledge from experience, there is quite a strong *negative* effect of robot introduction on the probability that senior workers will be on temporary contracts, while in industries with a low cumulativeness of knowledge, we find the *opposite*. This implies that the low (and in part insignificant) coefficients for robots and workers_30-64 obtained in models 1 and 2 for the *total* sample come from two opposite patterns that emerge when we identify the dominant innovation regime in a sector.

In both countries, an increase of robots in high cumulativeness industries *reduces* the probability of senior workers to be hired on temporary contracts. In other words, in a context in which 'person-embodied' knowledge from experience is important for innovation, firms have an incentive to employ more people on permanent contracts if robots are introduced. The opposite holds in industries characterised by low knowledge cumulativeness, where the probability for older workers to be hired on temporary contracts even becomes *higher* when robots are introduced (see columns 5-6). Seemingly, in a context in which person-embodied knowledge from experience is less important, workers are more easily interchangeable and have no power to demand permanent contracts.

Table 3: The probability of getting a temporary job: the impact of high versus low cumulativeness of knowledge (IV Probit Model with interactions, APEs)						
	Dependent variable: Probability of temporary jobs					
	Total sample:		High & medium cumulativeness industries:		Low cumulativeness industries:	
Independent variables:	(1) Italy	(2) Germany	(3) Italy	(4) Germany	(5) Italy	(6) Germany
Robots x Workers_30-64	0.000 (0.000)	-0.003** (0.001)	-0.012*** (0.003)	-0.008*** (0.001)	0.020*** (0.006)	0.060*** (0.016)
Workers_30-64	-0.026*** (0.007)	-0.007 (0.033)	-0.262*** (0.044)	-0.447*** (0.065)	-0.296** (0.140)	-0.501*** (0.106)
Productivity dispersion	0.055*** (0.015)	0.212*** (0.059)	0.382*** (0.095)	-0.055 (0.391)	0.971*** (0.211)	0.806*** (0.277)
ICT_exposure	-0.001 (0.001)	0.006 (0.004)	-0.006 (0.013)	-0.006 (0.013)	0.010** (0.004)	0.060 (0.195)
Other controls (as in previous table)	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Sector dummies	No	No	No	No	No	No
Observations:	177,495	857,038	78,568	365,656	26,833	152,906
Perc. of correctly classified obs.	96.06	91.73	97.84	95.08	98.16	95.65
Correlation between structural and reduced form residuals (ρ) and Wald Test of exogeneity:						
ρ	0.023	0.003	0.049	0.021	0.028	0.047
H0: Rob x Workers_30-64 is exogeneous (p-value)	0.257	0.904	0.000	0.135	0.083	0.015

Note: Sector-level cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *% correctly classified obs.* measure the goodness of fit for the raw coefficient estimates of the second stage equation. *Other Controls*: all other control variables displayed in Table 2 apply. *Rob x Workers_30-64* is an interaction term between *robot exposure* and *Workers_30_64*. Robot and ICT exposure are sector-level variables calculated as cumulative change of sector level number of industrial robots and ICT capital (2000-2010 and 2004-2014) on sector-level employees in 1999. Rob x Workers_30-64 has been instrumented with sectoral robot exposure of Finland, France, UK and Sweden (see Table A.1 for the first stage of IV-Probit). Product_disp is a proxy for productivity dispersion at sector-region level, that is, the inter-quantile ratio of firm level average wages. The dependent variable and all other regressors are worker level variables. *High & Medium Cumulativeness* and *Low Cumulativeness* industries according to the Peneder's taxonomy are discussed in section 3 and reported in Table 1.

Another possible explanation for these results relates to the different quality of the new tasks for workers after the introduction of robots (Acemoglu and Restrepo, 2019). When reliance on person-embodied knowledge from experience is high, the emerging new labour-intensive tasks are further specialisations of the former tasks that have been taken over by robots. In this case the productivity gains come from older workers with permanent contracts that know the productive organisation of the firm and easily adapt to new tasks complementary to the new machines.

In the opposite case, when reliance on a worker's accumulated knowledge from experience is low, firms are less dependent on permanent workers, and, in the context of rapid change, creative destruction and uncertainty, they may choose for flexible hiring.

5.3 Results for robots and wages

In the following, we investigate the impact of robot adoption on wages. Assuming that the wage gap between temporary and permanent workers is a measure of the lower quality of flexible jobs, we can study in which innovation regime they are most harmful and how robots affect this wage gap. Due to the econometric problems related to the analysis of temporary workers and wages (Picchio, 2006; Bosio, 2014), we remain cautious about causalities when interpreting the wage equations in Table 4.

In the Mincerian equations reported in Table 4, the natural logarithm of real hourly wages (in Euros 2015 purchasing power parities) is regressed on the interaction between robot exposure and the temporary worker dummy and on the usual set of individual-level and industry-level characteristics. We omit, however, the control for productivity dispersion. Since the proxy for productivity dispersion is based on wages it may be somehow correlated with our dependent variable. We add numbers of monthly hours worked as a control for business cycles. The latter reflect the relative scarcity of workers and are expected to have a positive sign.

The reported coefficients for control variables in Table 4 suggest that the model is well specified. For example, workers at higher age, workers with a longer tenure in the firm, and highly educated workers earn higher wages. We also find a substantial gender wage gap. As expected, an increase in labour demand (i.e., more hours worked) positively affects hourly wages. Moreover, we find that workers employed in large firms get higher pay compared to their colleagues in medium-sized firms and the latter earn still more than workers in the reference group of small firms. This finding is well documented but poorly understood in the literature (see Brown & Medoff 1989).

The dummy for temporary (versus permanent) workers shows a significant wage penalty for temporary workers, which is in line with results in the literature for both Italy (Picchio, 2006) and Germany (Mertens et al., 2007). There is, however, a remarkable difference by degree of cumulativeness of knowledge. We find significantly higher wage penalties for temporary workers in industries with a high or medium degree of cumulativeness of knowledge compared to low cumulativeness industries (-9% vs -4.1% in Italy and -11.7% vs -1.7% in Germany).

In other words, when accumulation of firm-specific (and often worker-embodied) knowledge from experience is important for innovative competencies, temporary jobs seem to be most harmful for wages (or: for productivity, as far as wages reflect productivity). In the latter case, however, a higher robot exposure *reduces* the pay penalty for temporary workers modestly, that is +0.3% in Italy and +0.6% in Germany, while the corresponding coefficients in low-cumulativeness industries show *opposite* signs with weak significance. The named effects imply that an increase by one robot per thousand workers in industries with a high or medium cumulativeness brings about a reduction of the wage penalty from -9.0% to -8.7% in Italy and from -11.7 to -11.1% in Germany. The wage penalty for temporary workers remains nonetheless substantially higher than that observed in low-cumulativeness industries (i.e., -4.1% in Italy and -2% in Germany).

As far as wages reflect workers' productivity, these outcomes imply that the use of temporary contracts *reduces* workers' productivity if innovation is dependent on accumulation of person-embodied knowledge from experience, but introduction of robots slightly counteracts this tendency. On the other hand, in low-cumulativeness industries, when innovation is hardly dependent on accumulated and person-embodied knowledge, introduction of robots rather increases than reduces the wage penalty for temporary workers, but this wage penalty is smaller than in high-cumulativeness industries. The latter is consistent with the finding by Vergeer et al. (2015) that, in high-cumulativeness industries, flexible contracts are detrimental to productivity growth, while in low-cumulativeness industries they have less influence.

Our interpretation depends of course on whether wages indeed reflect productivity. A high (measured) productivity could be due either to technological progressiveness or it could result from market power that allows appropriating higher margins that are then (wrongly) interpreted as higher productivity. The same holds for wages. Wages can either reflect productivity of workers or workers' negotiation power. In principle, under perfect competition, measured productivity should of course reflect real productivity and wages should reflect the productivity of workers. In the context of innovation, however, the assumption of perfect competition is highly unrealistic, notably if one realizes that perfect competition is a bad milieu for innovation, innovation being enhanced by market imperfections, notably by labour market rigidities (Kleinknecht 2020).

Table 4: Robots and the temporary workers wage gap: the importance of cumulativeness of knowledge (Summary of OLS wage equations)

	Dependent variable: Ln(Hourly wages)					
	High & Medium Cumulativeness		Low Cumulativeness		Total sample:	
	(1)	(2)	(3)	(4)	(5)	(6)
Independent variables:	Italy	Germany	Italy	Germany	Italy	Germany
Rob x Temporary workers	0.003*	0.006***	-0.001	-0.003**	0.002*	0.005***
	(0.002)	(0.000)	(0.003)	(0.001)	(0.001)	(0.000)
Temporary workers	-0.090***	-0.117***	-0.041**	-0.017***	-0.088***	-0.099***
	(0.008)	(0.003)	(0.018)	(0.005)	(0.004)	(0.002)
Ln(Paid monthly hours)	0.034***	0.086***	0.064***	0.086***	-0.175***	0.140***
	(0.007)	(0.002)	(0.010)	(0.003)	(0.005)	(0.001)
Workers_30_64 years	0.162***	0.128***	0.138***	0.071***	0.152***	0.168***
	(0.004)	(0.002)	(0.006)	(0.003)	(0.003)	(0.001)
ICT_exposure	-0.009***	0.021***	0.015***	-0.047***	0.001*	0.026***
	(0.001)	(0.000)	(0.001)	(0.009)	(0.000)	(0.000)
State-owned firms	0.090***	-0.106***	0.053***	0.018**	0.116***	-0.234***
	(0.004)	(0.002)	(0.011)	(0.009)	(0.002)	(0.001)
Year_2014	-0.070***	-0.071***	-0.050***	-0.136***	-0.057***	-0.040***
	(0.003)	(0.001)	(0.005)	(0.002)	(0.002)	(0.001)
Tenure (years in same firm)	0.065***	0.090***	0.048***	0.081***	0.068***	0.086***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)
Women	-0.124***	-0.152***	-0.172***	-0.231***	-0.166***	-0.138***
	(0.003)	(0.001)	(0.004)	(0.002)	(0.002)	(0.001)
Education						
Secondary Education	0.095***	0.114***	0.102***	0.144***	0.096***	0.124***
	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)
Tertiary Education	0.229***	0.289***	0.212***	0.341***	0.239***	0.349***
	(0.004)	(0.003)	(0.009)	(0.006)	(0.003)	(0.002)
Occupation						
Professionals	-0.443***	-0.349***	-0.488***	-0.291***	-0.389***	-0.301***
	(0.012)	(0.004)	(0.025)	(0.012)	(0.008)	(0.003)
Technicians	-0.589***	-0.419***	-0.630***	-0.371***	-0.611***	-0.301***
	(0.012)	(0.004)	(0.024)	(0.010)	(0.008)	(0.003)
Clerical Support Workers	-0.653***	-0.615***	-0.731***	-0.604***	-0.737***	-0.557***
	(0.012)	(0.004)	(0.024)	(0.011)	(0.008)	(0.003)
Service and Sales Workers	-0.689***	-0.731***	-0.789***	-0.786***	-0.747***	-0.647***
	(0.014)	(0.006)	(0.025)	(0.011)	(0.010)	(0.004)
Skilled Agricultural Workers	-0.796***	-0.748***	-0.933***	-0.689***	-0.948***	-0.577***
	(0.048)	(0.011)	(0.027)	(0.048)	(0.015)	(0.008)
Craft Workers	-0.773***	-0.717***	-0.864***	-0.759***	-0.804***	-0.582***
	(0.012)	(0.004)	(0.024)	(0.010)	(0.008)	(0.003)
Machine Operators	-0.797***	-0.734***	-0.865***	-0.738***	-0.811***	-0.627***
	(0.012)	(0.004)	(0.024)	(0.010)	(0.008)	(0.003)
Elementary Occupations	-0.858***	-0.883***	-0.891***	-0.708***	-0.880***	-0.635***
	(0.013)	(0.005)	(0.024)	(0.011)	(0.008)	(0.003)
Firm Size						
Medium-sized Firms	0.080***	0.078***	0.105***	0.093***	0.068***	0.081***
	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.001)
Large Firms	0.124***	0.250***	0.138***	0.225***	0.103***	0.204***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.001)
Constant	2.752***	2.603***	2.666***	2.597***	3.872***	2.155***
	(0.039)	(0.013)	(0.060)	(0.020)	(0.025)	(0.007)
Observations	78,568	365,588	26,833	105,853	177,495	856,965
R-squared	0.373	0.515	0.384	0.539	0.473	0.522

Note: Sector-level cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Robot and ICT exposure are sector-level variabl calculated as cumulative change of sector level number of industrial robots and ICT capital (2000-2010 and 2004-2014) on sector-level employees 1999. The dependent variable (real hourly wages in Euros PPP 2015) and all other regressors are worker level variables. *Rob x Temp.Workers* is : interaction between robot exposure and temporary workers dummy. The main effect for robot exposure has been omitted because ICT_exposure alreac captures most of the industry level variance. For the same reason we do not use industry dummies in this model. *High & Medium Cumulativeness*, *Lc Cumulativeness* and *Other* group industries according to the Peneder's taxonomy discussed in section 3 and reported in Table 1.

Whatever interpretation one prefers, the above results are intriguing. In Table 3 we found that, in industries with a high or medium cumulativeness of knowledge, firms *reduce* temporary contracts for older workers when robots are important. But in low-cumulativeness industries, a higher impact of robots is related to an *increase* of temporary contracts for older workers! In parallel, Table 4 suggests that the wage penalty for temporary workers is quite strong in industries with a high or medium cumulativeness of knowledge, and it is lower in low-cumulativeness industries.

One possible interpretation is that, under a higher cumulativeness of knowledge, firms realize that permanent workers are more productive in their interaction with robots. Hence, they offer more permanent jobs (Table 3) and better pay (Table 4). But this does not seem to hold for industries in which accumulated knowledge from experience is of low importance. In the contrary, in industries with a low cumulativeness of knowledge, robots even seem to *increase* the probability that older workers are hired temporarily, and they bring about a (small) wage penalty.

An alternative interpretation relates to market power. If an efficient use of robots depends on accumulated knowledge from experience (this knowledge being mainly 'embodied' by workers), workers have some negotiation power. They can more easily demand permanent contracts and higher wages. In a low-cumulativeness regime, however, when relying primarily on general and generally available knowledge, workers are more easily interchangeable and hence their negotiation power is weak. As a consequence, they are more often trapped in dead end flexible contracts and suffer a wage penalty.

6 Conclusions

Does robotization enhance the quality of jobs? Our literature survey suggests that robots may affect employment and the quality of work, but effects found in various studies are not unambiguous and often the reported effects are not overwhelmingly strong (as is also the case in our above Table 2 for the *total* sample). But once we take into account the innovation model that is dominant in an industry (Table 3), the picture changes decisively. A key distinction between innovation models relates to the dominant type of knowledge required for innovation. We distinguish two types of innovation model:

(1) A *low* cumulativeness model in which innovation is mainly drawing from general and generally available knowledge;

(2) A *high* cumulativeness model in which innovative competencies of firms strongly rely on accumulated knowledge from experience, much of this knowledge being embodied by employees.

In general, we find that robot use has opposite effects on workers in 'high-cumulativeness' industries as opposed to 'low-cumulativeness' industries. This holds for the quality of contracts (temporary versus permanent contracts), but also for wages. In industries with as higher cumulativeness of knowledge, a higher robot intensity *reduces* the probability that older workers (>30 years) will get a temporary, rather than a permanent job. An explanation is that knowledge accumulation is easier if people stay longer in the firm. In low-cumulativeness industries, however, we find an *opposite* effect: a higher robot intensity increases the probability of older workers being hired on temporary contracts. If accumulated knowledge from past experience is less important, a higher labour turnover does not need to be a big problem, and this can enhance the use of temporary contracts.

Results from our Mincer type wage equation are consistent with those findings. We find a substantial wage penalty for temporary workers in high cumulativeness industries, indicating that temporary workers are less productive than their tenured colleagues. But a high impact of robots slightly reduces this wage penalty. This is consistent with earlier findings that, in high-cumulativeness industries, high shares of flexible workers reduce productivity growth (Vergeer et al. 2015) or reduce the probability that a firm will innovate (Kleinknecht et al. 2014; Wachsen & Blind 2016; Hoxha & Kleinknecht 2020), while in low-cumulativeness industries, effects are weaker. We find in Table 4 that, in industries with a low cumulativeness of knowledge, the wage penalty for temporary workers is substantially lower, but robot intensity rather increases than reduces it.

In conclusion, the question of whether robots do or do not enhance job quality depends decisively on the knowledge base underlying the innovation model that is dominant in an industry. If innovative competencies in an industry depend strongly on worker-embodied and historically accumulated knowledge from experience, workers have a degree of negotiation power. This means they can demand permanent rather than temporary contracts, and they earn higher wages. A complementary (neoclassical) explanation is that permanent workers' interaction with robots is more productive, and higher productivity, in turn, allows for better contracts and wages.

If firms are not so dependent on accumulated knowledge, relying primarily on generally available knowledge, workers are more easily interchangeable and have low negotiation power. Even in industries with a high robot impact, firms can then offer temporary contracts that are dead ends rather than stepping stones towards a better job. This somehow reminds the perspectives described by Harry Braverman (1974) in his classic *Labor and Monopoly Capital* on the degradation of labour under a Taylorian regime.

Our results also carry a suggestion with respect to the studies mentioned in our above literature survey. These studies tend to report ambiguous outcomes and often the effects found are not so big. It might be rewarding if the various models were re-estimated, including controls for the dominant innovation model in an industry. Rather than using 'blind' sector dummies, one should include 'informed' sector dummies according to the taxonomy by Peneder (2010), which may shed new light on the impact of robotization.

A key conclusion (also from related literature) for European industrial policy is that unqualified pleas by supply-side economists for more 'dynamic' labour markets, including easier firing and a higher labour turn-over, should be reconsidered. More flexibility in labour markets might have a negative impact on innovation and the productive use of robot technology in industries with a high knowledge cumulativeness, while offering little for low-cumulativeness industries.

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APPENDIX

Table A.1: IV Probit Model with interactions, Reduced Form (first stage) from estimations reported in Table 3 (raw coefficients).

	Total sample:		High &Medium Cumulativeness:		Low-Cumulativeness:	
	(1)	(2)	(3)	(4)	(5)	(6)
	Italy	Germany	Italy	Germany	Italy	Germany
DEP. VAR.	*RobxWorkers_30_64*	*RobxWorkers_30_64*	*RobxWorkers_30_64*	*RobxWorkers_30_64*	*RobxWorkers_30_64*	*RobxWorkers_30_64*
Excluded Instruments						
Robot_exposure_FR	0.516***	0.255**	0.424*	-0.017	5.221***	9.134***
	(0.133)	(0.127)	(0.245)	(0.053)	(0.006)	(0.266)
Robot_exposure_UK	-0.470	2.765***	-1.435	2.483***	6.616***	0.784***
	(1.036)	(0.359)	(1.307)	(0.266)	(0.037)	(0.006)
Robot_exposure_SE	0.718***	0.094	0.875***	-0.072	2.182***	2.654***
	(0.216)	(0.085)	(0.179)	(0.137)	(0.011)	(0.157)
Robot_exposure_FI	0.311	2.182*	1.809	5.185***	17.138***	40.224***
	(0.944)	(1.213)	(2.617)	(0.575)	(0.045)	(1.574)
Included Instruments	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*yes*
Sectoral Dummies	No	No	No	No	No	No
Observations	177,495	857,038	78,568	365,656	26,833	152,906
F_stat	58345.88	160000	62215.72	168500	51445.90	21864.62

Note: Sector-level cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the endogenous variable Rob x Workers_30-64. The set of excluded instruments includes sectoral robot exposure of Finland, France, UK and Sweden. The included instruments are all the exogenous variables reported in Table 2. F_stat is the Kleinbergen-Paap Wald F statistic used to test the relevance of instruments. *High & Medium Cumulativeness* and *Low-Cumulativeness* group industries according to the Peneder's taxonomy discussed in section 3 and reported in Table 1.