

What workers and robots do: An activity-based analysis of the impact of robotization on changes in local employment

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Abstract

This work investigates the impact that changes in the local exposure to robots had on changes in Italian employment over the period 2011-2018. It contributes to the debate by providing novel and granular evidence on the impact of robot adoption on new activity-based groups of occupations and by focusing on the overlap between the functional similarities of robot applications and occupations. This framework, consistently centered on workers' and robots' activities, reveals highly heterogeneous effects of robotization, ranging from positive to negative across different groups of occupations, thereby supporting a nuanced and granular reading of this debated phenomenon. In particular, the local share of robot operators increases where the increase in robot adoption is larger, while the local share of workers using intensively their torso decreases.

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1 Introduction

The effects of automation technologies on the economy have been the subject of a long debate, dating centuries back and becoming popular again and again (Autor, 2015; Mokyr et al., 2015). Recently, the discussion has received a boost from the influential contributions of Brynjolfsson and McAfee (2011; 2014), who argue that the pace of technological innovation and the introduction of ever more sophisticated technologies would have rapidly disrupted labor markets as we know them. Two major strands of research have emerged hereafter: the first focuses on identifying which occupations are and prospectively will be more exposed to the introduction of robots and other forms of innovative technologies (Arntz et al., 2017; Dengler and Matthes, 2018; Felten et al., 2021; Frey and Osborne, 2017; Manyika et al., 2017; Nedelkoska and Quintini, 2018; Webb, 2020); the second focuses on the impact that the introduction of automation in the past has had on employment in industries, local labor markets and the economy in general (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019; 2020; Autor, 2015; Autor and Salomons, 2018; Baldwin et al., 2021; Blanas et al., 2020; Caselli and Manning, 2019; Cheng et al., 2019; Dauth et al., 2021; Dekle, 2020; de Vries et al., 2020; Dottori, 2021; Graetz and Michaels, 2018; Kariel, 2021; Klenert et al., 2023; Mann and Puttmann, 2023).

This paper contributes to this lively debate by providing some novel and granular evidence on the employment impact of robot adoption, defined as the imputed growth rate of the stock of robots at the local labor market level, by exploiting the overlap between the activities carried out by the different types of robots and those that characterize different occupations, thereby bridging the two strands of the literature mentioned above. Indeed, robots are not identical among themselves, and each one performs only a narrow set of activities, called in jargon robot applications.¹ This is an important aspect to consider because, following Autor et al. (2003)’s path-breaking intuition to appreciate the impact of computers based on routine and codifiable tasks, it is what robots actually do that matters for their interaction with different categories of workers.

Accordingly, our analysis introduces three main novelties. First, based on data from the Italian Continuous Labor Force Survey for the period 2011-2018, matched with detailed information on occupations’ characteristics from a dedicated survey comparable to the American O*Net, we explore the evolution of local employment in robot-related activity-based groups of occupations, rather than in broad occupational groups (e.g., skilled/unskilled, manufacturing/services, low/high education, routine/non-routine, manual/cognitive). This allows us to provide granular insights into the highly heterogeneous impact of robotization across occupations, even within industries. To begin with,

¹See Pratt (2015) for a discussion of the relationship between technological developments and the diversification and applicability of robotics.

the new activity-based groups of occupations that we propose include *robot operators*, i.e., workers who are involved in the design, installation, maintenance and operation of forms of automation related to robotization (and whose activities cannot be performed by any robot application). In addition, following de Vries et al. (2020)’s definition of robots as a narrow form of automation that includes multi-purpose manipulators moving in three or more axes, this work proposes new groupings of occupations characterized by general robot-related activities that take into account the nature of robots as multi-purpose manipulators. In particular, these groups of occupations are characterized by torso-intensive activities, physical movement-intensive tasks, intense use of hands, and object manipulation, as well as automation-intensive and machinery-intensive activities.

Second, we propose a new activity-based approach to build a shift-share measure of local exposure to robots based on data from the International Federation of Robotics, the Italian Continuous Labor Force Survey and the Italian Census of Industry and Services.² Previous contributions allocate the national stocks of robots at the local level by matching robots and workers according to the industry in which they are employed *à la* Acemoglu and Restrepo (2020). In so doing, ‘traditional’ industry-based shift-shares implicitly assume that every worker in an industry faces the same level of exposure to robots, regardless of his/her actual activity. In contrast, we focus on the functional analogies between robot applications and workers’ specific activities and manually match occupations to specific robot applications (e.g., welders and welding robots). Our approach accounts for workers’ heterogeneity within industries and exploits the inter-sectoral variability in the shares of occupations within industries. Our activity-based approach allows us to treat those workers performing services within industrial companies as not exposed to robots (as in Autor and Dorn, 2013) and to account for the diffusion of industrial robots in non-manufacturing sectors, such as in logistics, which is a service sector where industrial robots have been widely adopted. In line with the literature (Acemoglu and Restrepo, 2020), we take into account that our measure of local exposure to robots is potentially endogenous due to omitted demand factors: any unobservable and unevenly distributed shocks across labor market areas that affect both employment outcomes and the local exposure to robots would confound the estimated impact of the component of robot exposure driven by technological change. For example, firms may adopt robots in response to changes in labor demand at the LLMA level, such as a recession in an area with a large exposure to robots, or in response to other changes that also impact on labor demand, such as an increase in workers’ bargaining power (Acemoglu and Restrepo, 2020). Therefore, we propose an analogous shift-share instrumental variable that

²Our shift-share measure of local exposure to robot adoption is based on the growth of robots rather than changes per worker, similar in fashion to the traditional Bartik-like shock popularized in Blanchard and Katz (1992) and recently used in Kovak (2013) and Dix-Carneiro and Kovak (2017).

combines historical (i.e., pre-determined) local employment shares and the evolution of robot adoption in Japan, South Korea and the United States.

Third, from an empirical point of view, by exploring the regional variation across Italian local labor market areas (LLMAs) during the period 2011-2018, we provide more granular insights into the displacement and job creation effects of robotization in Italy and offer a more nuanced view of the differentiated impact of local robot exposure on employment dynamics with respect to previous findings (Dottori, 2021).

To preview our main findings, we show, for the first time, that the share of local employment of robot operators in the working-age population has grown more where the adoption of robots has been more intense. The estimates reveal that a local labor market with a 1 percentage point larger increase in robot adoption experienced a 0.321 percentage point larger increase in the local share of robot operators between 2011 and 2018. This finding is consistent with the view that where firms invest more in robots, the number of workers taking care of them also increases (Autor, 2015). This could be due to higher productivity or the expansion of existing robot-related tasks (including programming, design, and maintenance of high-tech equipment). In addition, we provide novel evidence that the impact of robot adoption on the dynamics of local employment over the working-age population is highly heterogeneous across occupations, depending on the characteristics of the activities performed by workers. For instance, the local share of occupations in which workers use more intensively their torso tends to decrease where robot adoption is more intense; conversely, the local share of workers who monitor machinery and equipment sequences and perform cognitive tasks increase where robot adoption is higher. These different occupation-specific results help to explain the insignificant average effects of robot adoption on local employment dynamics in previous studies using less granular approaches, such as Dauth et al. (2021) and Dottori (2021). We also show that an activity-based shift-share measure of local exposure to robots outperforms empirically the traditional industry-based measure: while this conclusion cannot be generalized due to time- and country-specific empirical issues, it suggests that adopting a consistent activity-based approach to build the dependent and the independent variables is conducive to meaningful and robust conclusions. Finally, our results are robust to the inclusion of different sets of controls for potential confounding factors, the exclusion of potential outliers, the use of unweighted regressions, clustered standard errors and an alternative definition of the national stock of robots.

It is worth noting that Italy represents an appropriate and relevant case study for a number of reasons. First of all, it is the second European country, after Germany, for robot use. Second, from a methodological perspective, we can take advantage of the 2013 Italian National Institute for Public Policies Analysis (Inapp) Survey of Pro-

fessions (Indagine Campionaria sulle Professioni, hereafter Inapp ICP), which represents the Italian equivalent of the American O*NET and provides information on the generalized tasks and the specific activities and duties of over 800 five-digit level occupations in Italy, combining survey-based information at the worker level and post-survey validation by expert focus groups. This ensures that our occupation-related variables are based on a survey that is specifically tailored to the Italian occupational structure and avoids the problems associated with the use of imperfect crosswalk tables with the American O*NET, which reflects the characteristics of the US labor market.³ Third, Italian local labor markets are highly differentiated in terms of employment composition (Garibaldi and Taddei, 2013) and quite heterogeneous in terms of labor market dynamics over the last decade. This heterogeneity is particularly valuable given that the empirical strategy relies on cross-regional variation to identify the parameters of interest.

The rest of the paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the methodological novelties and the empirical strategy used to estimate the effects of the local exposure to robot adoption on employment dynamics at a granular level. Section 4 provides details on the construction of our dataset and our data sources. Section 5 presents and discusses the estimation results. Finally, Section 6 provides some concluding remarks.

2 Literature review

This work relates to three different strands of the literature. The first one includes those studies exploring the consequences of automation and robot adoption on national or local labor market outcomes. As mentioned in the Introduction, due to the limited availability of data on firm-level investment in robots, most studies have analyzed macro- and meso-level effects, thereby exploiting cross-country, cross-region, cross-industry or cross-occupation variation in the empirical analysis.⁴ By exploiting the categorization of robots in terms of the industry of adoption provided by the International Federation of Robotics (IFR), in a seminal paper Acemoglu and Restrepo (2020) create a shift-share

³INAPP’s approach is mainly based on interviews with workers themselves. This decision was made to prioritize the perspective of those who directly practice the professions, allowing for a direct assessment of the importance of specific characteristics, skills, tasks, and activities within each occupation. Furthermore, the data collected from workers’ interviews are post-validated by Inapp experts’ focus groups. Although our work is the first to match occupations and robots based on Inapp ICP, this survey has been used to discuss several other aspects of the Italian labor market, such as working from home (Bonacini et al., 2021), exposure to infectious diseases (Barbieri et al., 2022), diffusion of key digital tasks (Cirillo et al., 2021), manual and routing tasks (Antonietti et al., 2023; Vannutelli et al., 2022), and educational mismatch (Esposito and Scicchitano, 2022).

⁴Recent works at the firm level are Acemoglu et al. (2020); Aghion et al. (2020); Benmelech and Zator (2022); Bessen et al. (2020); Bonfiglioli et al. (2023); Dixon et al. (2021); Domini et al. (2021); Harrigan et al. (2021); Hirvonen et al. (2022); Koch et al. (2021) and Montobbio et al. (2022).

measure of the local exposure to robot adoption in the US that combines the national penetration of robots into each industry with the local distribution of employment across industries within each US commuting zone. Acemoglu and Restrepo (2020) show that robots and other computer-assisted technologies negatively affected the US local labor markets during the period 1990-2007. Additional analyses using this industry-based approach to match robots and workers were subsequently conducted by several scholars (Adachi et al., 2023; Aghion et al., 2019; Chiacchio et al., 2018; Dauth et al., 2021; Dottori, 2021; Paba et al., 2020).⁵ In general, these studies fail to ascertain important effects of robot adoption on aggregated local labor dynamics, and do not explore more granular aspects as we do in this work.⁶

In addition to the studies exploiting within-country regional variation of employment dynamics and robot exposure, there exist a few industry-level cross-national studies that are worth mentioning. In particular, Graetz and Michaels (2018) estimate national robot density in 14 industries and 17 countries from 1993 to 2007 and find that increased robot density has a positive effect on labor, total factor productivity and wages, despite a negative impact on the low-skilled workers' labor share. de Vries et al. (2020) offer relatively more granular insights by investigating the relationship between robot density and employment dynamics across country-industry pairs for 19 industries and 37 countries over the period 2005-2015. They distinguish 13 two-digit occupational groups into four broad categories of jobs (i.e., analytic/manual and routine/non-routine), and analyze the differentiated employment outcomes: they find that a rise in robot density relates significantly to a fall in the employment share of routine manual task-intensive jobs. Blanas et al. (2020) analyze the impact of software and robots on the within-industry share of different types of workers in 10 high-income countries over the period 1982-2005; they maintain that software and robots had a negative impact on the demand for low- and medium-skilled workers, the young and women in manufacturing industries and led to higher demand for high-skilled workers, older workers and men in service industries.⁷ As

⁵Chiacchio et al. (2018) explore 116 NUTS2 regions of six Western European Union countries, Aghion et al. (2019) study French employment zones, Dottori (2021) and Paba et al. (2020) analyze Italian local labor market areas, Adachi et al. (2023) focus on Japanese commuting zones, and Dauth et al. (2021) look at German local labor markets.

⁶More negative results are found by Aghion et al. (2019), who focus on artificial intelligence (AI) as well as robots, and Adachi et al. (2023), who rely on a different identification strategy based on heterogeneous price changes across robot applications. By linking automation-related patents (rather than robot stocks) to industries and to commuting zones, Mann and Puttmann (2023) find an overall positive effect of automation on the US local employment due to the growth in the service sectors, whereas Kariel (2021) finds a negative impact in the automobile manufacturing industry and positive effects in other sectors, such as services, in the UK.

⁷Using EU Labor Force Survey data instead of EU KLEMS data, Klenert et al. (2023) find no relationship between the increased use of robots and changes in total employment levels or in the share of low-skilled employment between 1995 and 2015 in 14 countries of the European Union. Negative effects for employment are instead found by Compagnucci et al. (2019), who focus on 16 OECD countries over

anticipated, our work differs from this industry-based strand of the literature in that it adopts a new measure of regional exposure to robots that is based on the overlap between the activities carried out by the different types of robots and those characterizing the various occupations; moreover, it provides novel and granular insights on the heterogeneous impact of robot adoption on new robot-related activity-based groups of occupations.

Within the literature described so far, the paper most closely related to our own is the work by Adachi (2021), as it also focuses on the effects of robot adoption on occupations (rather than industries) and it builds a (substantially different) match between occupations and robot applications. However, Adachi (2021) looks at how US aggregate wages by occupation are affected by robot adoption measured by the cost of robot applications from Japan, and goes on to estimate a general equilibrium model in which robots and labor are substitutable, with heterogeneity across occupations, to study the effects of robot adoption on US wage inequality.⁸ As such, his analysis does not look at the employment dynamics of robot operators and our new activity-based groups of occupations.

This work relates to a second broad strand of the literature that looks at the extent to which automation and computerization substitute workers in certain occupations. The seminal article by Frey and Osborne (2017) calculates the exposure of US professions to the risk of automation and computerization by building on the SOC/O*NET database that codes several hundred job titles and offers a detailed description of their characteristics, generalized tasks and specific activities. A number of scholars have applied Frey and Osborne (2017)'s methodology on countries different from the US (see, for instance, David, 2017), while others, such as Arntz et al. (2017); Manyika et al. (2017) and Nedelkoska and Quintini (2018), modified Frey and Osborne (2017)'s methodology so as to take into account the tasks characterizing the occupations (Dengler and Matthes, 2018; Montobbio et al., 2022; Squicciarini and Staccioli, 2022; Webb, 2020).⁹ Although these works vary considerably in their quantitative findings, they concur in emphasizing the importance of occupations' characteristics and tasks in assessing their exposure to technological advances.¹⁰ Notably, the identification of the occupations in principle most susceptible to robotization does not make it possible to produce a measure of local robot

the period 2011-2016.

⁸See also Battisti and Gravina (2021) for an analysis of the degree of substitutability and complementarity between robots and workers by age group.

⁹For instance, Dengler and Matthes (2018) calculate the automation probabilities, as substitution potentials, of those occupations that could be replaced by computers or computer-controlled machines according to programmable rules. Other works develop measures of similarity between occupations and specific forms of automation measured in terms of patents: Webb (2020), Montobbio et al. (2022) and Squicciarini and Staccioli (2022) explore the text of patents descriptions to identify the occupations that are potentially more exposed to robotization and labor-saving forms of automation.

¹⁰A recent strand of the literature investigates, along this line, the relationship between advancements in AI and tasks (Felten et al., 2021; Fossen and Sorgner, 2021).

adoption. Indeed, building a shift-share variable for the local distribution of the national stock of robots requires to classify the occupations in groups that refer to the available categories in which robots are classified, that is either industries or applications. Still, our work is linked to this literature via the idea of looking at workers' activities to measure the potential exposure of occupations to robot applications, but it offers a new shift-share measure of the local exposure to robotization that takes into account the extent to which robot applications have been actually adopted in the country.

Our focus on the main activities of individual professions connects this work to a third strand of the literature that looks at skill-biased technical change (SBTC) (Acemoglu, 2002; Autor et al., 2006; Goos and Manning, 2007; Goos et al., 2009; Katz and Murphy, 1992; Katz and Autor, 1999) and routine-biased technical change (RBTC) (Acemoglu and Autor, 2011; Autor et al., 2003; Autor and Dorn, 2013; Autor et al., 2015; Cortes et al., 2020; Goos et al., 2014). The works in this literature build on a canonical model that includes different groups of workers performing imperfectly substitutable tasks, and where technological advances affect different workers in different ways.¹¹ Looking at Finland, Hirvonen et al. (2022) find that physical technological advances are not associated with any differential employment changes in typical measures of skill bias. While the SBTC approach points to the (mis-)match between technology advances and workers' education, the RBTC approach focuses on the complementarity or substitutability between occupations' tasks and the features of the technical innovations in a way that is close in spirit to our work. Despite the common focus on the heterogeneity of tasks across occupations, the analyses adopting the RBTC approach differ from ours in a few dimensions. First, these studies focus on routine occupations that, due to their repetitive and codifiable tasks, are suited to computerization (Autor et al., 2015), whereas we identify new groups of occupations that are more precisely characterized by robot-related activities, thereby capturing those narrow technical capabilities that robots have with respect to other forms of automation.¹² Second, these studies typically use the initial employment shares in routine occupations as the main explanatory variable of employment and wage dynamics, whereas we build a shift-share measure for the local extent of robot adoption

¹¹According to the SBTC story, technological change affects negatively (positively) the less (more) skilled workers, thereby exercising a monotonically increasing impact on the occupational structure in terms of skills. The RBTC story, instead, focuses on occupations' tasks, and hinges on the idea that occupations with routine-intensive tasks are negatively impacted upon by computerization and digitalization innovations. As routine tasks are typically performed by workers in manufacturing jobs with middle skills, the RBTC hypothesis helps to account for job polarization and between-industry shifts in the structure of employment observed in the US and other advanced economies. For an overview see Fernandez-Macias and Hurley (2016).

¹²Autor et al. (2015) distinguish US occupations in routine and non-routine ones on the basis of their tasks and show that long-term changes in the employment structure of US commuting zones are not significantly associated with the initial specialization in routine-intensive occupations (suited to computerization).

to explain local employment dynamics.

3 Methodology and empirical strategy

3.1 Novel activity-based categories of occupations

To assess the impact of local robot exposure on employment dynamics in Italy taking into account the heterogeneity across occupations’ activities, we start off by identifying at a granular level novel activity-based categories of occupations that are potentially linked to robotization. To this end, we use detailed information on occupations’ characteristics provided by the 2013 Inapp ICP.

Inapp ICP codifies occupations according to the 2011 Inapp-Istat Classification of Occupations (*Classificazione delle Professioni* - CP2011 hereafter), which is the Italian version of the current ILO International Standard Classification of Occupations (Isco08). At its finest level of aggregation (i.e., five digit level), the CP2011 classification contemplates about 800 occupational units that account for as many as 6000 job titles.¹³

By following the design of the American O*NET, but tailoring it to the Italian context, Inapp ICP documents the generalized tasks and the specific activities and duties of the workers belonging to each different occupational unit. In particular, it reports quantitative measures (varying on a scale from 1 to 5) of the frequency and the importance of various specific activities associated with each occupational unit at the five-digit level of the taxonomy.¹⁴

The first novel group of occupations we identify is what we refer to as robot operators, that is workers who are involved in the design, installation, maintenance and operation of forms of automation related to robotization and whose activities cannot be performed by a robot application. We identify robot operators by performing a manual text-based analysis of occupations’ general descriptions as well as the three primary occupation-specific activities according to Inapp ICP scores. Table A1 in Appendix A reports the top activities of the occupations identified as robot operators, such as “Automated assembly line management and control technicians” and “Automated assembly line operators”. As explained, robot operators include occupations that work on robots. Hence, one could

¹³The CP2011 occupational units include for instance “Welders and flame cutters” (code 6.2.1.2.0), and this group contains several job titles (namely, Lead Welder; Oxyacetylene Welder; Plumber Welder; Autogenous Cutter; Oxyacetylene Cutter; Flame Fret-Sawing Worker; Fusion Welder; Water Gas Welder; Braze Welding Welder; Tin Welder; Atomic Hydrogen Welder; Aluminium-Thermal Welder; Autogenous Welder; Special Metal and Metal Alloy Welder).

¹⁴For example, consider the occupational unit “Shoe manufacturers” (code 6.5.4.2.3). According to the frequency and importance indices, it includes both rare and unimportant specific activities (such as crimping the uppers, with a value of 1.3 for importance and 0.3 for frequency) and specific activities that are frequent and important (such as packaging or wrapping finished products, with a value of 3.4 for importance and 2.9 for frequency).

reasonably expect to find a positive effect of robot adoption on the employment variation of this group of occupations.

Next, we construct new groups of occupations characterized by general features that potentially relate with robotization. This approach is inspired by the well-known approach adopted to investigate the RBTC hypothesis, according to which automation impacts differently on occupations depending on their intensity in the use of routine and codifiable tasks. Rather than focusing on the routine intensity of occupations' tasks, which is mainly a characteristic of computer-related activities, we notice that other functional characteristics of occupations may determine the nature of the interaction between workers and robots. Indeed, as pointed out by de Vries et al. (2020), robots are a narrow form of automation and their technical capabilities determine their interaction with a restricted set of tasks. For instance, robots are useful to carry out heavy weight lifting in logistics operations: robots are suitable for these activities not because of their being programmable (i.e., automated) as a routine-based approach would imply, but rather because robots are multipurpose manipulators in three or more axes.

To explore these functional similarities between occupations and robots, we exploit the questions in Inapp ICP to draw information on a number of features characterizing each occupation at the five-digit level. We consider, in particular, the answers given to the following four questions: 1) "To what level is it necessary in your profession to be able to use the abdominal and lumbar muscles to support the body in a continuous and repeated manner over time without fatigue or giving in to the effort?" (Torso strength, question D35); 2) "To what level is it necessary in your profession to perform physical activities that require moving the entire body or a substantial use of the arms and legs, such as climbing, climbing stairs, balancing, walking, bending, and manipulating materials?" (Performing general physical activities, question G16); 3) "To what level is it necessary in your profession to use hands and arms to handle, install, position, and move materials or to manipulate objects?" (Handle and move objects, question G17); 4) "How much of your time do you use your hands to manipulate, check, or feel objects, tools, or control systems?" (question H40). Respondents can answer using a scale from 1 to 7 for the first three questions and a scale from 1 to 5 for the last question.

These questions allow us to identify four groups of occupations that are similarly intense in terms of general activities suitable for robots. Indeed, differently from other forms of automation, robots are typically associated with either the precise manipulation of small objects (to process/assemble them, to perform quality checks, to place them in packages) or repeated movements of heavy equipment and objects. When performed by humans, these activities require repeated and tiring physical activities (questions 1 and 2 above), precise handling and moving objects (question 3), or intense use of the hands

(question 4). While robot operators are identified on the basis of the overlap in robot applications and occupation-specific activities, these groups are based on general features of the activities performed by workers and robots.

It is worth noticing that workers employed in occupations that perform intensively these general robot-related activities are not necessarily more likely to be displaced by robots. Let us consider, for instance, the occupations characterized by frequent handling of objects. On the one hand, particular robots, such as those designed for handling operations, can potentially displace workers in handling activities. On the other hand, such workers may be more intensively involved in assisting and accompanying the robots performing their handling operations as the introduction of such robots changes the production process and the allocation of tasks across workers and robots. The overall impact of robotization on employment of these groups of occupations depends on the prevalence of one of these opposing effects. This is an empirical issue and in this paper we offer some novel empirical evidence on the impact of robots on these occupational groups that are homogeneous in terms of robot-related tasks.

The richness of the Inapp ICP survey allows us to identify further groups of occupations that is worth exploring. The occupational groups described so far have been created by exploiting the overlap between robot-related tasks performed by workers and robots and, as in Autor et al. (2003), the occupations' relative intensity in such robot-related tasks. The Inapp ICP survey, however, also allows us to identify those occupations that use relatively more intensively forms of automation and machines. The survey contains two relevant questions, in addition to the four questions considered above: 5) "How automated is your work?" (question H49); 6) "How important is it to keep track of sequences of machinery and equipment in your work?" (question H55). Respondents can answer using a scale from 1 to 7 for these two questions. By exploiting these questions, we can investigate the differences in employment dynamics among occupations depending on the intensity of the use of automation and machines. The advantage of constructing these additional groups of occupations is that we can more directly focus on the importance of automation and machines rather than having to rely on the use of general activities potentially linked to robotization (e.g., torso-intensive and manual-intensive activities), despite the fact that the questions do not refer precisely to robots. Notwithstanding these relevant differences among the occupational groups, the analysis contributes to draw novel evidence on the differentiated set of employment dynamics by juxtaposing robot operators (i.e. workers performing specific activities for which robot applications exist), workers performing general robot-related activities, and workers employed in occupations characterized by the intensive use of automation and machines.

Based on the above questions, we create six indices varying by occupation over the

interval 0-100 and we identify those (five-digit level) occupations that are in the top third of the distribution within each index.¹⁵ Accordingly, we obtain six groups: torso-intensive occupations (ToI); physical movement-intensive occupations (PmI); manual-intensive occupations (ManI); object-intensive occupations (ObI); automation-intensive occupations (AuI); machinery-intensive occupations (MacI). We then calculate the changes in the share of employment over the working-age population at the LLMA level for each one of these six groups. It is worth noticing that these six groups are not mutually exclusive, e.g., different occupations can be both manual-intensive and torso-intensive. Differences in the results based on different groups are then directly linked to the different underlying composition of occupations across groups. Table A3 in Appendix A reports some examples of occupations categorized in each group (namely, those in the top third of the distribution of occupations ranked according to the intensity of the characteristic of interest) and occupations for which such characteristics are not important.

Although there may be some change in the task content of occupations, the task-based literature on the impact of technological change on labor markets assumes that the task requirements of occupations change slowly, so that the rank of occupations (which is what is used to construct such ordinal indices) is essentially time-invariant. Indeed, recent research by Consoli et al. (2023) shows that tasks change within occupations only in the long run. In addition to the various contributions focusing on routine task intensity (RTI), the assumption of task-related rank invariance was adopted by Graetz and Michaels (2018) in their classification of occupations (at the 3-digit level) exposed to robots, as well as by Frey and Osborne (2017) in their classification of occupations exposed to digitization. Similarly, we compute our task-based measures under the assumption of task rank stability over the time span of interest. Notwithstanding this assumption, in the interpretation of the results, we discuss why small changes in the task content of occupations may help to preserve the employment of workers in a firm introducing robotization.

3.2 Novel activity-based shift-share measure of local exposure to robot adoption

Following the seminal work by Acemoglu and Restrepo (2020), the local exposure to robots is typically calculated on the basis of the combination of the national stock of robots into each industry, on the one hand, and the local distribution of employment across industries, on the other. The application of this shift-share approach *à la* Bartik (1991) makes it possible for researchers to allocate the national stocks/changes of robots in an industry across the local areas on the basis of the local concentration of workers

¹⁵Table A2 in Appendix A provides summary statistics for the six indices.

employed in that industry.¹⁶ This approach exploits the fact that the IFR classifies robots with respect to the industry in which the companies installing them operate.

Such industry-based approach presents some potential limitations. In particular, it prevents from accounting for the high degree of workers’ heterogeneity within an industry, as it implicitly assumes that every worker employed in a sector is equally exposed to robots, independently from the activities performed. This is a gross approximation in all industries: according to our estimates (obtained with the matching method illustrated below), the fraction of workers in an industry who are not exposed to any robot application is typically large, ranging from around 35 % in the “Wood and furniture” sector to close to 100% in the “Education/research/development” sector.

Focusing on the features of the occupations, we develop a novel shift-share measure of the local exposure to robots that is based on the activities performed by workers and robots and that also takes the actual robot adoption in the country into account. First, we identify those occupations whose main activities match those performed by specific robot applications. Subsequently, exploiting the (initial) local composition of the workforce in terms of exposed occupations, we measure the local exposure to the national growth rates of installed robots. In what follows, we first describe the activity-based match between occupations and robot applications and then the novel shift-share measure.

We start off by exploring the functional overlap between the occupations’ main activities and those carried out by each robot application. We use the information contained in Inapp ICP and we manually match each IFR robot application with one or more occupations on the basis of the occupation’s description, its three primary occupation-specific activities according to Inapp ICP scores and, where necessary, additional information provided in the survey. By relating robots and occupations on the basis of functional analogies, we determine whether an occupation is “exposed” to a given robot application, that is if its main activities can be associated with a specific industrial robot application, or not. This approach is in line with the intuition in Graetz and Michaels (2018), who use the robot taxonomy by application to assess whether various broad groups of professions (at three-digit level) are replaceable by robots or not.¹⁷ Overall, we identify 123

¹⁶This approach mimics the methodology adopted by Card (2001) to redistribute national immigration flows on the basis of the local composition of migrants in terms of the nationality of origin. In the economic literature, proxies of the local exposure to trade competition in each industry have been built along the same line (see Autor et al., 2013).

¹⁷Graetz and Michaels (2018) produce a manual match between the titles of broad groups of professions and the IFR robot applications. In a similar vein, more recently, Adachi (2021) performs a match between (US) occupations and robot applications based on robot applications’ titles and the web search feature of O*NET Code Connector. Dengler and Matthes (2018) calculate the automation probabilities of German occupations on the basis of the characteristics of their tasks. Caselli et al. (2021b) identify broad groups of Italian occupations that are exposed both to robots and to transmissible diseases, such as Covid-19. Montobbio et al. (2022), Squicciarini and Staccoli (2022) and Webb (2020) identify the occupations potentially exposed to robotization and labor-saving forms of automation on the basis of a match between

occupations (at the five-digit level) that are exposed to 13 different robot applications. Table B1 in Appendix B reports detailed examples of matches between occupations and robot applications, such as “Welders and flame cutters” matched with “Welding and soldering robots”. It also reports occupations not matched to any robot application, such as “Weavers”.

A few caveats are in order. Our matching approach between occupations’ activities and robot applications requires that each occupation is associated only with one application, whereas the same type of robot can be associated with more occupations. As a drawback, this leads to neglect all the minor activities in a profession that might be exposed to other robot applications. The assumption underpinning this matching approach is that firms refrain from installing robots for unimportant and infrequently repeated activities in a profession. While this is a demanding assumption, it is worth recalling that any occupational taxonomy and any occupation-robot matching procedure does involve some implicit simplifications. The second caveat to consider is that, notwithstanding the wealth of information in Inapp ICP, a non-negligible dose of judgment is used in matching occupations’ activities and robot applications. To the extent that possible errors are not systematic, this should not represent a problem in our estimations that exploit cross-regional differences in the local exposure and in employment dynamics.

The new measure of the local exposure to robots, which will be the explanatory variable of interest in the empirical model, is formally defined as follows:

$$\Delta RX_i = \sum_a \mu_{a,i} \log R_{a,t} - \sum_a \mu_{a,i} \log R_{a,t0} = \sum_a \mu_{a,i} (\log R_{a,t} - \log R_{a,t0}), \quad (1)$$

where $R_{a,t}$ and $R_{a,t0}$ indicate the national stock of industrial robots in application a respectively at the end and at the beginning of the period, and $\mu_{a,i}$ stands for the local share of workers performing activities mapped to application a in LLMA i in 2011. Hence, this activity-based measure combines the local distribution of occupations and their prevalent activities with the growth rate in the national stocks of installed robots performing the various applications.

It should be noted that our measure of the local exposure to robots is based on proportional changes and corresponds to a traditional Bartik-like shock, popularized in Blanchard and Katz (1992) and recently used in Kovak (2013) and Dix-Carneiro and Kovak (2017), where the shift-share variable is constructed based on national growth rates rather than changes per worker. Acemoglu and Restrepo (2020) construct similar shift-share variables using log changes, thereby normalizing the changes by the initial level of each variable, when they introduce controls for capital and IT capital. As they

occupations’ tasks and the text of robot-related patents.

refer to these measures as capital deepening, our local exposure to robots can be seen as capturing robot capital deepening, rather than changes in robot density.¹⁸

In Section 5.3 we compare the empirical results using our new activity-based approach to match occupations and robots with those obtained using the traditional, industry-based method. Although the approaches lead to qualitatively similar results on aggregate, only the activity-based method makes it possible to detect the heterogeneous effects of robotization across the various groups of occupations. Moreover, we show that the industry-based approach suffers of problems of identification and this also complicates the interpretation of the empirical results. While we do not claim that our approach is always superior to the industry-based one, in our setting this is indeed the case. It seems fair to maintain that, besides being an internally consistent approach based entirely on the activities carried out by robots and workers, the activity-based method might also perform empirically better in certain empirical settings.

3.3 Empirical model

In order to estimate the effects of the local exposure to robot adoption on Italian local employment changes, we estimate different variants of the following empirical model:

$$\Delta y_i = \beta \Delta RX_i + \mathbf{x}'_{i,t0} \boldsymbol{\alpha} + \mathbf{z}'_{i,t0} \boldsymbol{\delta} + \mathbf{p}'_{i,t0} \boldsymbol{\gamma} + \mathbf{r}'_m \boldsymbol{\phi} + \varepsilon_i, \quad (2)$$

where $\Delta y_i = y_{i,t} - y_{i,t0}$ denotes the change in the outcome variable y for local labor market i between $t0$ and t (i.e., from 2011 to 2018), and ΔRX_i indicates the measure of the change in the local exposure to robots, which is based on our matching between workers' and robots' activities (see Section 3.2), over the period of interest. In particular, we study the dynamics of local employment (measured as changes in the employment share of the working-age population aged 15-64)¹⁹ for robot operator jobs and other new groups of occupations identified on the basis of the relative intensity of certain robot-related activities (namely, ToI, PmI, ManI, ObI, AuI and MacI occupations). Moreover, in order to assess the overall net employment effects at the local level, both employment and unemployment rates are considered as dependent variables. The coefficient β captures

¹⁸In a robustness check, we show how the results change when we normalize the national stock of robots in application a by the total number of workers (at the national level) employed in occupations mapped to robot application a , following the approach of Acemoglu and Restrepo (2020). In this case, our measure of the local exposure to robots, i.e., our main explanatory variable, is $\Delta RX_{2,i} = \sum_a \mu_{a,i} \left(\frac{R_{a,t} - R_{a,t0}}{L_a} \right)$, where L_a represents the total number of workers in thousands (at the national level) employed in occupations mapped to robot application a in 2011. The instrumental variable described below is also adjusted accordingly.

¹⁹As a robustness check, we use the prime-aged local population, i.e., the population aged 25-54, in the denominator of the local shares. The results are robust to this different specification of the local shares. The additional results are available upon request.

only relative effects across local labor markets and, given the relatively long time span of the analysis, should be interpreted as the long-term structural effect of robot exposure on labor market outcome i , as in Acemoglu and Restrepo (2020). However, as the local exposure to robot adoption is measured on the basis of national growth rates, it should be interpreted as the effect of a 1 percentage point larger increase in robots in a given local labor market on changes in the outcome of interest from 2011 to 2018 (see Dix-Carneiro and Kovak, 2017; Kovak, 2013).

Although the specification in first differences eliminates most of the effects associated with the unobserved time-invariant heterogeneity across local labor markets, to control for further possible confounding factors we include in the estimations a set of lagged demographic controls ($\mathbf{x}_{i,t0}$), a set of lagged controls to capture industry-related factors ($\mathbf{z}_{i,t0}$), a set of lagged occupation-related controls ($\mathbf{p}_{i,t0}$), all calculated at the beginning of the period (2011), and four macroarea (North West, North East, Center, South) fixed effects (\mathbf{r}_m). The term ε_i indicates the idiosyncratic error term. All the model estimates are weighted on the basis of local labor markets' resident population at the beginning of the period (2011). Weighted regressions are typically adopted in this literature to ensure that sampling issues in small geographical areas do not drive the results. As LLMA are unplanned domains in the design, we conduct some robustness checks to show that the results are consistent across samples where very large and very small areas are excluded. We will also show the results of unweighted regressions.

We include different sets of controls to reduce the impact of potential confounding factors correlated with changes in the local exposure to robots and changes in local employment. In particular, we want to account for different trends in terms of the baseline demographic characteristics, the baseline industrial structure and, given our focus on the evolution of the employment shares of task-related groups of occupations, the baseline occupational structure in each local labor market area. The choice of the economic indicators to include in the specification to deal with possible confounding factors is informed by Acemoglu and Restrepo (2020); Dauth et al. (2021) and Dottori (2021) as well as other works in the literature reviewed in Section 2. Among the lagged demographic controls, $\mathbf{x}_{i,t0}$, we include the log of the resident population, the share of residents aged over 65, the share of residents with a tertiary education, the share of female residents and the share of foreign-born residents. Since the size and the age structure of the population are likely to influence (along with other characteristics of the local demography) both the labor market dynamics and the likelihood of robot adoption, the inclusion of control variables of this kind is warranted. We also add the local employment rate because of the preliminary balancing tests for regional characteristics reported in Table C1. The lagged industry-related controls, $\mathbf{z}_{i,t0}$, include the local exposure to trade competition from China

(measured as in Autor et al., 2013), the share of employees in the manufacturing sectors, the share of employees in the transportation and logistics industry, the share of employees using a personal computer (based on a shift-share approach), and the local exposure to ICT capital per worker (based on EU-KLEMS data and a shift-share approach).²⁰ The lagged occupation-related controls, $p_{i,t0}$, include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations calculated at the beginning of the period.²¹

We also conduct some balancing tests to see whether other regional economic indicators are correlated with predicted robot exposure, as in this case they should also be controlled for. We consider the local employment and unemployment rates, calculated at the beginning of the period, as well as the local share of employees in the private sector (to control for structural differences in the private and public sector during the austerity period), and the share of local units in non-light manufacturing sectors with at least 50 employees (since Acemoglu et al., 2020, find that firms adopting robots tend to be large). The results of the tests, available in Table C1 in Appendix C, reveal that, conditional on the included controls, the local unemployment rate is not significantly correlated with the predicted change in robot exposure, and needs not to be included in the model. On the contrary, the local employment rate, the local share of employees in the private sector and the share of local units in non-light manufacturing sectors with at least 50 employees are significantly correlated with the adoption of robots. Accordingly, we add these variables among the controls in the main specification. Although studying the association of these controls with local labor market outcomes may be of interest *per se*, these terms are included exclusively to mitigate the risks of biased estimates, and therefore we shall not discuss the estimated coefficients.

The inclusion of the macroarea fixed effects allows us to control for the large-scale labor market dynamics that characterize the Italian macro regions (i.e., North-West, North-East, Centre, and South and Islands) because of long-lasting structural differences within the country. It is worth noticing that the inclusion of macroarea fixed effects is demanding, as the identification relies only on variability within such relatively homogeneous areas,

²⁰The share of employees in the manufacturing sector may capture structural changes related to the long-term declining trend in the employment share of this macro sector (Dottori, 2021). The share of employees in the transportation and logistics industry helps to control for trends in the services sector characterized by large stocks of industrial robots. Exposure to trade competition with China and the decline of routine occupations have certainly affected labor market outcomes in recent decades (Citino and Linarello, 2022) and could also be related to firms' investment policies. The share of employees using a personal computer and the local exposure to ICT capital per worker are intended to cleanse the estimations from possible confounding effects of other technology-related investments at the local level (Dauth et al., 2021; Dottori, 2021).

²¹Autor and Dorn (2013) and Autor et al. (2015) classify as routine occupations those in the top third of the employment-weighted distribution of the routine-task intensity. We follow this approach as well.

but it is fairly common in the literature. For example, Acemoglu and Restrepo (2020) adopt state-level fixed effects for the US and Dauth et al. (2021) include three macro regions for Germany. In a robustness check we shall also report the results obtained with even more flexible (and thus demanding) regional (NUTS2) fixed effects.

3.4 Addressing endogeneity concerns

In the presence of unobservable and unevenly distributed shocks that simultaneously influence local labor market outcomes and the local exposure to robots, OLS estimates of the coefficient β would be biased and inconsistent, as they would not identify the component of robot exposure driven by changes in technology. For example, firms may adopt robots in response to changes in labor demand at the LLMA level, such as a recession in an area with a large exposure to robots, or in response to other changes that also impact on labor demand, such as an increase in workers' bargaining power (Acemoglu and Restrepo, 2020).

Accordingly, to capture the impact of the exogenous component of robot adoption on local employment dynamics we resort to an instrumental variable (IV) approach. More precisely, we build a shift-share IV *à la* Bartik that combines historical (i.e., pre-determined) local employment shares and the evolution of robot adoption abroad to proxy for the increase of robots in Italy. This strategy, which has become standard in the literature (e.g., Acemoglu and Restrepo, 2020; Caselli et al., 2021a; Dauth et al., 2021), is an effective way to capture only the part of robot exposure that is exogenously determined by advancements in robot technology. As the evolution of the stocks of robots in the European countries may be determined by common demand factors and by regional value chains in the manufacturing sectors, we consider the process of robot adoption in Japan, South Korea and the United States (JPKRUS, hereafter). These are all developed economies whose business cycle is only partially correlated with the Italian one and that started adopting robots much earlier than 2011 (and therefore are not involved in a rapid catching-up process as the one observed in countries like China). We consider all extra-European countries in a robustness check.

In building this instrument, we allocate the changes in the foreign stocks of robots by application on the basis of the local employment shares in occupations exposed to such applications. We mimic the methodology adopted to construct the explanatory variable ΔRX_i , thus our IV reads as follows:

$$\Delta \widetilde{RX}_i = \sum_a \widetilde{\mu}_{a,i} \left(\log \widetilde{R}_{a,t}^{JPKRUS} - \log \widetilde{R}_{a,t0}^{JPKRUS} \right), \quad (3)$$

where $\widetilde{\mu}_{a,i}$ is the share of workers in occupations matched to robot application a in local

labor market i in 2001, and $\tilde{R}_{a,t}^{JPKRUS}$ and $\tilde{R}_{a,t0}^{JPKRUS}$ are the total stocks of industrial robots performing application a in JPKRUS (in particular, the sum of the stocks over the three countries), respectively at time t (2018) and $t0$ (2011). To prevent endogeneity problems, the employment shares are lagged ten years prior to the beginning of the period of interest.²²

Finally, it is important to notice that the occupations in Inapp ICP are not influenced by the most recent developments in the realm of robotics as the classification was developed at the beginning of the period of interest. Hence, neither the recent changes in the activities associated with the occupations, nor the recent modifications in the array of professions for which new vacancies are posted influence our measure of exposure. Accordingly, as recommended by Graetz and Michaels (2018), the adopted classification is not endogenous with respect to the social and technical innovations introduced in the last decade.

4 Data

Our study is based on a panel that, for the years 2011 and 2018, integrates detailed information on the workforce occupational structure and on the demographic composition of 384 Italian local labor markets,²³ whose boundaries were identified by the Italian National Institute of Statistics (Istat) in 2011 on the basis of workers' commuting patterns.²⁴

Data on the occupational structure at the LLMA-level used to construct our dependent variables have been computed based on data taken from the Continuous Labor Force Survey ("Rilevazione Continua sulle Forze di Lavoro", RCFL), a quarterly survey carried out by Istat and which represents the most important source of official informa-

²²This shift-share IV has never been adopted in previous works because it is based on our new approach to perform a match between occupations and robots on the basis of the functional overlap between workers' activities and robots' applications. Conversely, previous studies resorted to shift-share industry-based IV exploiting changes in the foreign stocks of robots by industry, together with the local shares of workers employed in every industry. We believe that our set up is preferable as it offers internal consistency: we aim to explain the impact of robotization on employment dynamics by exploiting the cross-regional variation in the local exposure to robots, which is calculated on the basis of a match between occupations and robots based on their activities, and by instrumenting such variable with a shift-share IV using lagged shares of occupations and the foreign stocks of robots by application.

²³Local labor markets represent functional geographic areas that go beyond administrative boundaries and correspond to economically integrated spatial units, suitable to investigate various aspects of geographical heterogeneity (see, for instance, de Blasio and Poy, 2017).

²⁴The sample of LLMAs covered by the Continuous Labor Force Survey, which we use to derive the local shares of workers, counts 412 areas, but we trim the sample so as to remove the outliers (top and bottom one percent of the distribution) for changes in robot operators, employment rate and unemployment rate. Since the sample is correctly stratified, the absence of some LLMAs does not cause problems in terms of its representativeness, although some minor LLMAs are disregarded.

tion on Italian labor markets. Covering about 1,250 Italian municipalities, the survey involves approximately 77,000 households and 185,000 individuals each quarter.²⁵ The survey gathers information on the employment status of the respondents and other socio-demographic traits, such as age, gender, nationality, and municipality of residence. For the respondents who are employed, the survey records extremely detailed information on their occupation, sector of employment, type and duration of the contract, number of hours worked and salary.

The advantage of resorting to the RCFL survey is twofold. First, the RCFL makes it possible to match individual workers' occupations with detailed information on occupations' characteristics, as provided by the 2013 Inapp ICP. In both surveys, the occupations are codified according to the highly disaggregated five-digit level based on the CP2011 classification (see Section 3.1). The second advantage is that the RCFL provides sample weights, which we use to extend the results of the analysis to the overall population, as done in the literature.

The local exposure to robot adoption is calculated by combining information about the local employment structure together with data on shipments and operational stocks of industrial robots provided by the IFR. In particular, our measure of the local exposure to robots, ΔRX_i , makes use of data on the workforce structure retrieved from the 2011 Census of Industry and Services, organized every ten years by Istat, and from RCFL. In a similar way, our instrument, $\widetilde{\Delta RX}_i$, makes use of data from the 2001 Census of Industry and Services to derive the sectoral structure of employment at the local level and from RCFL.

Data from the Census of Industry and Services do not contain information about workers' occupations, but only about their industry of employment. To calculate the local shares of workers matched with robot application a (i.e., $\mu_{a,i}$), we take advantage of data on the workforce structure at a high level of disaggregation (four-digit level between 2004 and 2009, five-digit level thereafter) taken from RCFL. Thus, we proceed in three steps to calculate the local shares of workers matched with each robot application. First, we obtain the size of the local population aged between 15 and 74 and the number of workers employed in each industry at the three-digit level from the census data, which allow us to calculate the local shares of workers employed in each industry. Second, we calculate the national-level occupational structure of each industry using data from RCFL. Third, we combine the above information with the match between occupations and robot applications to obtain the local share of workers employed in occupations

²⁵As the RCFL is run on a quarterly basis, we computed annual data by merging the quarters. For 2018, however, we had to combine the last two quarters of that year with the first two of the following year. This is because the data relative to the first and second quarters of 2018 only provide information on occupations at the four-digit level and not at the five-digit level as in the subsequent waves.

matched with each robot application. Accordingly, $\mu_{a,i}$ is given by:

$$\mu_{a,i} = \sum_s \sum_o I_{oa} \theta_{os} \mu_{s,i}, \quad (4)$$

where I_{oa} is an indicator function taking value 1 if occupation o is exposed to robot application a (and zero otherwise), θ_{os} is the share of workers employed in occupation o in industry s , and $\mu_{s,i}$ is the ratio of workers employed in industry s over the residents (aged between 15 and 74) in local labor market area i .²⁶

Data on industrial robots, defined by the International Organization for Standardization as “automatically controlled, reprogrammable, multipurpose manipulator[s] programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications”, are derived from the IFR database, which contains the annual shipments and stocks of industrial robots for more than 50 countries. As previously explained, robots are classified according to either their application at the three-digit level (e.g., welding, processing, palletizing) or the economic activity of the installing companies at the two-digit level (based on ISIC rev. 4).

Other demographic and industry-related variables included as controls in our empirical specifications are retrieved from the above-mentioned censuses by Istat.

Table 1 shows some summary statistics for the dependent variables described in Section 3.1 along with the employment and unemployment rates, local robot exposure and our IV (shift-share variable based on the total stocks of robots in Japan, South Korea and the US) for the set of LLMA in our sample. These descriptive statistics reveal a great deal of heterogeneity in the evolution of local employment across LLMA, as anticipated in the Introduction. We point out that, on average, the share of robot operators over the working-age population grows substantially. Indeed, while these rates of change may appear as small, it is worth noticing that the local relative weight of robot operators in the working-age population increases on average by 50% in only 7 years.

Figure 1 shows a map of Italian LLMA and changes in robot exposure across them. The geographical heterogeneity of the robot adoption process in the period of interest is patent: all regions are affected and no clear-cut macro-regional divide can be spotted.

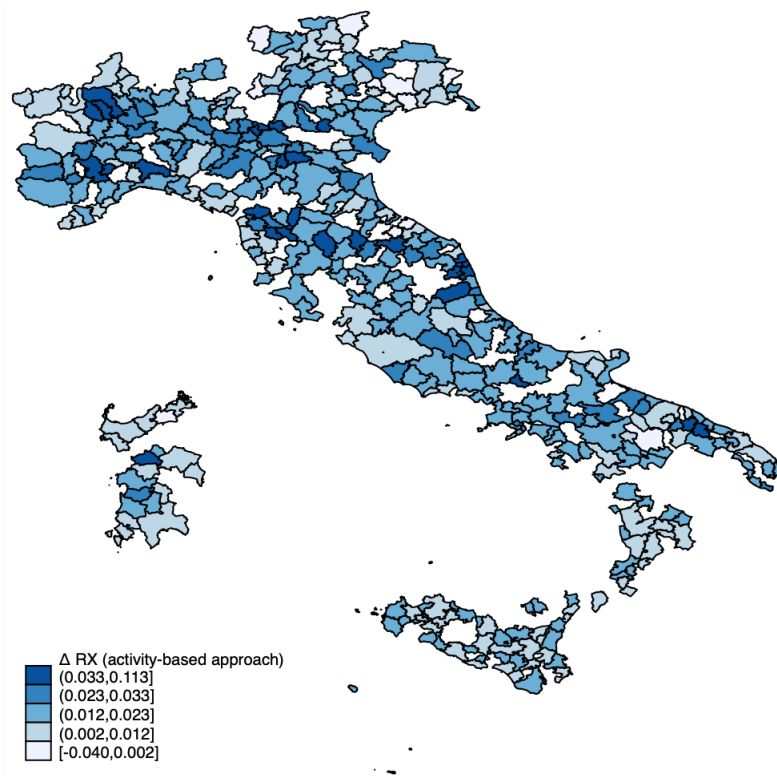
Figure 2 shows that our IV based on robot adoption in Japan, South Korea and the US seems to be informative for the part related to the change in the stocks of robots in Italy.

²⁶As the RCFL only provides representative data about occupations from 2004, we combine the 2001 census data on sectoral employment shares with the 2004 data on the occupational structure of the industries from the RCFL, using the same methodology employed for equation (4), to construct $\tilde{\mu}_{a,i}$ for our IV.

Table 1: Descriptive statistics

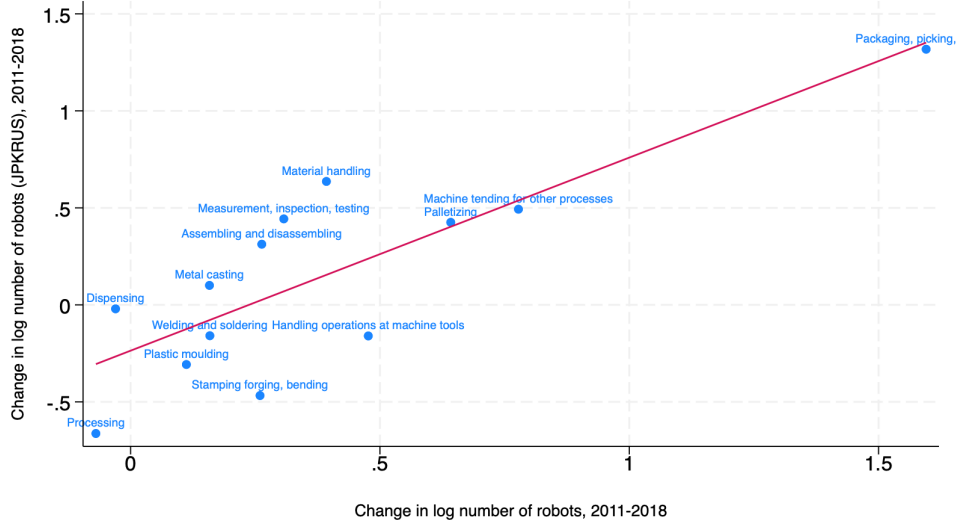
	Mean	Std. Dev.	Min	Median	Max
Δ Share of robot operators	0.005	0.009	-0.030	0.004	0.063
Δ Share of ToI occupations	0.006	0.034	-0.164	0.007	0.215
Δ Share of PmI occupations	0.006	0.035	-0.250	0.008	0.248
Δ Share of ObI occupations	-0.000	0.035	-0.166	0.002	0.281
Δ Share of ManI occupations	0.004	0.035	-0.251	0.007	0.155
Δ Share of AuI occupations	0.009	0.030	-0.271	0.006	0.169
Δ Share of MacI occupations	0.005	0.031	-0.221	0.004	0.204
Δ Employment rate	0.009	0.026	-0.117	0.013	0.146
Δ Unemployment rate	0.019	0.040	-0.089	0.008	0.171
Δ Robot exposure (applications)	0.016	0.009	-0.040	0.015	0.113
Δ Robot exposure, JPKRUS (applications)	0.054	0.024	0.022	0.048	0.217

Notes: All the variables are measured in differences between 2018 and 2011 at the LLMA level and weighted on the basis of the resident population in 2011. The shares of robot operators, torso-intensive (ToI) occupations, physical movement-intensive (PmI) occupations (PmI), object-intensive (ObI) occupations, manual-intensive (ManI) occupations, automation-intensive (AuI) occupations, and machinery-intensive (MacI) occupations are computed with respect to working-age residents (15-64 years old). Robot exposure, JPKRUS refers to our shift-share IV based on the total robot capital stock in Japan, South Korea and the US. The number of observations is 385.

Figure 1: Changes in local robot exposure across Italian LLMA, 2011-2018

Notes: The figure reports the change in local robot exposure in 384 Italian LLMA between 2011 and 2018. Local robot exposure is measured following the activity-based approach matching workers' occupations and robot applications.

Figure 2: Changes in robot adoption in Italy vs IV countries (JPKRUS) by application, 2011-2018



Notes: The figure reports changes in the log number of robots in Italy and in the set of countries used in the main IV (Japan, South Korea and the US) between 2011 and 2018.

5 Results

5.1 Main results

To assess the relationship between the change in the local exposure to robot adoption and local employment dynamics, we estimate the empirical model described by equation 2. We focus at a granular level on the changes in the local share of robot operators, torso-intensive, physical movement-intensive, object-intensive, manual-intensive, automation-intensive, and machinery-intensive occupations. All these shares are calculated relative to the beginning-of-the-period working-age population.

Table 2 shows the IV estimates of changes in the local robot exposure on our novel groups of occupations constructed on the basis of workers' activities.²⁷ Our shift-share instrument, based on lagged occupational shares and changes in the stocks of robot applications in Japan, South Korea and the US, is highly informative as shown by the Kleibergen-Paap F statistics, which is much larger than the critical values.^{28,29}

²⁷Table C2 in Appendix C shows similar results based on an IV specification without the full set of lagged controls. The results are generally robust to the exclusion of the lagged controls.

²⁸We also report the OLS estimates in Table C3 in Appendix C. The OLS results show that the coefficients on the variable of interest ($\Delta RX_{i,t}$) are not statistically different from zero, except for the case of robot operators, but a number of possible endogeneity problems discussed in Section 3.4 may lead to downward-biased OLS estimates. For this reason, the whole analysis is based on our shift-share IV.

²⁹See column (1) of Table C4 in Appendix C for the first-stage results.

The results reveal contrasting, but not contradictory, employment changes for different groups of occupations identified according to workers’ activities and, thus, show a heterogeneous impact of robot adoption on occupations. The estimated coefficient of $\Delta RX_{i,t}$ is positive and significant for what concerns the change in robot operators (column (1)). This finding is in line with expectations, and it is a new result in this strand of the literature that suggests that robotization leads to the expansion of occupations that are directly connected with the development and installation of robots. Other studies show a positive effect of robot adoption on skilled workers employed in jobs intensive in cognitive tasks (Dauth et al., 2021), which can only be indirectly associated with more general types of automation and computerization. Our categorization is different as we specifically focus on those jobs that are *explicitly* associated with activities related to robot installation, maintenance and use. According to the estimates, a local labor market with a 1 percentage point larger increase in robot adoption experienced a 0.321 percentage point larger increase in the local share of robot operators between 2011 and 2018. This implies that the overall increase in robot operators in Italy between 2011 and 2018 can be almost entirely explained by the increase in robot exposure that occurred during the same period.³⁰

Conversely, the estimates reveal a negative and significant effect of changes in the local exposure to robots on the changes of the employment share of occupations characterized by activities requiring continuous and repeated use of the torso, in particular abdominal and lumbar muscles (column (2)). This result indicates the presence of a net displacement effect, which is arguably caused by the fact that workers in torso-intensive occupations, such as “Porters, freight shifting workers and related products” and “Unskilled personnel for industrial activities”, may find it difficult to modify their activities so as to work alongside robots. Such displacement effect can probably be expected to the extent that robots progressively drive humans out of physically demanding and hazardous activities, such as those that are torso-intensive. This is a novel finding in the literature that reveals a specific type of displacement effect due to robotization that can only be detected by performing an analysis of employment dynamics at a high level of occupational disaggregation, as done in this paper. The coefficient estimate shows that a local labor market with a 1 percentage point larger increase in robot adoption experienced a 0.834 percentage point larger decrease in the local share of torso-intensive occupations between 2011 and 2018.

The estimates do not show any significant effect of robot exposure on groups of occu-

³⁰Following Muendler (2017), it is worth noticing that the methodological design of this empirical approach, based on differential effects across locations, does not allow us to infer the total numbers of additional workers in Italy due to robot adoption without also assuming that the estimated coefficient captures the overall national effect.

Table 2: Effects of local robot exposure on employment dynamics

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	0.321*** (0.115)	-0.834** (0.421)	-0.231 (0.420)	0.022 (0.425)	-0.125 (0.448)	0.878** (0.415)	0.957** (0.431)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385
Kleibergen-Paap F stat	94.57	94.57	94.57	94.57	94.57	94.57	94.57

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations’ characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

pations characterized by other kinds of physical activities, such as climbing, balancing, walking, bending, and manipulating materials (column (3)), or a great use of hands and arms to handle, manipulate and move objects or control systems (columns (4) and (5)). These findings suggest that robots do not exercise any net effect on these types of workers: some may lose their jobs whereas others may be hired to accompany the robots. Assembling, for instance, requires object manipulation, which can be performed by robots, as well as the supervision of the assembling process and the solution to emerging problems, which still require the intervention of humans.

In addition, Table 2 shows that an increase in robot exposure has a positive and significant effect on occupations characterized by a high level of automation and intensive in machinery (columns (6) and (7)). For example, these occupations include “Plant operators for the production of non-ferrous metals” and “Furnace and plant operators for

the hot treatment of minerals”. These findings corroborate our previous results based on robot operators, i.e., the integration of robots in firms is accompanied by the expansion of occupations connected with them. The introduction of robots leads to the creation of more specialized functions associated with such robots in which labor still has a comparative advantage. It should not be surprising, thus, that the local share of workers who answer that their job is highly automated and uses intensively machinery grows more in those areas where robot exposure expands.

It is interesting to note that the heterogeneous effects found at the granular level do not translate into a significant overall effect once we look at the impact of robot adoption on local employment and unemployment rates, as reported in Table C5 in Appendix C. This implies that the local exposure to robot adoption is not correlated with aggregate variations in the local employment and unemployment rates. This result is in line with the consensus view that, in most European countries, robot adoption has so far not been associated with important net effects at the aggregate level.

The null overall effect in combination with heterogeneous effects at a more granular level can be explained in various ways. A first reason why the estimated parameters on overall employment and unemployment rates are insignificant is that they reflect the fact that contrasting effects across occupations average out. While workers in torso-intensive occupations are displaced by robots, robot operators and workers in automation- and machinery-intensive occupations benefit from the introduction of robots as these professions are and remain relatively intensive in activities where humans have a comparative advantage (Acemoglu and Restrepo, 2019; Acemoglu et al., 2023; Caselli and Manning, 2019). It is also possible that the displacement effect of robots for certain occupations is counteracted by an increase in the overall scale of production of firms adopting robots. This would be in line with previous studies on the firm-level determinants of robot adoption, as they concur in discarding labor cost-saving objectives and in emphasizing firms’ attempts at standardizing quality, increasing control over the production process, introducing new sophisticated products and reaching new destination markets (Aghion et al., 2020; Backer et al., 2018; Hirvonen et al., 2022). This is likely to be true in Italy, where firms cannot undertake collective dismissals to save labor unless they face financial difficulties, a condition that is at odds with large investments in robots. However, by focusing on the exogenous supply-side determinants of robotization, our IV strategy is aimed at minimizing this last possibility. Following the arguments of Fernandez-Macias et al. (2021) and Benmelech and Zator (2022), it is also possible that the null overall effect owes to the fact that the share of robot investment in overall aggregate expenditures on equipment is too limited to have sizable overall employment effects, notwithstanding the significant impact exerted on specific occupations; finally, it is possible that each occu-

pation consists of a large number of activities and only a few of them can be performed by robots, whose introduction allows workers to stay employed and redirect their efforts to remaining/new activities, as found by Battisti et al. (2023). However, preliminary evidence (available upon request) does not show that the impact of robots on employment depends on the number and the concentration of tasks performed by workers.

Notably, our findings also help to interpret the inconsistent results reached by the studies conducted with industrial/regional data and those using firm-level data: the former find either negative or nil effects of robot exposure on local employment dynamics, whereas the latter suggest that firms investing in robots expand the number of employees (see Filippi et al., 2023b, for an overview of the alternative levels of analysis and associated methodological differences). All in all, opposite effects may indeed coexist across firms and across occupations, and their combined effects may be limited once highly aggregated. Instead, our approach combines the use of regional data with a granular taxonomy of occupations, allowing us to find highly differentiated effects for economically meaningful groups of occupations.

Next, we explore traditional occupational categories and, in particular, we study whether the change in local exposure to robot adoption is associated with a change in the share of routine-intensive occupations. As the RBTC literature maintains that intensively codifiable activities are well suited to computerization, it could be argued that routine intensity can also help to identify occupations affected by robots. Moreover, Webb (2020) shows that robot patents refer significantly more often to manual rather than routine tasks. Hence, we study the local employment dynamics of groups of workers that perform activities that are similar in terms of their routine-task and manual-task intensity.

For this purpose, we start by identifying the Italian occupations that are traditionally more routine intensive than others by adopting the operationalization proposed by Autor et al. (2003) using O*Net and implemented by Esposito and Scicchitano (2022) and Cassandro et al. (2021) on Italian data.³¹ In so doing, we also distinguish occupations in terms of manual and cognitive task intensity. Again, we exploit the richness of Inapp ICP and, following Autor et al. (2003) and considering occupations as routinary if they are in the top third of the distribution of the Routine Task Index, we distinguish the following groups: routine-intensive (RTI); routine cognitive (RC); non-routine cognitive (NRC); routine manual (RM); non-routine manual (NRM) occupations.

As can be seen in Table 3, the estimates suggest that there are no statistically significant effects on local employment dynamics on the basis of occupations' overall routine

³¹See Fernandez-Macias and Hurley (2016) for a discussion of the alternative operationalizations of the concept of routine in the RBTC literature.

Table 3: Effects of local robot exposure on employment dynamics, routine

	Δ employment shares				
	RTI (1)	RC (2)	NRC (3)	RM (4)	NRM (5)
ΔRX	0.380 (0.382)	1.117** (0.447)	0.796** (0.386)	0.661 (0.448)	0.696* (0.381)
Macroarea fixed effects	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓
Observations	385	385	385	385	385
Kleibergen-Paap F stat	94.57	94.57	94.57	94.57	94.57

Notes: The dependent variable is the difference in the share of workers in the top third of the distribution of different indices between 2018 and 2011: routine-intensive occupations (RTI) in column (1); routine cognitive occupations (RC) in column (2); non-routine cognitive occupations (NRC) in column (3); routine manual occupations (RM) in column (4); non-routine manual occupations (NRM) in column (5). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

intensity. However, our findings indicate that those who are employed in occupations that are intensive in routine cognitive tasks increase significantly their shares following a greater exposure to robots, in line with previous findings by Dauth et al. (2021). Also, workers in non-routine cognitive and non-routine manual occupations observe an average increase in their shares following a greater exposure to robots, although the latter effect is only slightly significant at the 10% level.

These findings confirm that the relationship between the change in the local exposure to robots and in the local employment conditions is not characterized by a net displacement of workers in routine manual jobs. Recent evidence from Battisti et al. (2023) suggests that, although robotization may reduce firms' demand for routine tasks relative to abstract tasks, the affected workers do not face a higher probability of non-employment because they receive retraining opportunities. Our result is also in line with recent studies assessing the limited relevance of the RBTC hypothesis in Italy, as they find that the

phenomenon is much less significant than in other developed economies because of the country’s specialization in low-tech and low-skill intensive sectors (Basso, 2020; Cassandro et al., 2021; Marcolin et al., 2018). Workers performing non-routine tasks, instead, tend to grow thanks to the adoption of robots, and this is consistent with our findings that robot operators (workers capable of developing, supervising, maintaining, fixing and operating robots) increase in absolute and relative size: as Pfeiffer (2016) explains, “what workers [interacting with robots] need to do is anything but mere routine work”.³²

5.2 Robustness checks and extensions

In this section we carry out a battery of auxiliary regressions to show that our results are robust across specifications and sample compositions.

The first set of robustness checks concerns the sample composition. To show that the results are driven neither by the few very large LLMAAs nor by the multitude of small ones, we build two sub-samples: the first one excludes the four cities with more than 1 million residents (i.e., Milan, Rome, Naples and Turin), whereas the second one drops the LLMAAs in the bottom 20% of the distribution in terms of population (namely, those with less than 33874 residents). As can be seen in Table C6 and Table C7 in Appendix C, the main results remain valid with these sub-samples, and the first stage of the 2SLS estimation is not affected negatively.

As a second robustness check, we show the results obtained by running unweighted regressions. The estimates in Table C8 in Appendix C reveal that our main results are confirmed, and thus are not driven by the largest LLMAAs, thus corroborating the results in the first set of robustness checks.

The third set of robustness checks is concerned with our assumption about the error term and the geographical fixed effects. In the first check, we assume that the error term is correlated across observations within provinces and, thus, we cluster standard errors at the (NUTS3) provincial level. Second, we substitute macroarea fixed effects with (NUTS2) regional fixed effects. This specification is particularly demanding as the identification of the parameter of interest hinges on the variation in labor dynamics and robot exposure across few LLMAAs within the same region. Table C9 and Table C10 in

³²Our classification of occupations is based on the relative intensity of robot-related tasks and, thus, we do not focus on employment outcomes for groups of individuals based on their characteristics (such as gender, age, education). Yet, it should be noticed that we find that there is a difference in the net employment effect between men (positive and statistically significant at 1%) and women (negative and statistically insignificant) (additional results are available upon request). Automation does not pose challenges that are gender-biased in nature, but gender-biased effects may stem from pre-existing differences in labor supply patterns, different work activities, socially determined educational/occupational choices, and different institutional contexts in terms of gender equality. This explains the different results found in the literature across countries (see Filippi et al., 2023a, for a review).

Appendix C show that the results remain qualitatively and quantitatively similar to the main results.

The fourth robustness check concerns the IV. So far, we have focused on robot developments in Japan, South Korea and the United States to construct our informative and valid IV. This group of countries should in principle minimize the risk of using an invalid IV that co-varies with fluctuations in aggregate demand in Italy. It is worth noticing that, differently from those studies using industry-based shift-share measures of robot exposure, our measure is based on the change in the stocks of robot applications: this reduces even further the possibility of inadvertently picking-up simultaneous trends in employment and robot adoption across industries. Yet, as a robustness check, we repeat the main estimations with an alternative IV that considers the variation in the stocks of robot applications in all extra-European countries. It should be noted that the Kleibergen-Paap F statistic has a much lower value and this suggests that the results based on this alternative IV should be treated with caution. Despite this, the results, reported in Table C11 in Appendix C, confirm qualitatively our main findings, with the exception of the coefficient on changes in the employment rate of torso-intensive occupations that loses its significance.

The IFR accounting methodology to calculate the stock of robots assumes a full active service life of 12 years for each robot and its immediate withdrawal from service afterwards. In previous studies, some scholars (see, among others, Graetz and Michaels, 2018) recalculated the evolution of the stocks of robots by means of a perpetual inventory method. This approach avoids large discontinuities in the robot stock series and is compatible with a smoother usage of robots over the large business cycle fluctuations observed in Italy in the period of interest. Hence, we reconstruct the national stocks of robots for Italy, Japan, South Korea and the US by using the perpetual inventory method with an annual depreciation rate of 10%, annual investment in robots reported by IFR, and the initial value of the stock based on 2006.³³ Thus, our fifth robustness check uses this alternative method for calculating the stocks of robots, in terms of robots applications, both for the measure of local exposure and the IV. Table C12 in Appendix C reports the estimates obtained using these alternative measures of robot stocks. The results are, once again, qualitatively and quantitatively similar to those obtained in our main specification. Notably, the first stage appears to be very robust, with the Kleibergen-Paap F statistic approximately equal to 250.

Related to the previous robustness check, we perform two additional checks related

³³We choose 2006 for the initial value for two reasons. First, before this year, a substantial portion of robots were assigned by IFR as “unspecified” applications or sectors. Second, in an effort to improve the harmonization of cross-national data, between 2004-2005 the IFR reviewed considerably the way in which information was collected.

to the construction of our local exposure to robot adoption (and the corresponding IV). First, in Figure 2, the robot application “packaging, picking, placing” can be seen as an outlier that drives up the correlation. Previous studies using industry-based local shares rather than activity-based local shares have raised similar concerns about the validity of the results once the automotive sector is removed. Accordingly, we reproduce our results after omitting this robot application. Table C13 in Appendix C reports the estimates. There are no major differences and, if anything, the estimated coefficients become larger and more significant. We therefore conclude that “packaging, picking, placing” should not be treated as an outlier.

Second, based on Acemoglu and Restrepo (2020), we normalize the change in the stock of robots by the initial level of employment, leading to a proxy for the changes in local robot density, rather than by the initial robot stocks, leading to a proxy for the local growth rates of robots, i.e., robot capital deepening. Table C14 in Appendix C reports the estimates when ΔRX_2 is the explanatory variable and $\Delta \widetilde{RX}_2$ is the corresponding IV.³⁴ The signs of the coefficient estimates generally do not change, but we observe a general loss of statistical significance. The reason is that in our specific case the IV calculated as in Acemoglu and Restrepo (2020) performs worse than the traditional Bartik instrument in the first stage as indicated by the lower Kleibergen-Paap F statistic and, thus, this alternative approach is undermined. Accordingly, given the superior empirical performance and the validity of the traditional Bartik instrument, we prefer to build our shift-share variables based on robot capital deepening rather than changes in robot density.³⁵

The next robustness check concerns the existence of pre-trends that could affect the results and their interpretation. If the adoption of robots in the period of interest (2011-2018) is statistically correlated, conditional on the controls variables used in the specification, with the employment dynamics in the previous period, one cannot exclude that our main regressions pick up pre-existing local trends rather than contemporaneous effects. As can be seen in Table C16 in Appendix C, this is not the case. Conditional on the control variables included in our specification, future robot exposure does not seem to be correlated with past growth in the employment shares of the occupation categories analyzed.

³⁴Table C15 in Appendix C reports the corresponding OLS estimates.

³⁵It should be noted that our measure of the local exposure to robotization, which is based on the extent of robot capital deepening rather than on changes in robot density as in Acemoglu and Restrepo (2020), can be also justified by the lack of correlation (0.05) between the changes in robot stocks and the initial ratio of labor to robots across the 13 robot applications and the fact that more automated applications are not more likely to show larger effects of robots on their employment, as evidenced by the robustness check in which the results do not change when we remove the robot application “packaging, picking, placing”, which shows the largest increase in robot stocks.

Our shift-share IV can be seen as the inner product of the (initial) local shares of workers in occupations matched to a given robot application (e.g, $\tilde{\mu}_{a,i}$ for application a) and the exogenous shocks due to changes in the stocks of each robot application in Japan, South Korea and the US (e.g., $g_a = \Delta \ln \tilde{R}_{a,t}^{JPKRUS}$). This IV is consistent with a research design based on pooling the differentiated local exposure to the exogenous shocks across the thirteen robot applications. As shown by Goldsmith-Pinkham et al. (2020), our two-stage least squares estimation is equivalent to a generalized method of moments estimator using the local shares of workers exposed to robot applications as instruments, and a specific weight matrix constructed using the robot application shocks. A shift-share IV estimator can then be seen as a weighted combination of just-identified estimations, each using the local shares of workers exposed to a given robot application as a separate instrument. Goldsmith-Pinkham et al. (2020) also show that the shift-share IV estimator can be decomposed so as to derive the underlying Rotemberg weights, which can be interpreted as the sensitivity-to-misspecification elasticities associated with each instrument. All this implies that a sufficient condition for the validity of the shift-share IV estimator is the validity of the local shares $\tilde{\mu}$ as instruments, conditional on the controls in the specification, in particular the shares associated to those applications with the largest Rotemberg weights.³⁶

Using this framework developed by Goldsmith-Pinkham et al. (2020), we can identify which robot applications have the largest weights ($\hat{\alpha}_a$) in the Rotemberg decomposition. As reported in Panel C of Table C17 in Appendix C, the largest-weight robot application (0.86) is “Handling for machine tending” (Application 115), which includes, for instance, the robots developed for handling operations in glass, ceramics or food production. One would expect these kinds of robots to accompany the workers, who remain engaged in various complementary activities. Accordingly, to be in line with the theoretical mechanism inspiring the analysis, one would expect the estimated coefficient for the largest-weight robot application in the regression for robot operators to be positive and similar to the average effect reported in Table 2. This is indeed the case, as the estimated coefficient ($\hat{\beta}_{a=115}$) is equal to 0.333, which is close to the value in the main regression. Among the other comforting results from the decomposition, we would like to mention the small share accruing to negative weights (Panel A). The validity of our identification strategy is also supported by the large correlations (Panel B) between the local shares of workers exposed to a given robot application (α_a), on the one hand, and the aggregate shocks g_a , the F-statistic (F_a) from the first stage of the just-identified estimations using the local share of workers associated to robot application a as an instrument, and the dispersion

³⁶As we have a large sample of locations and a fixed number of robot applications, the consistency of our shift-share IV estimator requires the exogeneity of the shares as the number of locations goes to infinity.

of these shares across locations ($\text{Var } \mu_a$), on the other hand.

Finally, we check the effect of robotization on a new set of related dependent variables, i.e., the change in the share of weekly hours worked by our novel categories of occupations over the total number of weekly hours worked. All variables are measured over the same period, 2011-2018. The results in Table C18 in Appendix C show that an increase in exposure to robots leads to a significant increase in the number of hours worked by robot operators and workers in machinery-intensive occupations relative to other workers and a significant decrease in the number of hours worked by workers in torso-intensive occupations relative to other workers. These estimates imply that our main results are not driven by an increase in part-time workers and a corresponding substitution of hours per worker, but rather by an actual increase in full-time equivalent employees.

5.3 Industry-based measure of local exposure to robot adoption

In Section 3.2 we have discussed how our activity-based shift-share measure of local robot exposure differs from the traditional industry-based approach. For the sake of completeness, in this section we report the results obtained using the traditional industry-based approach, thereby matching workers and robots on the basis of one of the 27 industries in which they are employed, rather than using workers' activities and robot applications.

Following the literature, we calculate the variable ΔRX_i^{ind} and the corresponding industry-based shift-share IV, $\widetilde{\Delta RX}_i^{ind}$. Following the notation above, we have:

$$\Delta RX_i^{ind} = \sum_s \mu_{s,i} (\log R_{s,t} - \log R_{s,t0}), \quad (5)$$

where $\mu_{s,i} = L_{s,i}/L_i$ is the 2011 share of workers in sector s in local labor market i , and $R_{s,t}$ and $R_{s,t0}$ are the Italian stocks of industrial robots in sector s at time t (2018) and $t0$ (2011). Similarly, the shift-share industry-based instrumental variable $\widetilde{\Delta RX}_i^{ind}$ can be defined as:

$$\widetilde{\Delta RX}_i^{ind} = \sum_s \widetilde{\mu}_{s,i} \left(\log \widetilde{R}_{s,t}^{JPKRUS} - \log \widetilde{R}_{s,t0}^{JPKRUS} \right), \quad (6)$$

where $\widetilde{\mu}_{s,i} = L_{s,i}^{2001}/L_i^{2001}$ is the 2001 share of workers in sector s in local labor market i , and $\widetilde{R}_{s,t}^{JPKRUS}$ and $\widetilde{R}_{s,t0}^{JPKRUS}$ are the stocks of industrial robots in Japan, South Korea and the US in sector s at time t (2018) and $t0$ (2011).

The results based on an industry-based approach to measure the local exposure to robot adoption are shown in Table C19 in Appendix C for changes in the employment shares of our novel groups of occupations. The results are qualitatively similar, but

quantitatively different from those obtained with the activity-based approach. In general, the estimated impacts are now smaller and less significant, in line with an attenuation bias caused by the approximation related to the treatment of all workers in an industry as equally exposed to robotization. In addition, the industry-based IV strategy barely passes the tests for the informativeness of the instrument: the Kleibergen-Paap F statistic in the regressions using ΔRX^{ind} is approximately equal to 23, while the Stock-Yogo critical value at the 10% significance level is equal to 16.4.³⁷

Table C20 in Appendix C shows the results from the analysis of the Rotemberg weights. The evidence reported in this table indicates a relatively weak performance of the industry-based shift-share IV. The share of negative weights is particularly high, and the correlations between the Rotemberg weights, the just-identified coefficients from the regression for robot operators and the national component of growth indicate the possible existence of some underlying issues. Moreover, as the just-identified coefficients associated with the sectors with high Rotemberg weights differ significantly from the estimated shift-share coefficient and tend to be close to zero, the interpretation of what drives the identification becomes less straightforward.³⁸

This does not imply that the activity-based approach is always empirically preferable to the traditional one, as its superior performance might be contingent to the Italian case and the period of interest. As explained by Goldsmith-Pinkham et al. (2020), the validity of the shift-share IV method relies on the characteristics of the data (e.g., the distribution of the local shares, the number of the geographical units and of the categories for the classification of the shocks, the correlation between the local shares and the Rotemberg weights) and it remains an empirical issue to address on a case-by-case basis.

Finally, it is important to appreciate that the preference for an activity-based shift-share measure reflects not only its empirical prominence in our sample, but also its greater internal consistency. As the identification of robot operators and the other new groups of occupations requires to look at the activities performed by workers, building an activity-based measure of local robot exposure allows us to incorporate the observation that not all occupations within an industry are equally exposed to the robots installed in that industry (as the industry-based approach implicitly entails).

³⁷The first stage is reported in column (2) of Table C4 in Appendix C.

³⁸It should be noted that some of these issues are also present in the analyses by Dottori (2021), in which low Kleibergen-Paap F statistics are also reported when other countries are used to construct the shift-share instrument, and Caselli et al. (2021a) in a related work on the evolution between robot adoption and regional voting patterns in Italy.

6 Closing remarks

In this work we empirically investigate the effects that the change in local exposure to robots (i.e., robot capital deepening) had on Italian local employment outcomes over the period 2011-2018. Our empirical strategy extends previous research in this field as it provides novel and granular evidence on the impact of robot adoption on new activity-based groups of occupations.

Our novel approach makes it possible to identify robot operators, that is workers employed in occupations clearly associated with robot installation, maintenance and use. We are also able to identify occupations characterized by torso-intensive activities, physical movement-intensive tasks, intense use of hands and object manipulation as well as occupations characterized by automation-intensive and machinery-intensive activities.

In addition, we build a new activity-based shift-share measure of local exposure to robots by singling out those professions that, because of the main activities they consist of, are most exposed to specific robot applications. In particular, we focus on the overlap between the functional similarities of robot applications and occupations, rather than on the overlap between the industries in which robots and workers are employed. This new shift-share measure of local exposure to robots does not refer only to the local industry composition, but it also takes into account the occupational composition of each industry and the different exposure to robots of each occupation. Besides being more in line with an interpretation of exposure to robots in terms of tasks and activities, this measure is internally consistent with the groups of workers whose local employment dynamics we study in this work, and it also performs better than the industry-based measure based on the results of our IV strategy.

From a theoretical viewpoint, as mentioned, our approach is more consistent with the theoretical task-based production frameworks, whereby tasks are allocated to labor and capital according to the available technology, whose progress alters labor demand across occupations according to their inherent tasks (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019; Autor et al., 2003). From an empirical viewpoint, our methodology makes it possible to build consistent measures of changes in local employment and local exposure to robots, thereby reducing the possible mismatch between industry-based measures of local robot exposure and the employment dynamics of groups of workers formed on the basis of skills and tasks. Besides offering greater internal consistency, this new approach also reduces possible interference in the estimation stemming from the presence of industry-related confounding factors.

Our empirical results suggest a limited aggregate impact of robot adoption in Italy in the most recent period of time. Although this finding is at odds with the seminal studies

conducted on the US (Acemoglu and Restrepo, 2020), it is in line with the conclusions reached by Dauth et al. (2021) for Germany and by Dottori (2021) for Italy following traditional industry-based approaches. As pointed out by Gentili et al. (2020), the process of robot adoption and its implications on local labor markets are time-sensitive and depend on the local socio-economic system. Hence, it should not be controversial that the negative impact of robot exposure found in the US does not carry over to Germany and Italy.

More interestingly, we show that the lack of significant effects of robot adoption on aggregate labor market dynamics hides more complex employment dynamics for specific groups of workers, when properly identified. Our novel approach to look at the occupations (at five-digit level) allows us to discern clear signs of positive effects for robot operators, that is workers employed in occupations concerned with the installation and use of robots, as well as for automation-intensive and machinery-intensive occupations. In line with these findings, we also show that routine cognitive occupations grow together with robot adoption. On the other hand, occupations performing activities that require an intensive use of the torso are significantly reduced by robot adoption. This suggests that the lack of significant effects of local robot exposure on aggregate local employment dynamics is probably due to both the heterogeneous impact of robot adoption on different jobs and inappropriate (i.e., not clearly connected to robot-related activities) pooling of professions. In turn, our findings appear consistent with recent microeconomic evidence showing that the firms that install robots also expand employment both to maintain robots and to perform activities alongside them. Thus, our findings suggest that future research should focus on the effects of robotization on highly disaggregated robot-related groups of workers and occupations, as these can provide a link between microeconomic and macroeconomic studies.

This uneven effect of robotization on different occupations within and across sectors has relevant social and policy implications. While the attention has most often fallen on the overall net effects of automation and other technological advances on employment dynamics, our results warn that the adoption of robots performing certain activities may affect negatively specific types of workers who cannot grasp the opportunities created by the increase in the positions in other occupations. As a matter of fact, our findings entail that, even short of a negative overall impact on local employment, robotization may nonetheless have important redistributive effects through significant changes in the relative dynamics of the various occupations. This suggests the importance of supporting education and training policies that focus on the skills associated with the activities whose demand grows with robot adoption (Di Giacomo and Lerch, 2023). To prevent that the heterogeneous impact of robots on occupations may lead to labor market segmenta-

tion and prolonged spells of unemployment for those holding a job negatively affected by robotization, retraining and upskilling must facilitate workers' transition towards occupations whose main activities are in higher demand. This does not only concern workers in sectoral and occupational job transitions. Firms investing massively in robots can also contribute by reassigning workers to new activities, as occurred in Germany (Dauth et al., 2021), thereby gradually altering the content of occupations (Atalay et al., 2020; Battisti et al., 2023; Freeman et al., 2020). Indeed, investment in human capital is fundamental to generate the skills that complement new technologies (Autor, 2015). In Italy, whose economy is based on low-skill and low-tech productions, this is particularly relevant. The case will be even stronger in the aftermath of the Covid-19 pandemic, as this latter has pushed for a more intense use of robots and other innovative technologies that can help reduce the risk of contagion (Caselli et al., 2021b; Hantrais et al., 2021).

As shown, our results suggest that a displacement effect may regard occupations characterized by torso-intensive and physical-intensive activities. Although the lack of health-related data does not allow us to test empirically whether robot adoption is associated with fewer injuries and physical problems, our results confirm that robots tend to displace those occupations that are more likely to be associated with musculoskeletal disorders among workers. This is consistent with recent evidence from Gihleb et al. (2022) on the robot-induced reduction in annual work-related injury rates in the US.

Notwithstanding these generally positive considerations, a note of caution is in order. It could be argued that more advanced robotic solutions, often integrated with AI, continue to be introduced on a daily basis. If robots will gain enhanced dexterity and flexibility and AI will efficiently undertake monitoring and precision tasks, the scope of activities that are at risk of displacement may become broader and within-occupation shifts may be more difficult. The extent to which this may happen is not dictated only by technology though, as it depends also on work organization and social factors (Fernandez-Macias et al., 2023). Hence, more research will be necessary in the future to explore how more advanced forms of robotization will impact on aggregate and granular employment dynamics.

References

- Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of Economic Literature*, 40(1):7–72.
- Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, volume 4 of *Handbook of Labor Economics*, chapter 12, pages 1043–1171. Elsevier.
- Acemoglu, D., Koster, H. R. A., and Ozgen, C. (2023). Robots and workers: Evidence from the Netherlands. Working Paper 31009, National Bureau of Economic Research.
- Acemoglu, D., Lelarge, C., and Restrepo, P. (2020). Competing with Robots: Firm-Level Evidence from France. *AEA Papers and Proceedings*, 110:383–88.
- Acemoglu, D. and Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, 33(2):3–30.
- Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6):2188–2244.
- Adachi, D. (2021). Robots and wage polarization: The effects of robot capital by occupations. mimeo.
- Adachi, D., Kawaguchi, D., and Saito, Y. U. (2023). Robots and employment: Evidence from japan, 1978-2017. *Journal of Labor Economics*, forthcoming.
- Aghion, P., Antonin, C., and Bunel, S. (2019). Artificial Intelligence, Growth and Employment: The Role of Policy. *Economie et Statistique / Economics and Statistics*, 510-511-512:149–164.
- Aghion, P., Antonin, C., Bunel, S., and Jaravel, X. (2020). What Are the Labor and Product Market Effects of Automation? New Evidence from France. CEPR Discussion Papers 14443, C.E.P.R. Discussion Papers.
- Antonietti, R., Cattani, L., Gambarotto, F., and Pedrini, G. (2023). Education, routine, and complexity-biased Key Enabling Technologies: evidence from Emilia-Romagna, Italy. *Industry and Innovation*, 30(1):103–134.
- Arntz, M., Gregory, T., and Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters*, 159:157–160.
- Atalay, E., Phongthientham, P., Sotelo, S., and Tannenbaum, D. (2020). The evolution of work in the United States. *American Economic Journal: Applied Economics*, 12(2):1–34.
- Autor, D. and Salomons, A. (2018). Is Automation Labor Share-Displacing? Productivity Growth, Employment, and the Labor Share. *Brookings Papers on Economic Activity*, 2018:1–87.

- Autor, D. H. (2015). Why are there still so many jobs? the history and future of workplace automation. *Journal of Economic Perspectives*, 29(3):3–30.
- Autor, D. H. and Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, 103(5):1553–97.
- Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103(6):2121–68.
- Autor, D. H., Dorn, D., and Hanson, G. H. (2015). Untangling trade and technology: Evidence from local labour markets. *The Economic Journal*, 125(584):621–646.
- Autor, D. H., Katz, L. F., and Kearney, M. S. (2006). The polarization of the US labor market. *The American Economic Review*, 96(2):189–194.
- Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.
- Backer, K. D., DeStefano, T., Menon, C., and Suh, J. R. (2018). Industrial robotics and the global organisation of production. Technical report, OECD Science, Technology and Industry Working Papers 2018/03).
- Baldwin, R., Haaland, J. I., and Venables, A. (2021). Jobs and technology in general equilibrium: A three elasticities approach. CEPR Discussion Papers 15739, C.E.P.R. Discussion Papers.
- Barbieri, T., Basso, G., and Scicchitano, S. (2022). Italian Workers at Risk During the COVID-19 Epidemic. *Italian Economic Journal*, 8(1):175–195.
- Bartik, T. J. (1991). *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute for Employment Research.
- Basso, G. (2020). The Evolution of the Occupational Structure in Italy, 2007-2017. *Social Indicators Research*, 152(2):673–704.
- Battisti, M., Dustmann, C., and Schonberg, U. (2023). Technological and Organizational Change and the Careers of Workers. *Journal of the European Economic Association*.
- Battisti, M. and Gravina, A. F. (2021). Do robots complement or substitute for older workers? *Economics Letters*, 208:110064.
- Benmelech, E. and Zator, M. (2022). Robots and Firm Investment. NBER Working Papers 29676, National Bureau of Economic Research, Inc.
- Bessen, J., Goos, M., Salomons, A., and van den Berge, W. (2020). Firm-level automation: Evidence from the Netherlands. *AEA Papers and Proceedings*, 110:389–93.
- Blanas, S., Gancia, G., and Lee, S. Y. T. (2020). Who is afraid of machines? *Economic Policy*, 34(100):627–690.
- Blanchard, O. J. and Katz, L. F. (1992). Regional Evolutions. *Brookings Papers on*

- Economic Activity*, 23(1):1–76.
- Bonacini, L., Gallo, G., and Scicchitano, S. (2021). Working from home and income inequality: Risks of a ‘new normal’ with COVID-19. *Journal of Population Economics*, 34:303–360.
- Bonfiglioli, A., Crino’, R., Fadinger, H., and Gancia, G. (2023). Robot Imports and Firm-Level Outcomes. Working Papers 528, University of Milano-Bicocca, Department of Economics.
- Brynjolfsson, E. and McAfee, A. (2011). *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy*. Digital Frontier Press.
- Brynjolfsson, E. and McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.
- Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, 19(1):22–64.
- Caselli, F. and Manning, A. (2019). Robot arithmetic: New technology and wages. *American Economic Review: Insights*, 1(1):1–12.
- Caselli, M., Fracasso, A., and Traverso, S. (2021a). Globalization, robotization, and electoral outcomes: Evidence from spatial regressions for Italy. *Journal of Regional Science*, 61:86–111.
- Caselli, M., Fracasso, A., and Traverso, S. (2021b). Robots and risk of COVID-19 workplace contagion: Evidence from italy. *Technological Forecasting and Social Change*, 173:121097.
- Cassandro, N., Centra, M., Esposito, P., and Guarascio, D. (2021). Employment–unemployment transitions? evidence from italian task-based data. *Economia Politica*, 38:1109–1147.
- Cheng, H., Jia, R., Li, D., and Li, H. (2019). The rise of robots in China. *Journal of Economic Perspectives*, 33(2):71–88.
- Chiacchio, F., Petropoulos, G., and Pichler, D. (2018). The impact of industrial robots on EU employment and wages: A local labour market approach. Working Papers 25186, Bruegel.
- Cirillo, V., Evangelista, R., Guarascio, D., and Sostero, M. (2021). Digitalization, routineness and employment: an exploration on italian task-based data. *Research Policy*, 50:104079.
- Citino, L. and Linarello, A. (2022). The impact of Chinese import competition on Italian manufacturing. *Review of International Economics*, 30(3):702–731.
- Compagnucci, F., Gentili, A., Valentini, E., and Gallegati, M. (2019). Robotization and labour dislocation in the manufacturing sectors of OECD countries: a panel VAR

- approach. *Applied Economics*, 51(57):6127–6138.
- Consoli, D., Marin, G., Rentocchini, F., and Vona, F. (2023). Routinization, within-occupation task changes and long-run employment dynamics. *Research Policy*, 52(1):104658.
- Cortes, G. M., Jaimovich, N., Nekarda, C. J., and Siu, H. E. (2020). The dynamics of disappearing routine jobs: A flows approach. *Labour Economics*, 65:101823.
- Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association*, 19(6):3104–3153.
- David, B. (2017). Computer technology and probable job destructions in Japan: An evaluation. *Journal of the Japanese and International Economies*, 43(C):77–87.
- de Blasio, G. and Poy, S. (2017). The impact of local wage regulation on employment: A border analysis from Italy in the 1950s. *Journal of Regional Science*, 57(1):48–74.
- de Vries, G. J., Gentile, E., Miroudot, S., and Wacker, K. M. (2020). The rise of robots and the fall of routine jobs. *Labour Economics*, 66:101885.
- Dekle, R. (2020). Robots and industrial labor: Evidence from Japan. *Journal of the Japanese and International Economies*, 58(C).
- Dengler, K. and Matthes, B. (2018). The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany. *Technological Forecasting and Social Change*, 137:304 – 316.
- Di Giacomo, G. and Lerch, B. (2023). Automation and human capital adjustment. *Journal of Human Resources*.
- Dix-Carneiro, R. and Kovak, B. K. (2017). Trade Liberalization and Regional Dynamics. *American Economic Review*, 107(10):2908–46.
- Dixon, J., Hong, B., and Wu, L. (2021). The robot revolution: Managerial and employment consequences for firms. *Management Science*, 67(9):5586–5605.
- Domini, G., Grazi, M., Moschella, D., and Treibich, T. (2021). Threats and opportunities in the digital era: Automation spikes and employment dynamics. *Research Policy*, 50(7):104137.
- Dottori, D. (2021). Robots and employment: evidence from Italy. *Economia Politica*, 38:739–795.
- Esposito, P. and Scicchitano, S. (2022). Educational mismatch and labour market transitions in Italy: Is there an unemployment trap? *Structural Change and Economic Dynamics*, 61:138–155.
- Felten, E., Raj, M., and Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12):2195–2217.

- Fernandez-Macias, E., Bisello, M., Peruffo, E., and Rinaldi, R. (2023). Routinization of work processes, de-routinization of job structures. *Socio-Economic Review*, 21(3):1773–1794.
- Fernandez-Macias, E. and Hurley, J. (2016). Routine-biased technical change and job polarization in Europe. *Socio-Economic Review*, 15(3):563–585.
- Fernandez-Macias, E., Klenert, D., and Anton, J.-I. (2021). Not so disruptive yet? characteristics, distribution and determinants of robots in europe. *Structural Change and Economic Dynamics*, 58:76–89.
- Filippi, E., Banno', M., and Trento, S. (2023a). Automation technologies and the risk of substitution of women: Can gender equality in the institutional context reduce the risk? *Technological Forecasting and Social Change*, 191:122528.
- Filippi, E., Banno', M., and Trento, S. (2023b). Automation technologies and their impact on employment: A review, synthesis and future research agenda. *Technological Forecasting and Social Change*, 191:122448.
- Fossen, F. M. and Sorgner, A. (2021). Digitalization of work and entry into entrepreneurship. *Journal of Business Research*, 125:548–563.
- Freeman, R. B., Ganguli, I., and Handel, M. J. (2020). Within-occupation changes dominate changes in what workers do: A shift-share decomposition, 2005-2015. *AEA Papers and Proceedings*, 110:394–99.
- Frey, C. B. and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114(C):254–280.
- Garibaldi, P. and Taddei, F. (2013). Italy: a dual labour market in transition. Country case studies on labour market segmentation. Employment Working Paper 144, International Labour Organization.
- Gentili, A., Compagnucci, F., Gallegati, M., and Valentini, E. (2020). Are machines stealing our jobs? *Cambridge Journal of Regions, Economy and Society*, 13(1):153–173.
- Gihleb, R., Giuntella, O., Stella, L., and Wang, T. (2022). Industrial robots, workers' safety, and health. *Labour Economics*, 78:102205.
- Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.
- Goos, M. and Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *The Review of Economics and Statistics*, 89(1):118–133.
- Goos, M., Manning, A., and Salomons, A. (2009). Job polarization in Europe. *American Economic Review*, 99(2):58–63.
- Goos, M., Manning, A., and Salomons, A. (2014). Explaining Job Polarization:

- Routine-Biased Technological Change and Offshoring. *American Economic Review*, 104(8):2509–2526.
- Graetz, G. and Michaels, G. (2018). Robots at work. *The Review of Economics and Statistics*, 100(5):753–768.
- Hantrais, L., Allin, P., Kritikos, M., Sogomonjan, M., Anand, P. B., Livingstone, S., Williams, M., and Innes, M. (2021). Covid-19 and the digital revolution. *Contemporary Social Science*, 16(2):256–270.
- Harrigan, J., Reshef, A., and Toubal, F. (2021). The March of the Techies: Job Polarization Within and Between Firms. *Research Policy*, 50(7).
- Hirvonen, J., Stenhammar, A., and Tuhkuri, J. (2022). New Evidence on the Effect of Technology on Employment and Skill Demand. ETLA Working Papers 93, The Research Institute of the Finnish Economy.
- Kariel, J. (2021). Job creators or job killers? heterogeneous effects of industrial robots on uk employment. *LABOUR*, 35(1):52–78.
- Katz, L. F. and Autor, D. (1999). Changes in the wage structure and earnings inequality. In *Handbook of labor economics*, volume 3, pages 1463–1555. Elsevier.
- Katz, L. F. and Murphy, K. M. (1992). Changes in relative wages, 1963–1987: supply and demand factors. *The Quarterly Journal of Economics*, 107(1):35–78.
- Klenert, D., Fernandez-Macias, E., and Anton, J.-I. (2023). Do robots really destroy jobs? evidence from europe. *Economic and Industrial Democracy*, 44(1):280–316.
- Koch, M., Manuylov, I., and Smolka, M. (2021). Robots and Firms. *The Economic Journal*, 131(638):2553–2584.
- Kovak, B. K. (2013). Regional Effects of Trade Reform: What Is the Correct Measure of Liberalization? *American Economic Review*, 103(5):1960–76.
- Mann, K. and Puttmann, L. (2023). Benign Effects of Automation: New Evidence from Patent Texts. *The Review of Economics and Statistics*, 105(3):562–579.
- Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., and Dewhurst, M. (2017). *A future that works: automation, employment, and productivity*. McKinsey Global Institute.
- Marcolin, L., Miroudot, S., and Squicciarini, M. (2018). To be (routine) or not to be (routine), that is the question: a cross-country task-based answer. *Industrial and Corporate Change*, 28(3):477–501.
- Mokyr, J., Vickers, C., and Ziebarth, N. L. (2015). The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different? *Journal of Economic Perspectives*, 29(3):31–50.
- Montobbio, F., Staccioli, J., Virgillito, M. E., and Vivarelli, M. (2022). Robots and the origin of their labour-saving impact. *Technological Forecasting and Social Change*,

174(C).

- Muendler, M.-A. (2017). Trade, technology, and prosperity: An account of evidence from a labor-market perspective. WTO Staff Working Papers ERSD–2017–15, World Trade Organization.
- Nedelkoska, L. and Quintini, G. (2018). Automation, skills use and training. OECD Social, Employment and Migration Working Papers 202, OECD.
- Paba, S., Solinas, G., Bonacini, L., and Fareri, S. (2020). Robot, ICT e globalizzazione: gli effetti sui sistemi locali del lavoro in Italia. *L'industria, Rivista di economia e politica industriale*, 1/2020:71–100.
- Pfeiffer, S. (2016). Robots, industry 4.0 and humans, or why assembly work is more than routine work. *Societies*, 6:16.
- Pratt, G. A. (2015). Is a Cambrian Explosion Coming for Robotics? *Journal of Economic Perspectives*, 29(3):51–60.
- Squicciarini, M. and Staccioli, J. (2022). Labour-saving technologies and employment levels: Are robots really making workers redundant? OECD Science, Technology and Industry Policy Papers 124, OECD Publishing.
- Vannutelli, S., Scicchitano, S., and Biagetti, M. (2022). Routine-biased technological change and wage inequality: do workers' perceptions matter? *Eurasian Business Review*, 12(3):409–450.
- Webb, M. (2020). The impact of artificial intelligence on the labor market. University of Stanford.

Appendix

A Novel categories of occupations

Table A1: Robot operators

5 digit	Occupation	Description	Act 1	Act 2	Act 3
22130	Electrical and factory automation engineers	Design, engineer, control, manufacture and maintain systems, motors, apparatus and equipment (electrical energy)	Verifying safety conditions	Performing tests	Inspecting and producing estimates
22141	Electronics engineers	Conduct research, design and functionally control systems, equipment, and electronic components	Developing electronic systems, equipment, circuits or components	Carrying out research on electronics and the electronic properties of materials	Analyzing or processing data or information
31220	Application experts	Install, configure, manage and maintain software applications	Checking and testing functioning of manufactured product	Analysing or identifying customer requirements	Providing consultancy for customers
31340	Electronics technicians	Design, build, install and modify components, parts, apparatuses and electronic circuits, and identify and solve operational problems	Changing systems	Providing instructions on how to make components	Performing maintenance of equipment or machinery
31415	Automated assembly line management and control technicians	Apply procedures and technology to control through automated systems, and manage the operation and safety of automated assembly lines	Carrying out maintenance on equipment/installations	Signaling anomalies	Supervising application of safety norms
31530	Manufacturing production technicians	Manage, organize, control and guarantee the efficiency, correct functioning and safety of manufacturing production processes	Monitoring process or product quality	Organizing and supervising the execution of activities	Selecting tools or methods to optimize production
71710	Automated assembly line operators	Lead and control the activity of automated assembly lines and industrial robots	Controlling quality	Supervising process	Choosing tools
72110	Operators of automatic and semi-automatic industrial machine tools	Lead and support the operation of semi/automatic and numerically controlled industrial machine tools	Programming, controlling, driving operations of industrial machine tools	Reading technical designs	Carrying out work on semi-finished metal products

Notes: Act 1, Act 2 and Act 3 stand for the top, second top and third top activities.

Table A2: Descriptive statistics for novel indices of occupations

	Mean	Std. Dev.	Bottom third	Median	Top third
Torso intensive (ToI)	15.027	15.778	3.896	9.188	19.728
Physical movement intensive (PmI)	20.467	16.742	8.571	16.770	26.984
Object intensive (ObI)	33.436	21.610	18.571	34.515	47.619
Manual intensive (ManI)	53.474	25.102	36.905	55.000	70.238
Automation intensive (AuI)	28.824	17.370	18.750	26.064	34.524
Machinery intensive (MacI)	30.451	26.540	11.905	22.673	40.909

Notes: The number of observations (occupations) is 796.

Table A3: Examples of top and bottom third occupations by robot-related features

	Top third occupations	Bottom third occupations
Torso intensive (ToI)	71321 - Furnace operators for glass production 81310 - Porters, freight shifting workers and related products 84310 - Unskilled personnel for industrial activities and related professions	12280 - General managers and executives of companies for business and people services 21132 - Statisticians 33220 - Bank clerks
Physical movement intensive (PmI)	62150 - Metal cable fitters for industrial use and industrial transport 71120 - Mineral and stone first treatment plant operators 71610 - Steam boiler and heat engine operators in industrial plants	25430 - Highly skilled interpreters and translators 31210 - Programmers 43210 - Accounting clerks
Object intensive (ObI)	63221 - Glass-blowers and modellers 71252 - Electrochemical plant operators for the production of non-ferrous metals 72790 - Mass production assemblers of industrial composite items	11310 - Senior officials of ordinary judiciary system 33131 - Client information clerks 33420 - Business agents
Manual intensive (ManI)	62170 - Electric welders and under ASME regulations 63162 - Precious and semiprecious stone workers 71252 - Electrochemical plant operators for the production of non-ferrous metals	25230 - Notaries 31623 - Aerospace technicians 43220 - Pay packet clerks
Automation intensive (AuI)	71230 - Furnace and plant operators for the hot treatment of minerals 71251 - Plant operators for the production of non-ferrous metals 71341 - Plant operators for the modelling of bricks	11241 - General and department managers and related professionals in Public Administrations, non-profit public bodies and local authorities 25342 - Art experts 32128 - Occupational therapists
Machinery intensive (MacI)	71230 - Furnace and plant operators for the hot treatment of minerals 71251 - Plant operators for the production of non-ferrous metals 71810 - Mill and kneading machine operators	25343 - Specialists in political science 26555 - Language teachers 51252 - Distance salespersons

Notes: The table reports three occupations in the top and bottom third of the distribution of occupations ranked according to the intensity of the characteristic described in the first column.

B Novel matching procedure between occupations and robot applications

Table B1: Examples of matching between occupations’ activities and robot applications

5 digit	Occupation	Act 1	Act 2	Act 3	Robot application
61120	Stone-cutters	Cutting stones (imp: 4.5, freq: 4.4)	Sanding stones (imp: 4.3, freq: 3.9)	Polishing stones (imp: 4.1, freq: 3.8)	190 - Processing: enduring changing, the robot leads the workpiece or the tool, material removal
62211	Blacksmiths	Cutting metals (imp: 4.1, freq: 4.2)	Assembling metal pieces (imp: 4, freq: 4.2)	Welding and repairing metal pieces (imp: 3.9, freq: 3.9)	190 - Processing: enduring changing, the robot leads the workpiece or the tool, material removal
62120	Welders and flame cutters	Using tools (imp: 4.7, freq: 4.6)	Welding pieces (imp: 4.6, freq: 4.6)	Supervising machines (imp: 4.2, freq: 4.2)	160 - Welding and soldering (all materials)
62360	Inspector mechanics	Identifying malfunctions or anomalies (imp: 4, freq: 3.5)	Performing tests on engines and machines (imp: 3.9, freq: 3.4)	Reading technical designs (imp: 3.8, freq: 3.7)	No match
63450	Bookbinders and after print finishers	Binding books (imp: 3.9, freq: 3.7)	Gluing materials (imp: 3.8, freq: 3.7)	Folding paper (imp: 3.8, freq: 3.7)	No match
65321	Weavers	Working on looms (imp: 3.9, freq: 3.3)	Replacing threads (imp: 3.8, freq: 3.4)	Maintaining machinery and equipment (imp: 3.6, freq: 2.1)	No match

Notes: Act 1, Act 2 and Act 3 stand for the top, second top and third top activities; imp stands for importance; freq stands for frequency.

C Additional results

Table C1: Balancing tests for effects of local robot exposure on employment dynamics

	Employment rate (1)	Unemployment rate (2)	Non-light manufacturing (3)	Private sector (4)
ΔRX	0.744** (0.362)	0.221 (0.293)	2.223*** (0.581)	0.159** (0.072)
Macroarea fixed effects	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓
Observations	385	385	385	385

Notes: The dependent variables are: the local employment rate in 2011 in column (1); the local unemployment rate in 2011 in column (2); the share of non-light manufacturing firms in 2011 in column (3); the share of workers in the private sector in 2011 in column (4). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, and the share of foreign-born residents. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, and the local exposure to ICT capital per worker. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C2: Effects of local robot exposure on employment dynamics, no controls

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	0.237*** (0.075)	-0.345 (0.272)	0.086 (0.259)	0.138 (0.265)	-0.039 (0.279)	0.508* (0.261)	0.491* (0.256)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385
Kleibergen-Paap F stat	139.8	139.8	139.8	139.8	139.8	139.8	139.8

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Four macroareas are included: North-West, North-East, Centre, South and Islands. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C3: Effects of local robot exposure on employment dynamics, OLS

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	0.078 (0.056)	-0.197 (0.220)	0.034 (0.223)	-0.123 (0.203)	-0.258 (0.223)	-0.271 (0.222)	-0.063 (0.225)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated via OLS. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C4: Effects of local robot exposure, first stage

	ΔRX (1)	ΔRX^{ind} (2)
$\widetilde{\Delta RX}$	0.338*** (0.035)	
$\widetilde{\Delta RX}^{ind}$		0.296*** (0.061)
Macroarea fixed effects	✓	✓
Lagged demographic controls	✓	✓
Lagged industry controls	✓	✓
Lagged occupation controls	✓	✓
Observations	385	385
Kleibergen-Paap F stat	94.57	23.43

Notes: First-stage results for the effects of robot exposure on employment dynamics. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C5: Effects of local robot exposure on employment dynamics

	Δ employment (1)	Δ unemployment (2)
ΔRX	0.259 (0.281)	-0.449 (0.443)
Macroarea fixed effects	✓	✓
Lagged demographic controls	✓	✓
Lagged industry controls	✓	✓
Lagged occupation controls	✓	✓
Observations	385	385
Kleibergen-Paap F stat	94.57	94.57

Notes: The dependent variable is the difference in employment rates between 2018 and 2011 in column (1), and the difference in unemployment rates between 2018 and 2011 in column (2). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C6: Effects of local robot exposure on employment dynamics, robustness I: No large LLMAAs

	<i>Δ employment shares</i>						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	0.319*** (0.112)	-0.810** (0.403)	-0.228 (0.410)	0.044 (0.418)	-0.123 (0.434)	0.856** (0.418)	0.952** (0.430)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	381	381	381	381	381	381	381
Kleibergen-Paap F stat	95.11	95.11	95.11	95.11	95.11	95.11	95.11

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The sample excludes the four LLMAAs with more than 1 million residents. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C7: Effects of local robot exposure on employment dynamics, robustness I: No small LLMA

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	0.299** (0.117)	-0.738* (0.433)	-0.128 (0.419)	-0.020 (0.430)	-0.224 (0.440)	0.813* (0.431)	0.904** (0.444)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	308	308	308	308	308	308	308
Kleibergen-Paap F stat	93.87	93.87	93.87	93.87	93.87	93.87	93.87

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The sample excludes the 20% smallest LLMA. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C8: Effects of local robot exposure on employment dynamics, robustness II: Unweighted

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	0.437** (0.174)	-0.981 (0.662)	-0.029 (0.615)	0.414 (0.587)	0.526 (0.652)	1.629** (0.668)	1.411** (0.577)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385
Kleibergen-Paap F stat	29.67	29.67	29.67	29.67	29.67	29.67	29.67

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are *not* weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C9: Effects of local robot exposure on employment dynamics, robustness III: Clustered SE

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	0.321*** (0.117)	-0.834** (0.385)	-0.231 (0.429)	0.022 (0.408)	-0.125 (0.436)	0.878* (0.479)	0.957** (0.471)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385
Kleibergen-Paap F stat	89.88	89.88	89.88	89.88	89.88	89.88	89.88

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Standard errors in parentheses are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C10: Effects of local robot exposure on employment dynamics, robustness III: Region FE

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	0.277** (0.114)	-0.794** (0.396)	-0.241 (0.439)	-0.128 (0.427)	-0.272 (0.433)	0.827** (0.404)	0.881** (0.435)
Region fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385
Kleibergen-Paap F stat	95.96	95.96	95.96	95.96	95.96	95.96	95.96

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Fixed effects for twenty regions are included. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C11: Effects of local robot exposure on employment dynamics, robustness IV: Alternative IV

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	0.715** (0.308)	-1.385 (0.931)	-0.343 (0.817)	0.301 (0.863)	0.509 (0.983)	2.898** (1.389)	2.277** (1.125)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385
Kleibergen-Paap F stat	8.127	8.127	8.127	8.127	8.127	8.127	8.127

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in extra-European countries. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C12: Effects of local robot exposure on employment dynamics, robustness V: PIM

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	0.315*** (0.115)	-0.773* (0.420)	-0.148 (0.410)	0.113 (0.416)	-0.034 (0.440)	0.913** (0.394)	0.943** (0.407)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385
Kleibergen-Paap F stat	248.7	248.7	248.7	248.7	248.7	248.7	248.7

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and the growth of robots in Japan, South Korea and the US. The stocks of robots are calculated with the perpetual inventory method and a 10% depreciation rate. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C13: Effects of local robot exposure on employment dynamics, robustness VI: No “packaging, picking, placing”

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	0.511*** (0.174)	-1.358** (0.574)	-0.592 (0.570)	-0.182 (0.590)	-0.156 (0.646)	1.560** (0.682)	1.427** (0.665)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385
Kleibergen-Paap F stat	35.66	35.66	35.66	35.66	35.66	35.66	35.66

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations’ characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and the growth of robots in Japan, South Korea and the US. The stocks of robots do not include the robot application “packaging, picking, placing”. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C14: Effects of local robot exposure on employment dynamics, robustness VII: Changes in robot density

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX_2	0.026** (0.011)	-0.009 (0.035)	0.050 (0.031)	0.047 (0.033)	0.037 (0.032)	0.044 (0.029)	0.049* (0.029)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385
Kleibergen-Paap F stat	23.32	23.32	23.32	23.32	23.32	23.32	23.32

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). Robot exposure is a shift-share measure based on changes in the number of robots per worker (ΔRX_2). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and the change of robots per worker in Japan, South Korea and the US. The first-stage coefficient on $\Delta \widehat{RX}_2$ is 0.029***. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C15: Effects of local robot exposure on employment dynamics, robustness VII: Changes in robot density, OLS

	<i>Δ employment shares</i>						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX_2	-0.002 (0.004)	-0.002 (0.011)	0.012 (0.012)	-0.001 (0.012)	0.002 (0.013)	-0.016 (0.014)	-0.007 (0.013)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated via OLS. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C16: Effects of local robot exposure on employment dynamics, pre-trends

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	-0.082 (0.122)	0.054 (0.441)	0.584 (0.459)	-0.106 (0.388)	-0.290 (0.372)	0.125 (0.354)	-0.402 (0.371)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	365	365	365	365	365	365	365
Kleibergen-Paap F stat	131.4	131.4	131.4	131.4	131.4	131.4	131.4

Notes: The dependent variable is the difference between 2011 and 2004 in the share of robot operators in column (1), and the difference between 2011 and 2004 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of workers employees in the private sector. Lagged occupation controls include the local share of employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C17: Rotemberg weights

Panel A: Negative and positive weights				
	Sum	Mean	Share	
Negative	-0.181	-0.023	0.133	
Positive	1.181	0.236	0.867	

Panel B: Correlations of application aggregates					
	α_a	g_a	$\hat{\beta}_a$	F_a	Var(μ_a)
α_a	1				
g_a	0.529	1			
$\hat{\beta}_a$	0.061	0.006	1		
F_a	0.732	0.633	-0.123	1	
Var(μ_a)	0.826	0.148	-0.173	0.386	1

Panel C: Top 3 Rotemberg weight applications				
	$\hat{\alpha}_a$	g_a	$\hat{\beta}_a$	App Share
Machine tending (115)	0.856	0.778	0.333	3.240
Packaging, picking, placing (118)	0.292	1.595	-0.084	0.822
Palletizing (117)	0.016	0.642	0.075	0.501

Notes: This table reports statistics about the Rotemberg weights based on the regression for robot operators. Panel A reports the sum, mean and share of negative and positive Rotemberg weights. Panel B reports the correlations between the weights (α_a), the national component of growth (g_a), the just-identified coefficients from the regression for robot operators $\hat{\beta}_a$, the first-stage F-statistic of our local shares of workers associated to robot application a (F_a), and the variation in robot application shares across locations (Var(μ_a)). Panel C reports the top three robot applications according to the Rotemberg weights.

Table C18: Effects of local robot exposure on employment dynamics, weekly hours

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX	0.396* (0.206)	-1.632** (0.688)	-0.535 (0.663)	-0.570 (0.647)	-0.508 (0.664)	0.981 (0.669)	1.211* (0.679)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385
Kleibergen-Paap F stat	94.57	94.57	94.57	94.57	94.57	94.57	94.57

Notes: The dependent variable is the difference between 2018 and 2011 in the share of weekly hours worked by robot operators in column (1), and the difference between 2018 and 2011 in the share of weekly hours worked by workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C19: Effects of local robot exposure on employment dynamics, industry-based approach

	Δ employment shares						
	Operators (1)	ToI (2)	PmI (3)	ObI (4)	ManI (5)	AuI (6)	MacI (7)
ΔRX^{ind}	0.074* (0.042)	-0.263* (0.152)	-0.065 (0.171)	-0.029 (0.143)	0.028 (0.139)	0.338** (0.136)	0.235* (0.125)
Macroarea fixed effects	✓	✓	✓	✓	✓	✓	✓
Lagged demographic controls	✓	✓	✓	✓	✓	✓	✓
Lagged industry controls	✓	✓	✓	✓	✓	✓	✓
Lagged occupation controls	✓	✓	✓	✓	✓	✓	✓
Observations	385	385	385	385	385	385	385
Kleibergen-Paap F stat	23.43	23.43	23.43	23.43	23.43	23.43	23.43

Notes: The dependent variable is the difference between 2018 and 2011 in the share of robot operators in column (1), and the difference between 2018 and 2011 in the share of workers in the top third of the distribution of various occupations' characteristics: torso-intensive occupations (ToI) in column (2); physical movement-intensive occupations (PmI) in column (3); object-intensive occupations (ObI) in column (4); manual-intensive occupations (ManI) in column (5); automation-intensive occupations (AuI) in column (6); machinery-intensive occupations (MacI) in column (7). Shares are calculated with respect to the resident working-age population (15-64 years old). The local robot exposure is measured following an industry-based approach in all columns. All regressions are estimated with the 2SLS estimator. The instrument for robot exposure is measured using a shift-share approach with lagged weights and growth of robots in Japan, South Korea and the US. Four macroareas are included: North-West, North-East, Centre, South and Islands. Lagged control variables are measured in 2011. Lagged demographic controls include the log of the resident population, the share of residents aged over 65, the share of female residents, the share of residents with tertiary education, the share of foreign-born residents, and the local employment rate. Lagged industry-related controls include the local exposure to trade competition from China, the share of employees in the manufacturing sector, the share of employees in the transportation and logistics industry, the share of employees using a personal computer, the local exposure to ICT capital per worker, the share of local units in non-light manufacturing sectors with at least 50 employees, and the local share of workers employees in the private sector. Lagged occupation controls include the local share of workers employed as craftsmen, plant operators and unskilled professionals (categories 6, 7 and 8 of ISCO 08), and the local diffusion of routine occupations. The estimations are weighted on the basis of the resident population in 2011. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C20: Rotemberg weights: industry-based approach.

Panel A: Negative and positive weights				
	Sum	Mean	Share	
Negative	-0.751	-0.075	0.300	
Positive	1.751	0.103	0.700	

Panel B: Correlations of sectoral aggregates					
	α_s	g_s	$\hat{\beta}_s$	F_s	$\text{Var}(\mu_s)$
α_s	1				
g_s	0.644	1			
$\hat{\beta}_s$	0.043	-0.300	1		
F_s	0.703	0.436	-0.079	1	
$\text{Var}(z_s)$	-0.177	0.066	-0.282	-0.115	1

Panel C: Top 3 Rotemberg weight sectors				
	$\hat{\alpha}_s$	g_s	$\hat{\beta}_s$	Sec Share
Basic metals (24)	0.828	2.320	0.001	0.675
Other chemical products (20-21)	0.332	1.470	-0.023	0.561
Pharmaceuticals (19)	0.140	0.478	-0.049	0.627

Notes: This table reports statistics about the Rotemberg weights based on the regression for robot operators. The local robot exposure is measured following an industry-based approach. Panel A reports the sum, mean and share of negative and positive Rotemberg weights. Panel B reports the correlations between the weights (α_s), the national component of growth (g_s), the just-identified coefficients from the regression for robot operators $\hat{\beta}_s$, the first-stage F-statistic of our local shares of workers associated to sector s (F_s), and the variation in robot shares across locations ($\text{Var}(\mu_s)$). Panel C reports the top three sectors according to the Rotemberg weights.