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Robots, Occupations, and Worker Age: A Production-unit Analysis of Employment

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Abstract

We analyse the impact of robot adoption on employment composition using novel micro data on robot use in German manufacturing plants linked with social security records and data on job tasks. Our task-based model predicts more favourable employment effects for the least routine-task intensive occupations and for young workers, with the latter being better at adapting to change. An event-study analysis of robot adoption confirms both predictions. We do not find adverse employment effects for any occupational or age group, but churning among low-skilled workers rises sharply. We conclude that the displacement effect of robots is occupation biased but age neutral, whereas the reinstatement effect is age biased and benefits young workers most.

Keywords: automation, employment, industrial robots, occupation, worker age, workforce composition

JEL classification: D22, J23, J24, O33

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1 Introduction

The impact of new technology on the labor market is one of the oldest and most widely discussed topics in economics. Recent technological advances in robotics have again sparked both high hopes and dire fears. Those more on the enthusiastic side hope that robots may play an important role in overcoming growing labor shortages in ageing societies. Pessimists fear that robots will destroy decently paid middle-class jobs in unprecedented magnitudes. Whether such hopes and fears ever materialize only partly depends on whether robots are substitutes or complements for *gross* labor input. As robots could be substitutes for certain labor inputs, e.g., for workers least adaptable to change and for those performing routine tasks, but complements for others, e.g., for those supervising robots and production processes such as engineers or managers, it is even more important to understand the impact of robotization on workforce *composition*. Ageing societies lacking young workers will benefit more from robots substituting for young workers, and societies with abundant high-skilled labor will benefit more from robots complementing those workers and taking over routine tasks. As robots could have very different effects on, say, young production workers versus young engineers, the young generation making its occupational decisions should consider how robots may substitute or complement their jobs to make informed choices.

We will argue theoretically and demonstrate empirically that robot adoption has very heterogeneous effects by occupation and worker age. Based on the seminal work of Acemoglu and Restrepo (2018), we build a task-based model of robot adoption to examine the effects of robot adoption on workforce composition through both displacement and reinstatement channels. The latter hinges on workers' (differential) ability to adapt to new tasks. We follow the basic implications of human capital theory and core findings of the cognitive science literature on fluid and crystalline intelligence and predict that young workers are complements to technological change.

Individual robot-using firms decide which workers to hire or to replace. Documenting heterogeneous effects of robots thus requires granular micro-level data on robot use and workers' occupation, age, and tasks. While the number of micro-level studies is growing, most existing studies utilize industry-level variation in robots and therefore cannot test whether robots and certain groups of workers are substitutes or complements at the level of the production unit. Core contributions adopt a local labor market (LLM) approach (Acemoglu and Restrepo

2020a, Dauth et al. 2021). Whereas firm-level evidence allows one to directly observe the technological relationship between robot technology and various labor inputs, i.e., it reveals which types of labor are complements and substitutes to robot technology in production, the LLM perspective mixes the user firm reaction with the competitive reaction of other firms. The LLM approach is thus informative on the gross employment effect at the market level but not on the production-level technological relationship between robots and various labor inputs.

To make progress in this important topic, we developed and integrated a battery of questions on robot use into Germany's leading establishment panel survey, the IAB Establishment Panel. Whereas most other micro-level analyses worldwide have had to rely on robot imports, we are among the very first papers observing actual robot *use* in production.[1] A further unique feature of our data is that we are able to connect them to high-quality social security records, which circumvents common survey data issues with sample attrition and allows us to analyse robots' impacts on employment composition and worker turnover in terms of worker age and occupation. Using detailed data on worker tasks, we assign job tasks to occupation-age groups, which enables us to compare our empirical results with our task-based framework. In doing so, we also provide initial plant-level evidence on whether robots are indeed substitutes for routine manual occupations and complements for non-routine occupations as predicted by task-based models and generally assumed in the robot literature.

Our study is among the first to analyse the effects of plant-level robot adoption in Germany, which is a large technologically advanced economy that ranks among the top robot users in the world. Unlike the US, Germany features a highly developed apprenticeship training system and managed to preserve its industrial core even during the recent decades of import competition from China and other low-income countries (Dauth et al. 2014) by focusing on high-quality manufacturing and exporting. Little is known about the firm-level impact of robots on the German economy. Deng et al. (2021) use the same survey data as we do and are the first to describe establishment-level robot adoption in Germany. They find robot adoption to be rare and highly concentrated within a few industries. Larger firms are more likely to

[1] Robot imports can be a poor proxy for robot use because many robot importers resell imported robots instead of using them in production (cf. Bonfiglioli et al. 2020, Humlum 2021). Even if a treatment group of robot-using importers can be identified, some control group firms will source robots from resellers. Robot imports are a flow concept, and arriving at a robot stock at the firm level requires assumptions on the depreciation rate. Finally, using robot imports makes little sense when analysing robot-producing countries, such as Germany. Very recently, firm-level data on robot *use* became available for the US (Acemoglu et al. 2022, Brynjolfsson et al. 2023).

use and adopt robots.[2]

There is no study using establishment panel data on robot use to jointly study the micro effects of robot adoption on workforce composition in terms of occupation and age. We analyse the impact of robot adoption on employment and employment composition by confronting the predictions of our task-based model with event-study analyses of German manufacturing plants following them before and after their first robot adoption. The reason we focus on first-time robot adopters instead of (usually large) firms buying just another robot is that first-time adoption is more likely to capture a major technological reorganization of the production process.

We demonstrate descriptively that the task content of work determines replaceability primarily along the occupational dimension and much less so along the age dimension. We document rising employment upon robot adoption, reinforcing firm-level results by Acemoglu et al. (2020), Bonfiglioli et al. (2020), Dixon et al. (2020), and Koch et al. (2021). In line with theoretical perceptions, robot adoption is more beneficial for the least routine-intensive occupations. In particular, employment increases among technicians, engineers, and managers. Workers performing routine manual tasks see their employment opportunities unchanged. This task bias confirms core predictions of the standard task-based models (Autor et al. 2003, Acemoglu and Restrepo 2018) in the robot context at the production-unit level. The results are also in line with Dauth et al. (2021) who use industry-level variation in robot intensity across German LLMs. We find that the increase in total employment and in the shares of technicians, engineers, and managers is achieved by adopter firms' increased hiring but unchanged worker attrition. Constant employment levels for low-skilled manual workers, however, mask increased churning for this group, confirming another prediction of our model.

Importantly, the fraction of younger workers *increases* after robot adoption because of intensified hiring of young workers. This confirms the predictions of cognitive science literature on adaptability to new tasks by age and standard predictions of human capital theory. This result sheds new light on the findings of Dauth et al. (2021) who document that a decrease in the hiring of younger workers is associated with robot exposure in their LLM setting, which could imply that, within automating industries, those firms that do not adopt robots hire fewer young workers. When jointly analysing the occupation and age dimensions, we find that young workers' employment rises among low- and middle-skilled workers, whereas the employment

[2]Recently, Benmelech and Zator (2021) use the same data to analyse robot adoption patterns. Their analysis focuses on the effects of robots on overall employment at the plant level and in industry-region cells.

increase for technicians/engineers and managers is concentrated among middle-aged and older workers, respectively. In sum, our results support hypotheses that robots are complements to high-skilled labor and to younger workers and offer a nuanced view on the very heterogeneous effects of age by occupation. Through the lens of our model and the concepts of displacement and reinstatement effects theorized by Acemoglu and Restrepo (2018), our results imply that the displacement effect of robots is primarily occupation-dependent (i.e. task-dependent), whereas the reinstatement effect (or 'new task channel') mostly depends on workers' age.

We contribute to the growing firm-level robot literature on employment effects. Using firm-level data on robot *imports* for France, Bonfiglioli et al. (2020) find mostly statistically insignificant pre-post adoption changes in employment.[3] Acemoglu et al. (2020) use similar data but support them with additional data sources and consider the 2010-2015 period. They find positive effects on employment and argue that the positive employment effect masks reallocation effects where adopters grow at the expense of non-adopters. Humlum (2021) finds increased employment in Denmark. To overcome issues of robot import data, a recent wave of studies leverage data on robot *use* at the production unit level. Koch et al. (2021) employ firm-level panel data for the Spanish manufacturing sector containing a robot use question (yes/no). Applying event-study estimates, Koch et al. (2021) report positive short- and medium-run effects of robot adoption on output and employment. Acemoglu et al. (2022) exploit a new technology module of the 2019 Annual Business Survey in the US. They show descriptively that robot users self-report negligible employment effects.[4] We add to this literature a study on employment for a major Western economy using high-quality data on robot use (instead of imports) and support the generally favourable effects of robot adoption found previously. We are among the first to show that this employment increase is accompanied by a sharp increase in worker churning for the most routine task-intensive occupations.

We further contribute to the literature on the micro effects of robots on skill composition.[5] Barth et al. (2020) combine import data for Norwegian manufacturing firms with worker-level data to analyse within-firm wage inequality. Robotization yields a wage premium for college education and managers, implying that robots are complements to skilled and managerial

[3]Their IV procedure yields relatively weak first-stage F-statistics, while their second-stage results display very large point estimates (e.g., value added per worker increases by $100 \times (-1 + e^{1.19}) = 230\%$ after robot adoption, whereas employment is reduced by 43%).

[4]Aghion et al. (2023) and Bessen et al. (2020) use firm-level data on automation expenditures. The data do not allow them to disentangle robots from the various other automation techniques. Similarly, Dinlersoz and Wolf (2018) use aggregated technology categories in their analysis of US establishments.

[5]Acemoglu and Restrepo (2020b) discuss theoretically how displacement and reinstatement effects of automation can lead to a skill bias and present corresponding aggregate sector-level evidence for the US.

tasks. Dixon et al. (2020) merge Canadian robot import data with surveys on employment and workforce composition and find an increase in worker turnover, positive overall employment effects, and a decline in managerial headcount. Humlum (2021) identifies a decline in the wage bill and the employment shares of production workers relative to tech workers after robot adoption. Koch et al. (2021) report positive short- and medium-run effects of robot adoption on the employment of both high- and low-skilled workers. Acemoglu et al. (2022) find an increase in skill demand among robot-using firms. In work parallel to ours, Acemoglu et al. (2023) use data on robot imports in the Netherlands and combine them with various measures of worker replaceability to analyse the impact of robot adoption on workforce composition. Their results on overall employment effects are similar to ours, and they also report worse employment outcomes for workers performing routine or replaceable tasks. They do not examine worker turnover or worker age. We add to this literature by directly analysing the *occupational* dimension of employment. By demonstrating that the least routine manual task-intensive occupations, in particular supervising occupations, experience the strongest employment gains upon robot adoption, our results support a core theoretical concept of the task-based literature.

Finally, we contribute to the literature by asking how new technologies interact with worker age ("age-biased technological change"). Acemoglu and Restrepo (2018) formalize the reinstatement effect of new technologies, postulating that new technologies lead to employment growth because of the new tasks they create. New tasks created through new technologies require adaptability by workers. The theoretical foundations for potential age biases in the adaptability to new technology come from human capital theory and cognitive science. The former predicts larger investments in young workers' new technology skills because young workers have a longer payoff horizon for human capital investments. Cognitive science distinguishes between fluid and crystalline abilities (or "intelligences") and shows that the two abilities have very different age profiles.[6] Fluid abilities include perceptual speed and reasoning abilities and are conducive to the speed of finding solutions to new problems. They rapidly decline with age.

Studies tend to confirm that older individuals are less able to adapt to changes (Bosma et al. 2003). Due to their superior fluid abilities, young workers have a comparative advantage in adapting to new tasks. In line with those predictions from cognitive science and gerontology,

[6]The general theory of fluid and crystallized intelligence is often attributed to Cattell (1971) and builds on several earlier contributions of the author, e.g., Horn and Cattell (1966).

Aubert et al. (2006) find that new technologies enhance not only hires of younger workers in general[7] but also increase employment opportunities for young blue-collar workers. We will find exactly the same mechanisms upon robot adoption. Bartel and Sicherman (1993) start from a human capital investment perspective and find that an unexpected increase in the rate of technological change will decrease the employment of older workers. The reason is that retraining investments for older workers have a shorter pay-off horizon than those for younger workers, which makes the former comparatively less attractive for investment. In line with this research, we show that first-time robot adoption indeed sharply increased the separation rates of middle-aged and older workers.

2 Model

In this section, we introduce a simple model of robot adoption to guide our empirical analysis. The model features a task-based framework as in Acemoglu and Restrepo (2018). The baseline setup reproduces the prediction of self-selection into robot adoption and an overall ambiguous employment effect as in Koch et al. (2021) and Bonfiglioli et al. (2020), with an added prediction of increased churning. The main departure is an elaboration of the effects on workplace composition by incorporating the occupation and age dimensions.[8] The effects on workforce composition hinge on two margins of adjustment: workers' specialization in *existing* tasks and their differential adaptability to *new* tasks. In light of our model and empirical evidence based on the German task data, we will argue that the former drives the change in occupational structure through the displacement channel, whereas the latter is the primary cause of the shift in the age profile through the reinstatement channel.

2.1 Baseline Setting

We consider a partial equilibrium setting for a given industry. Each firm faces the same iso-elastic demand $y_i = \zeta p_i^{-\eta}$, where $\eta > 1$ is the price elasticity, y_i is the demand for firm i's products, p_i is the price charged by firm i, and ζ is a demand shifter, which is assumed for simplicity to be the same across firms. The supply-side specification follows the standard

[7]Vintage human capital models provide an additional explanation for some of these findings. According to those models, robot-adopting firms may hire more young workers because young workers' up-to-date knowledge may be a complement to new technology (Chari and Hopenhayn 1991).

[8]In their model, Koch et al. (2021) introduce different types of labor by skill level and Humlum (2021) places occupations and occupational choice at the centre of his analysis. We go beyond the occupation dimension by further introducing worker age and discussing the interplay between occupation and age.

task-based framework. Firm i combines a continuum of tasks to produce its output

$$y_i = \phi_i \left(\int_0^1 s_i(j)^{\frac{\sigma-1}{\sigma}} \,\mathrm{d}j \right)^{\frac{\sigma}{\sigma-1}},$$

where ϕ_i is the firm-specific productivity, $s_i(j)$ is the input of task j, and σ is the elasticity of substitution across different tasks.

Tasks are either routine or non-routine. Denote the set of routine tasks by $\mathcal{R} \subseteq [0,1]$ and the share of routine tasks by θ ($\theta \equiv \int_{\mathcal{R}} \mathrm{d}j$). Routine tasks are technologically automatable and can be performed by either robots or human labor, whereas non-routine tasks are not automatable and can only be performed by human labor. Firm i's input for task j is given by

$$s_i(j) = \begin{cases} \ell_i(j) + \lambda k_i(j) & j \in \mathcal{R} \\ \ell_i(j) & j \notin \mathcal{R} \end{cases},$$

where $\ell_i(j)$ is the employment of human labor and $k_i(j)$ is the robot input, both used in task j. Robots, which can only be used for routine tasks, are perfect substitutes for human labor. The parameter $\lambda > 0$ measures the efficiency of robots relative to workers. In this partial equilibrium setting, the wage rate w and the rental rate of robots r are exogenously given.[9] We assume $r < \lambda w$. In words, the productivity-adjusted wage rate is higher than the rental rate of robots. This implies that if firm i chooses to adopt robots, it would replace human labor with robots for all routine tasks.

Robot adoption incurs a one-time fixed cost F. Because the saving in variable production costs increases with firm size, only firms that are sufficiently productive and large are willing to pay the fixed cost and adopt robots. The following proposition concerning the self-selection into robot adoption is well known in the literature (Bonfiglioli et al. 2020; Koch et al. 2021).[10]

Proposition 1. *There exists a productivity threshold $\bar{\phi}$ such that firm i adopts robots if its productivity $\phi_i > \bar{\phi}$.*

Turning to the effect of robot adoption on overall firm-level employment, we find it to be generally ambiguous, in line with the predictions in Graetz and Michaels (2018) and Acemoglu and Restrepo (2018). Robots, on the one hand, replace workers that perform routine tasks

[9] Acemoglu and Restrepo (2021) consider an elegant setting in which wage rates are endogenous and can be expressed as functions of task shares. Since our empirical exercise focuses on the employment effects instead of wage effects, we abstract from the endogenization of the wage rates.

[10] All the proofs of our analytical results are relegated to the Appendix.

(displacement effect), but on the other hand, they may increase the demand for workers that perform tasks complementary to robots (productivity effect). If the degree of complementarity between different tasks is sufficiently high (σ is sufficiently small), then the second channel can potentially dominate the first, and the overall employment effect at the firm level becomes positive. We state this discussion formally in the next proposition and draw its testable implication.

Proposition 2. *If $\sigma \geq \eta$, total employment decreases following robot adoption. If $\sigma < \eta$, the effect of robot adoption on total employment is ambiguous.*

Implication 1. *Robot adoption has an ambiguous effect on firm-level employment.*

Because of the direct replacement effect of robots, job separation is expected to increase following adoption. If the productivity effect is present, hiring will also increase, and it will increase more than job separation if the net employment change is positive.[11] The next implication concerns the effect on job churning.

Implication 2. *If the effect of robot adoption on overall employment is positive, then both hiring and job separation rates are expected to increase.*

In what follows, we turn to the effects of robot adoption on workforce composition, which is the thrust of our empirical analysis. We will discuss the effects through two channels: the displacement channel and the reinstatement channel.

2.2 Effects on Workforce Composition: Displacement Channel

Robots replace workers performing routine tasks. Because task content varies across jobs, robot adoption can directly affect workforce composition through the task displacement channel. To investigate the effects on workforce composition, we enrich the model by introducing in turn the occupation and age dimensions.[12]

The Occupation Dimension

We introduce the occupation dimension into the task-based framework. Our formulation follows the task-based model that appeared in Humlum (2019), and both specifications would

[11] We abstract from re-training of workers within firms. Re-training would mute the effect of robot adoption on churning.

[12] In principle, robot adoption can also affect occupational composition through differential productivity effects, but since we do not have a direct measure of productivity effects at the task level and there is no strong theoretical predication about how productivity effects vary with occupation or age a priori, we focus solely on the displacement effect in this subsection.

yield qualitatively similar reduced-form production functions. Whereas his setup synchronizes multiple effects of robot adoption on workers, ours is more specific about the task-level source of variation by occupation, for which we will provide direct empirical evidence based on the task data.

There are O occupations with a generic element $o \in \mathcal{O} \equiv \{1, 2, ..., O\}$. For each task j, $o(j)$ denotes the occupation that performs task j. We define the share of tasks performed by occupation o simply as $\mu_o \equiv \int_0^1 \mathbb{1}(o(j) = o)\,\mathrm{d}j$ ($\mathbb{1}$ is the indicator function). Within the set of tasks performed by occupation o, we further define the share of routine tasks as

$$\theta_o \equiv \frac{\int_{\mathcal{R}} \mathbb{1}(o(j) = o)\,\mathrm{d}j}{\int_0^1 \mathbb{1}(o(j) = o)\,\mathrm{d}j},$$

where we recall that $\mathcal{R}$ is the set of routine tasks. Thus, θ_o is an occupation-level replaceability index, capturing the extent to which robots affect a given occupation through the displacement channel.

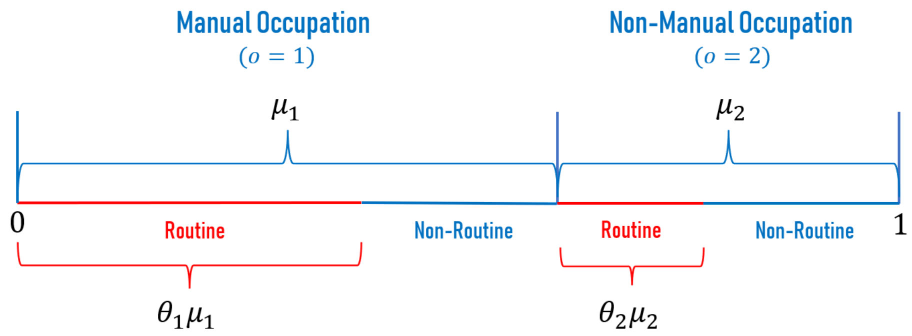

Figure 1: The Displacement Channel: A Two-Occupation Example

To illustrate the occupation dimension, consider an example in which there are only two occupations: manual ($o = 1$) and non-manual ($o = 2$) occupations. Figure 1 illustrates the distribution of the routine and non-routine tasks by occupation on the unit interval, where we sort tasks by occupation and routineness for illustrative purposes.

Evidently, in this two-occupation example, workers in the manual occupation (with $\theta_1 > \theta_2$) see a sharper decline in the range of tasks that they continue to perform after robot adoption, whereas workers in the non-manual occupation will see a relative increase in the share of non-routine tasks that demand their skills. Denote by $\ell_{i,o}$ firm i's employment in occupation o prior to robot adoption and by $\Delta\ell_{i,o}$ the employment change following robot adoption. The following proposition connects the occupation-level replaceability with the relative employment change.

Proposition 3. *If $\theta_o < \theta_{o'}$, then $\frac{\Delta \ell_{i,o}}{\ell_{i,o}} > \frac{\Delta \ell_{i,o'}}{\ell_{i,o'}}$.*

As we will describe later using the German survey data, the share of tasks replaceable by robots varies substantially by occupation.[13] Engineering and managerial occupations, for instance, perform a relatively low share of routine tasks (small θ_o). The next implication, in line with the earlier findings in Dauth et al. (2021) and Humlum (2021), follows directly from the proposition above.

Implication 3. *Robot adoption is more likely to raise employment for occupations that perform more non-routine tasks.*

Moreover, similar to the argument for the overall employment change, if the effect of robot adoption on employment in a particular occupation is positive, both hiring and job separations for that occupation are also likely to increase.

The Age Dimension

We further incorporate the age dimension into the model. Following Acemoglu and Restrepo (2022), we assume that workers of different ages have comparative advantage in performing different tasks and are thus sorted into different tasks. However, unlike their setting of two age groups with full specialization, we consider multiple age groups with more flexible task assignment by age. This more general setting helps tighten the connection between the model and empirics and enables an inquiry into the interplay between age and occupation in the subsequent analysis.

There are A age groups with a generic element $a \in \mathcal{A} \equiv \{1, 2, ..., A\}$. A younger age group takes a lower index from $\mathcal{A}$. For each task j, $a(j)$ denotes the age group that performs task j. Correspondingly, we define the share of tasks performed by age group a as $\mu^a \equiv \int_0^1 \mathbb{1}(a(j) = a)\,\mathrm{d}j$ and the share of tasks performed by age group a and occupation o as $\mu_o^a \equiv \int_0^1 \mathbb{1}(a(j) = a, o(j) = o)\,\mathrm{d}j$. We also define at both age and age-occupation levels the replaceability index as

$$\theta^a \equiv \frac{\int_{\mathcal{R}} \mathbb{1}(a(j) = a)\,\mathrm{d}j}{\int_0^1 \mathbb{1}(a(j) = a)\,\mathrm{d}j} \quad \text{and} \quad \theta_o^a \equiv \frac{\int_{\mathcal{R}} \mathbb{1}(a(j) = a, o(j) = o)\,\mathrm{d}j}{\int_0^1 \mathbb{1}(a(j) = a, o(j) = o)\,\mathrm{d}j}.$$

[13] The literature reports that the replaceability of workers by robots varies systematically by occupation (and industry); see Graetz and Michaels (2018) and Chapter 4.2 of the IFR report *World Robotics: Industrial Robots 2018.*

The employment effect by age group through the displacement channel hinges on θ^a and θ^a_o. As we will explain in greater detail in Section 4, the evidence based on the German data suggests that within each occupation, the share of routine tasks is relatively stable across age groups, and across occupations, the age profile of employment is similar. Those two empirical observations motivate two assumptions: $\theta^a_o = \theta_o$ for any a and $\mu^a = \mu^a_o/\mu_o$ for any o. It is straightforward to show that the two assumptions further imply $\theta^a = \theta$. Since the replaceability index does not vary with age either in aggregate or at the occupation level, robot adoption is not expected to affect either the overall or occupation-level age profile through the displacement channel.

Implication 4. *Robot adoption is unlikely to affect the age profile through the displacement channel.*

2.3 Effects on Workforce Composition: Reinstatement Channel

To further explore the potential effects of robot adoption on the age profile, we now consider the reinstatement channel as formalized in Acemoglu and Restrepo (2018) and emphasized in the subsequent discussion in (Acemoglu and Restrepo 2019). Robot adoption introduces new tasks into the production processes.[14] Those new tasks will be performed by human labor, and workers (of different age groups) face the challenge of adapting to the new tasks in a robotized production setting. We depart from the literature by explicitly considering age bias in workers' adaptability to new tasks. We will consider in turn occupation-neutral and occupation-specific age biases and discuss their empirical implications.

Occupation-Neutral Age Bias in Adaptability

Young workers are in general more adaptable to new tasks because of cognitive advantages in adaptability (Bosma et al. 2003), their newer human capital vintage (Chari and Hopenhayn 1991), and their greater willingness to acquire needed human capital arising from longer payoff horizons for human capital investment (Heckman and Jacobs 2011). This higher adaptability is primarily tied to worker age. Formally, new tasks of measure δ are introduced after robot adoption. For any new task $j \in (1, 1+\delta]$, $a(j)$ is the age group that performs j. We can define the measure of new tasks performed by age group a as $\nu^a \equiv \int_1^{1+\delta} \mathbb{1}(a(j) = a)\, \mathrm{d}j$.

[14] The new tasks under automation include tasks of operating and programming robots and technical maintenance work. See also Hirvonen et al. (2022) for empirical evidence on how firms use new production technologies to produce new products, which may lead to the introduction of new tasks.

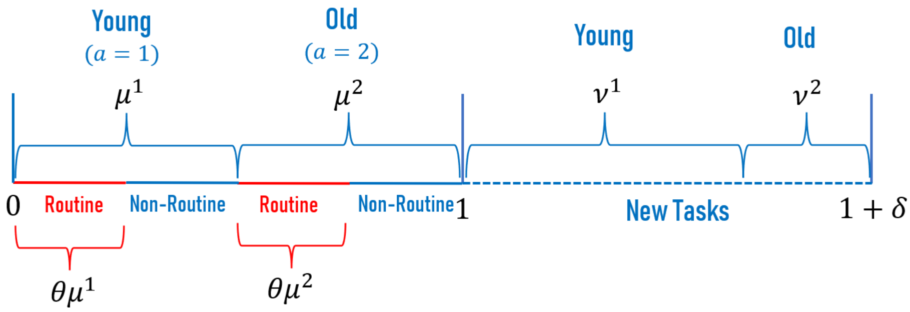

Figure 2: The Reinstatement Channel: A Two-Age-Group Example

To illustrate the (occupation-neutral) age bias in adaptability, we consider an example in which there are only two age groups: young ($a = 1$) and old ($a = 2$). Figure 2 illustrates the distribution of existing and new tasks by age, where we sort tasks by age and routineness for illustrative purposes. As discussed in the previous subsection, replaceability is assumed to be the same across age groups ($\theta^a = \theta$). In this example, young workers capture a relatively larger share of new tasks and will see an expansion in the share of tasks they perform following robot adoption.

Formally, (ν^a/μ^a) measures the (relative) adaptability of age group a to new tasks. We assume that (ν^a/μ^a) is decreasing in a, that is, younger workers are more adaptable to new tasks. Denote by ℓ_i^a firm i's employment in age group a prior to robot adoption and by $\Delta\ell_i^a$ the employment change following robot adoption. The following proposition describes the effects of robot adoption on the overall age profile.

Proposition 4. *Let $\theta^a = \theta$. If $\frac{\nu^a}{\mu^a}$ decreases with a, then $\frac{\Delta\ell_i^a}{\ell_i^a}$ also decreases with a.*

According to this proposition, since young workers will take over a relatively large fraction of the new tasks, the employment change for young workers under robot adoption is more positive (or less negative) than for older workers. Thanks to their greater adaptability, young workers may well be insulated from or even benefit from the automation shocks. This yields the next testable implication.

Implication 5. *Robot adoption is more likely to raise the employment of young workers.*

Occupation-Specific Age Bias in Adaptability

Finally, we revisit the occupation dimension in the context of age bias in adaptability. Although younger workers enjoy greater adaptability in general, there are certain occupations in which prior experience (or crystalline intelligence) may play a very important role in helping the workers navigate the change. For those occupations, middle-aged or older workers may see a relative increase in employment following adoption. Because of the occupation-specific age bias in adaptability, the effects of robot adoption on the age profile can vary substantially with occupation.

To formalize this idea, denote by $o(j)$ the occupation that performs new task $j \in (1, 1+\delta]$. For each occupation o and age group a, we can define the new-task adaptability measure (ν_o^a/μ_o^a) with $\nu_o^a \equiv \int_1^{1+\delta} \mathbb{1}(a(j) = a, o(j) = o)\, \mathrm{d}j$. Denote by $\ell_{i,o}^a$ firm i's employment in a and o prior to robot adoption and by $\Delta\ell_{i,o}^a$ the employment change following robot adoption. The following proposition is analytically a simple extension of Proposition 4.

Proposition 5. *Let $\theta_o^a = \theta_o$. If $\frac{\nu_o^a}{\mu_o^a} > \frac{\nu_o^{a'}}{\mu_o^{a'}}$, then $\frac{\Delta\ell_{i,o}^a}{\ell_{i,o}^a} > \frac{\Delta\ell_{i,o}^{a'}}{\ell_{i,o}^{a'}}$.*

Since within each occupation, there is little variation in replaceability across age groups, the reinstatement channel remains the primary channel through which robot adoption impacts the within-occupation age profile. The proposition states that the relative employment effects by age group closely follow the (relative) adaptability measure defined above. For many occupations, older workers are disadvantaged under robot adoption because they have a general disadvantage in adaptability and their human capital is more likely to be rendered obsolete. However, as argued above, in some occupations, older workers might defy this overall trend because of the nature of their jobs. The discussion suggests the last implication of our model.

Implication 6. *The effect of robot adoption on the employment of different age groups varies with occupation. For occupations in which prior experience plays an important role, the employment of middle-aged or old workers is more likely to increase.*

3 Data & Empirical Approach

3.1 Data

Our sample is constructed by combining four plant- and worker-level data sets. The plant-level robot data are from the IAB Establishment Panel, an annual survey of nearly 16,000 plants sampled from the population of German plants employing workers subject to social security contributions. The IAB Establishment Panel is a high-quality, long-standing panel that is nationally representative as a whole but also at the sector level, for firm-size classes, and across German federal states.[15] In the 2019 wave, we included a dedicated section on

[15] For further information on the IAB Establishment Panel, see Bechmann et al. (2019).

robot use. Our definition of robots follows the ISO definition: *A robot is any automated machine with multiple axes or directions of movement, programmed to perform specific tasks (partially) without human intervention.* The robot question has been intensively pre-tested and carefully designed to ensure that respondents know the difference between robots and other automation techniques such as traditional CNC machines. The survey questions of interest are (1) whether a plant used robots between 2014 and 2018 (extensive margin) and, if so, (2) how large the robot stock was in each year from 2014 to 2018 (intensive margin).[16] The latter enables us to distinguish between incumbent robot users, i.e., plants already using robots in 2014, and new robot adopters, i.e., plants that newly adopted this technology after 2014. It additionally allows us to observe the exact year of adoption, which is not possible in the micro-level studies of Koch et al. (2021) and Acemoglu et al. (2022).

The design of the robot question helps us identify robot adopters up to five years in the past, and in principle, the panel structure of our data allows us to also analyse pre-adoption time periods for those plants. However, although being a high-quality survey with very high response rates (80% response rate for plants that responded in the previous year), panel attrition substantially reduces the number of panel cases when going back in time for several years. Fortunately, we are able to link our survey plants via unique plant identifiers with administrative data from the IAB Establishment History Panel (BHP), which aggregates social security notifications to the plant level. We are thus able to observe plants for very long time spans without loss of observations[17]

Our main dependent variables from the BHP are total employment and the number of workers in certain occupational and age groups. When forming occupational groups, we follow the Blossfeld categorization provided by the IAB. This widely used occupational categorization is based on Blossfeld (1987) and classifies occupations into a total of 12 groups on the basis of the level of task requirements for the job held. We analyse the following six occupational categories more thoroughly: workers performing simple manual tasks, workers performing qualified manual tasks, engineers and technicians, managers, and service and administrative workers. The BHP additionally provides age categories, and we define three groups: young (20−35 years); middle-aged (35−54); and older (55−65).[18]

[16] An English translation of all survey questions on robots can be found in the Appendix. For further details on the survey design and quality of the robot data, see Plümpe and Stegmaier (2022), and for descriptive analysis on plant-level robot use and adoption in Germany using this data set, see Deng et al. (2021).

[17] For information on the BHP data, see Ganzer et al. (2021). Note that we use the full population instead of the 50% sample as explained in Ganzer et al. (2021).

[18] The results are very similar when we include workers younger than 20.

Last, we are also interested in answering whether robots complement or substitute specific age groups *within* our occupational groups. The BHP plant-level data do not offer interactions between age and occupation, and we therefore resort to worker-level data from the IAB Employment History (BeH) that we link with the BHP via unique plant identifiers.[19] For all plants surveyed in the 2019 IAB Establishment Panel wave that answered the extensive margin question on robot use, we merge worker-level information from the BeH for the years from 2012 to 2019. We only retain worker spells that cover June 30 to match the plant-level BHP data, which also report for June 30. Employees are grouped by age with identical cut-offs as described above. To create the Blossfeld occupational categories, we use a crosswalk between the latest classification of occupations (KldB2010) to that on which the original Blossfeld categorization is based (KldB1992). Combining our six occupation groups and our three age groups, we arrive at 18 occupation-age categories and finally compute the plant-level employment for each category.

Our time dimension will be the time relative to the adoption event taking place in t_0. We split the treatment group into four groups mirroring the four possible years of robot adoption (2015−2018). The control group consists of plants that had no robots in 2014 and did not subsequently install robots. We split the control group randomly into four equally sized groups and assign each of these groups to one of the treatment groups. The relative time for the control group is defined to be the same as that of the treatment group to which the control group is randomly assigned. We follow each plant from three years before adoption to the latest post-adoption year observed. In this way, we can observe pre-adoption trends and post-adoption outcomes. We only consider plants observed in all years from $t_0 - 3$ to $t_0 + 1$. Overall we have linked data on 116 robot-adopting manufacturing plants: 24 plants adopted robots in 2015, 27 plants did so in 2016, 21 plants did so in 2017, and 44 plants did so in 2018.

Table 1 presents basic summary statistics measured in the base year. In line with prior research, we confirm that robot adopters are initially larger and employed a higher fraction of simple manual occupations, i.e. occupations having the highest potential to be replaced by robots. We additionally show that the initial age structure of adopters closely resembles that of non-users. Interestingly, the higher incidence of simple manual occupations in adopting

[19] The BeH contains all employment spells of workers subject to social security contributions. It is the main data source behind the publicly available SIAB data described in Frodermann et al. (2021).

plants holds within all age groups.[20] Overall, initial differences between the two groups of plants are more related to occupations than to age.

Our fourth data set is the German qualification and career survey (QAC), which is a large worker survey conducted every six or seven years by the Federal Institute for Vocational Education and Training (BIBB) in cooperation with the Federal Institute for Occupational Safety and Health (BAuA).[21] The data contain very detailed information on tasks performed, worker occupation, age, and sector alongside standard worker demographics.

3.2 Empirical Approach

There is a recent econometric literature challenging commonly applied extensions of the standard two-period difference-in-differences (DiD) model to settings where, as in our study, units are treated at different points in time. In particular, Goodman-Bacon (2021) splits the commonly applied extended DiD model of the form $Y_{it} = \alpha + T_t + \beta^{DiD} D_{it} + \epsilon$ into the various standard two-period DiD comparisons of which the extended model implicitly is composed. He notes that comparisons where previously treated units serve as controls for subsequently treated units can yield misleading DiD coefficients.[22] To avoid any such misleading comparisons, we analyse the consequences of robot adoption within a parsimonious event-study design that accounts for the staggered implementation of robots. As explained in Section 3.1, we essentially divide our sample into four standard DiD models (i.e., one for each of the four robot adoption years), where we randomly assign to each treatment cohort a control group of firms never adopting robots. The final regression recombines those four DiD models within a standard event-study framework in relative time. Restructuring the data in *relative time to the event* ensures that we make only meaningful treatment-control comparisons.

The estimation equation

$$Y_{it} = \alpha_i + \sum_{k=-2}^{1} \beta_k \, T_t^k + \sum_{k=-2}^{1} \gamma_k \; Robot_i \, T_t^k + \epsilon_{it}, \tag{1}$$

relates plant i's outcome variable of interest Y_{it} in relative time t to the event of robot adoption. As described above, the outcome variables are total employment and the number of employees in certain occupational categories, age categories, and interactions of occupation and age. To

[20]For further summary statistics by occupation and age, see Table A1 in the Appendix.
[21]See Rohrbach-Schmidt and Hall (2013) for a description of the data.
[22]Callaway and Sant'Anna (2021) make a closely related point and extend it to an event-study setting with leads and lags.

directly analyse worker flows, we additionally analyse the number of hires and separations of all employees and within occupational and age categories. We control for an individual fixed effect α_i for each plant i. T_t^k is a relative time dummy that equals one if $t = k$. The coefficient vector β_k measures the development of Y_{it} over relative time in the control group. $Robot_i$ is the time-invariant treatment group dummy for robot adopters, and we interact it with relative time T_t^k. The coefficient of the interaction effect, γ_k, is our main coefficient of interest. It measures the development of Y_{it} in the treatment group relative to the control group. We will use γ_k to discuss the effects of robot adoption and potential pre-trends in our dependent variables. Finally, ϵ_{it} is an idiosyncratic error term. Recall that we exclude plants that already used robots in the initial year 2014 because they do not have a robot adoption decision to make.

Although our event-study setting accounts for time-invariant differences between adopters and non-adopters and allows us to assess pre-trends, it cannot dispel all endogeneity concerns. For instance, a positive product demand shock may induce firms to adopt robots and hire workers. We therefore view our results on total employment as potentially upward biased. Nevertheless, our result on worker churning will make clear that a simple demand story is not explaining the data either. More important, our paper is primarily about workforce *composition* and not about total employment. We would like to understand which types of workers are hired or displaced when robots are introduced. Even if robot adoption may be partly triggered by a demand shock, we argue that we can still learn important lessons about substitutability and complementarity from observing which types of workers come and go following robot adoption.

To reduce the influence of potential outliers and normalize estimated effects to a common metric, researchers commonly apply a logarithmic transformation of the dependent variable. However, our data contain zero-valued dependent variables, and taking logs would lead to a loss of observations. Therefore, we use an inverse hyperbolic sine (IHS) transformation.[23] Coefficients can be interpreted similarly to those from standard log-linear models. We will present robustness checks using alternative outlier-robust transformations. In particular, we will use percentile ranks and the standard logarithmic transformation.

[23] The IHS of a variable z is simply given by $\ln(z + \sqrt{z^2 + 1})$. See Burbidge et al. (1988) or MacKinnon and Magee (1990).

4 Results

4.1 Tasks, Occupations, and Age

We start by showing the routine task content of work by occupation and age in the German manufacturing sector. We classify worker tasks into manual routine tasks and non-routine tasks following the framework outlined in Autor et al. (2003) and Spitz-Oener (2006). Essentially, we assign tasks from the QAC data to these categories and compute within the manufacturing sector a worker-level task index that also accounts for the frequency with which workers perform the respective task. For each worker, we weight each task with the frequency of task performance (often = 1, sometimes = 0.5, rarely/never = 0) and then calculate the share of manual routine tasks (manufacturing and producing goods; monitoring and control of machines; transporting and storing) out of all tasks performed. We aggregate the routine task content i) per occupation, ii) per age group, and iii) at occupation$\times$worker age cells. These categories mimic the categories we use in the event-study regressions.

Table 2 reports the routine task content by occupation and age for the manufacturing sector. A first important result is that occupations differ markedly in their routine task content. Simple manual occupations show the highest routine task content. These are occupations that in most cases do not require formal vocational training. At the other end of the spectrum, we find high-skill occupations including managers and technicians/engineers. This supports the key assumption in our theoretical framework that the task content of jobs (replaceability) varies by occupation. We thus expect the displacement effect of robots to vary substantially by occupation and to be lowest for managers and technicians/engineers. We also present results for service and administrative occupations. These are back-office occupations, for instance, accountants or security officers, and we would not expect to see any direct displacement effect coming from robots. This implies that the routine task content of those occupations should not predict employment outcomes. However, if the productivity effect is strong enough, we expect a slight increase in employment for those occupations.

A striking new result is that the routine task content of work does not have an age bias. Overall, but also within each of the occupation groups, the routine task content does not vary with age. Additionally, Table 2 confirms that workers of different ages do not sort systematically into occupations with different routine task content. Based on these empirical facts, task-based models (including our own) predict that the displacement effect of robots is age-neutral. Taken together, the key result of our descriptive analysis of the task content of occupations and age groups is that the displacement effect of robots will vary along the occupational dimension of work but not along the age dimension.

4.2 Employment and Worker Turnover

The first implications of the model outlined in Section 2 are i) that the employment effect is ambiguous and ii) that, if it is positive, it is accompanied by increased worker reallocation. In our empirical test, we will directly examine these margins by analysing total employment, total hires, and total separations.

Our event study results are presented in Table 3. As discussed in the previous section, we use the IHS transformation yielding approximately a coefficient interpretation as in a log-linear model.[24]. Column 1 shows that total employment increases in the robot adoption year by approximately 5 per cent compared to the control group. This effect remains stable in the year after adoption. We do not see a statistically significant pre-trend.

Hiring, as reported in column 2, shows a pronounced spike in the robot adoption year: we observe an increase of 24 per cent compared to the base year, and this effect is highly statistically significant. We find some weak evidence that hiring increased already before robot adoption and strong evidence that excess hiring persists in the post-adoption period. We conclude that robot adoption triggers excess hiring and that excess hiring happens mostly in a time span from one year before to one year after adoption. Distributing hiring over time is rational when firms face convex hiring costs.[25]

Column 3 shows our results for separations. We find an increase in separations in the post-adoption period. Separation rates are also somewhat higher before and upon adoption, but the effect is relatively small and not statistically significant. Hence, overall, we find evidence for excess separations being smaller in magnitude than excess hiring, which leads to an overall increase in employment. In light of the model, we conclude that the degree of complementary between labor and robots is high enough to sustain positive employment effects. As predicted by the model, worker reallocation increases when robots are introduced and the productivity effect is strong.

Table A4 shows that these results are robust to modifications in the sample and the

[24] This approximation can be inaccurate for values smaller than 10 (Bellemare and Wichman 2020). For such cases, we use the exact transformation before interpreting estimation coefficients.

[25] We arrive at qualitatively similar results when we do not use the IHS transformation and compute semi-elasticities at the sample means of the dependent variable.

transformation of the dependent variable. Panel A in Table A4 shows that excluding plants with fewer than 20 employees does not change any of the results despite reducing the number of observations by approximately one-third. Panel B shows results from a percentile regression where we use the percentile rank of the dependent variable by relative time instead of IHS.[26] We again find that the employment percentile rank rises at robot adoption as do hirings. We also confirm that hiring and separations remain high in the year after robot adoption. Panel C in Table A4 uses the standard logarithmic transformation of the dependent variable instead of IHS and shows very similar results.

4.3 Occupational Groups

Column 1 of Table 4 shows zero employment effects for simple manual workers. The effect for qualified manual workers (Column 2) is noisily estimated but implies an employment increase of approximately 6 per cent. Importantly, Columns 3 and 4 show strong positive employment effects for technicians/engineers and managers. Hence, our results confirm the predictions of our task-based model, and we conclude that the displacement effect is indeed occupation specific. Appendix Table A2 shows how hiring and separation shape the evolution of employment in the occupational groups. We find increased hiring across *all* occupational categories and excess separations taking place more prominently among simple manual occupations, which again highlights the importance of the displacement effect for them.[27]

In summary, the occupational breakdown confirms the model predictions by showing that occupations performing the least (most) automatable tasks experience the strongest (weakest) gains in employment. We additionally confirm increased churning. Another interesting finding is that worker flows associated with robot introduction mostly happen in the exact year of robot adoption with no evidence of anticipation effects.

4.4 Worker Age

Our model implies that the impact of robot adoption on employment is more positive for younger workers because they should be able to make better use of the new tasks generated by robot adoption. This is because they find it easier or more profitable to adapt to new

[26]See Autor et al. (2022) for a similar approach to scrutinize the robustness of IHS results.

[27]Table A5 presents robustness checks along the same lines as those presented in the previous subsection. Excluding small firms yields quantitatively very similar results. The qualitative patters are preserved in the percentile regressions. The log transformation of the dependent variable also confirms the main results, but a high number of zero-valued observations for some occupations leads to severe reductions in sample size.

situations (see the discussion on age-specific adaptability in Section 1) or because of their more recent occupational training (newer vintage of human capital). Before delving into the occupation-age nexus, we present the overall impact on the workforce age profile.

Column 7 of Table 4 shows that the partial effect of robot adoption on young workers' employment is 11 per cent around adoption and further increases to 13 per cent one year after adoption. The employment of young workers was already increasing before robot adoption, which is however partly driven by a decline in the control group. We find small and marginally significant increases in employment for middle-aged and no effect for older workers.[28] Appendix Table A3 shows a spike in hires of young workers exactly around robot adoption, thereby confirming that the increase in young workers is (at least partly) triggered by robot adoption. The increase in young worker hires confirms results in Aubert et al. (2006), who analyse technology adoption at the firm level. Appendix Table A3 additionally shows an increased separation rate for older workers, which is in line with the results in Bartel and Sicherman (1993).

We argued above that negative effects on young workers' employment at the aggregate level as reported in Acemoglu and Restrepo (2022) and Dauth et al. (2021) are not necessarily a sign of young workers being substitutes for robots because the employment decline might be driven by non-adopters. Column 7 of Table 4 directly supports this notion by showing that the employment of young workers decreases in the control group. This is in line with the notion that both types of firms compete for young workers.

Acemoglu and Restrepo (2022) argue that younger workers are more likely to be displaced by robots. Our results in Table 2, however, imply that the displacement effect has no age bias. From this evidence and our theoretical discussion, we conclude that the age effect will have more to do with the reinstatement effect of robots. An interesting question is whether, in contrast to Germany, the routine task intensity does have an age bias in the US. While we cannot test this on our own, we believe that there are good reasons to believe that Germany and the US differ in that respect because of the marked differences in the vocational education training (VET) system. Young production workers in Germany usually undergo formal and sophisticated three-year VET (Acemoglu and Pischke 1998), which arguably enables them to take over quite complex tasks when they start their professional careers. The US does not have a large-scale similarly sophisticated VET system, implying learning by doing on the job.

[28] These results are confirmed by robustness checks in Appendix Table A5.

Hence, it is plausible that young production workers in the US will perform rather simple routine tasks when starting their careers and will take over more complex tasks as soon as they have gathered the required knowledge and experience.

4.5 Occupation by Worker Age

According to our model, the effect of robots on the employment age profile hinges on the two margins of adjustment in task requirement: initial task specialization and new task adaptation. As we showed that initial task specialization is age-neutral even within occupations, new task adaption will be key. Table 5 shows our event study results for young workers. Among young workers, all occupations except managers *benefit* from robot adoption. The most significant benefits seem to fall on simple manual tasks (+13 per cent), but this group also shows a strong pre-trend.[29] Analogously, Table 6 reports the results for middle-aged workers. In this age group, technicians and engineers stand out as the group that benefits the most. Among older workers (Table 7), the number of managers rises the most. Here, we again find a strong pre-trend suggesting that the stock of senior managers has been accumulated over a longer time span. Age effects seem to be more important among relatively less qualified workers[30] and partially for middle-aged technicians/engineers. Organizing the change in production towards robotics seems to require experienced managers.

5 Conclusion

We analyse novel and rich plant-level data on robot adoption to understand the employment impact of robotization. Our analysis allows us to directly observe the technological relationships between robots and various types of human labor in the production units. The degrees of substitution and complementarity between robots and heterogeneous labor measured with aggregate data (e.g., using industry variation in robot exposure at the LLM level) will include competitive reactions of employers not using robots and, thus, do not necessarily reflect the true micro-level mechanisms.

We combine plant-level data on robot use with administrative data on workers employed in those plants and data on the task content of jobs. This allows us to scrutinize at a very granular level which occupational groups, which age groups, and which age groups within

[29]Employment gains among young blue-collar workers are also found in Aubert et al. (2006).

[30]Young workers in service occupations additionally gain from performing less routine tasks than their older counterparts (see Table 2).

occupational groups are complements or substitutes to robot adoption and how this relates to the task content of jobs. We structure the analysis by setting up a partial equilibrium model of robot adoption with heterogeneous labor. The task-based model predicts that non-routine task-intensive occupations and workers who can better adapt to new tasks are more likely to gain from plant-level robotization. Our study is among the first production-unit studies on robots testing the main predictions of task-based models, i.e., more positive employment effects for occupations performing less routine manual tasks. We are first to analyse the age effects of robots using micro data.

We show descriptively that task replaceability varies primarily with occupation but barely with age, implying that the displacement effect of robots should be occupation-biased but age neutral. In line with the predictions of our model, robot adoption is accompanied by rising employment (+5 per cent) coupled with strongly increased hiring and modestly increased separations, particularly for the most routine task-intensive occupations. We do not find negative employment effects for any of the subgroups analysed. Employment gains are concentrated among younger workers and the least routine-intensive occupations, i.e., technicians/engineers and managers. The occupation-specific results thus directly confirm the predictions of the widely used task-based framework. The more positive effects for younger workers mainly reflect their greater adaptability to new tasks as predicted by the cognitive science literature and human capital theory and demonstrated in earlier empirical papers on technology adoption (e.g., Aubert et al. 2006). As we find that routine task intensity varies with occupation but not with age, the displacement effect will have no age bias but will be occupation-dependent. Through the lens of our model and the concepts of displacement and reinstatement effects theorized by Acemoglu and Restrepo (2018), our results thus imply that the displacement effect of robots is primarily occupation-dependent (i.e. task-dependent) and age-neutral, whereas the reinstatement effect (or 'new task channel') mostly depends on workers' age.

We conclude that micro-level evidence is important to understand which groups of workers are complements or substitutes for robots in production. The emerging picture is nuanced: we verify that routine-task-performing occupations are indeed relative substitutes for robots at the production-unit level and that young workers have an advantage in exploiting the opportunities of new technology. Our results imply that a shortage of young workers in low- and middle-skilled occupations will hinder the large-scale adoption of robot technology. They also imply that older workers in those occupations will see their relative demand decline. Accelerated adoption of robot technology may therefore not only increase the demand for robot-complementary occupations but also contribute to a divide between young and old production workers, where the former may see a rather bright future in growing high-tech plants with the latter being trapped in small low-tech companies.

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6 Tables

Table 1: Summary Statistics

	Robot Adopter (N=116)	Non-User (N=1962)
Employment	222.80	85.77
Hires	24.22	11.13
Separations	21.01	9.03
Occupation Structure (%)		
Simple manual	34	25
Qualified manual	29	30
Technician/engineer	12	13
Manager	3	3
Service	9	10
Admin	13	19
Age Profile (%)		
Young (20–34)	26	25
Mid-age (35–54)	50	50
Old (55–65)	20	20

Notes: (i) Based on BHP data, we report the plant-level averages for the manufacturing sample in the base year $t_0 - 3$. (ii) The numbers of employees, hires, and separations are in absolute terms, whereas all other variables are measured as percentage shares of *total* employment. (iii) Age shares do not sum to 100% because we exclude workers younger than 20 years old.

Table 2: Replaceability of Tasks by Occupation and Age (%)

Age	Occupation: simple manual	qualified manual	techn. engin.	manager	service	admin	overall
PANEL A: Share of Replaceable Tasks by Occupation and Age (%)							
Young (20−34)	28.82	22.19	10.67	9.80	20.80	9.19	19.11
Mid-age (35−54)	27.54	21.98	11.84	10.22	25.27	9.21	19.05
Old (55−65)	28.85	22.05	10.66	12.81	25.44	8.77	18.72
Overall	27.99	22.04	11.40	10.49	24.47	9.11	19.01
PANEL B: Age Distribution by Occupation (%)							
Young (20−34)	20.25	25.72	21.85	20.79	16.90	19.91	21.82
Mid-age (35−54)	64.17	55.44	62.57	65.39	59.07	57.43	60.23
Old (55−65)	15.58	18.83	15.58	13.82	24.03	22.66	17.95
Overall	100	100	100	100	100	100	100

Notes: (i) The calculations are based on the manufacturing sample of the BIBB/BAuA data (2012). (ii) In Panel A, we report the average ratio (%) of the three tasks that are potentially replaceable by robots (manufacturing and producing goods; transporting and storing; monitoring, control of technical processes) to the total number of tasks performed. (iii) The counting of tasks is adjusted to the frequency of task performance (often = 1, sometimes = 0.5, rarely/never = 0). (iv) Panel B displays the age profile of employees across occupations. (v) The last row reports the number of observations per column. (vi) N=2,921, and sampling weights are applied.

Table 3: Employment and Worker Flows

	(1) Employment	(2) Hires	(3) Separations
t−2	0.0009	-0.0636***	0.0539***
	(0.0040)	(0.0184)	(0.0193)
t−1	0.0091*	-0.0418**	0.0425**
	(0.0052)	(0.0192)	(0.0202)
t	0.0152**	0.0126	0.0938***
	(0.0068)	(0.0205)	(0.0199)
t+1	0.0141*	0.0029	0.1211***
	(0.0085)	(0.0214)	(0.0208)
t−2 × Robot	0.0141	0.0430	-0.0214
	(0.0103)	(0.0715)	(0.0623)
t−1 × Robot	0.0204	0.0918	0.0708
	(0.0153)	(0.0762)	(0.0614)
t × Robot	0.0477**	0.2442***	0.0503
	(0.0233)	(0.0757)	(0.0673)
t+1 × Robot	0.0511*	0.1705**	0.1168*
	(0.0281)	(0.0797)	(0.0705)

Notes: (i) This table reports the event-study results based on the estimation equation (1). The number of observations is 10,390 across all columns. (ii) The dependent variables are based on BHP data and rescaled by the inverse hyperbolic sine transformation. (iii) The plant fixed effect is included. (vi) Standard errors in parentheses are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 4: Employment by Occupation and Age

	Occupation						Age		
	(1) simple manual	(2) qualified manual	(3) technician engineer	(4) manager	(5) service	(6) admin	(7) young (20−34)	(8) mid-age (35-54)	(9) old (55−65)
t−2	0.0001	0.0031	0.0102*	0.0163***	0.0048	0.0101	-0.0074	-0.0084	0.0528***
	(0.0077)	(0.0068)	(0.0059)	(0.0055)	(0.0072)	(0.0064)	(0.0083)	(0.0054)	(0.0081)
t−1	0.0188*	0.0001	0.0344***	0.0219***	0.0174*	0.0249***	-0.0241**	-0.0173**	0.1146***
	(0.0101)	(0.0083)	(0.0079)	(0.0074)	(0.0095)	(0.0078)	(0.0107)	(0.0071)	(0.0100)
t	0.0414***	0.0072	0.0451***	0.0320***	0.0227**	0.0341***	-0.0261**	-0.0287***	0.1706***
	(0.0120)	(0.0099)	(0.0096)	(0.0087)	(0.0114)	(0.0092)	(0.0130)	(0.0087)	(0.0118)
t+1	0.0480***	0.0100	0.0509***	0.0395***	0.0234*	0.0420***	-0.0390***	-0.0538***	0.2188***
	(0.0139)	(0.0116)	(0.0113)	(0.0102)	(0.0132)	(0.0104)	(0.0149)	(0.0108)	(0.0140)
t−2 × Robot	0.0219	0.0005	0.0270	0.0243	0.0141	0.0218	0.0244	-0.0009	0.0435*
	(0.0217)	(0.0186)	(0.0197)	(0.0303)	(0.0205)	(0.0221)	(0.0191)	(0.0132)	(0.0249)
t−1 × Robot	0.0163	0.0509*	0.0012	0.0216	0.0164	-0.0139	0.0762***	0.0134	0.0206
	(0.0293)	(0.0280)	(0.0299)	(0.0360)	(0.0314)	(0.0271)	(0.0277)	(0.0210)	(0.0260)
t × Robot	-0.0001	0.0640	0.0657*	0.0793*	0.0735	0.0275	0.1161***	0.0453	0.0106
	(0.0491)	(0.0446)	(0.0358)	(0.0412)	(0.0491)	(0.0307)	(0.0355)	(0.0284)	(0.0370)
t+1 × Robot	0.0155	0.0611	0.0789**	0.1021**	0.0873	0.0301	0.1396***	0.0591*	0.0109
	(0.0577)	(0.0559)	(0.0390)	(0.0482)	(0.0545)	(0.0330)	(0.0408)	(0.0334)	(0.0411)

Notes: (i) This table reports the event-study results based on the estimation equation (1). The number of observations is 10,390 across all columns. (ii) The dependent variables are based on BHP data and rescaled by the inverse hyperbolic sine transformation. (iii) The plant fixed effect is included. (vi) Standard errors in parentheses are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 5: Young Employees (20−34 years old) by Occupation

	(1) simple manual	(2) qualified manual	(3) technician engineer	(4) manager	(5) service	(6) admin
t−2	-0.0050	-0.0013	0.0003	0.0017	-0.0033	0.0022
	(0.0092)	(0.0086)	(0.0075)	(0.0055)	(0.0077)	(0.0089)
t−1	0.0059	-0.0236**	0.0231**	-0.0008	0.0013	-0.0064
	(0.0114)	(0.0108)	(0.0098)	(0.0070)	(0.0103)	(0.0113)
t	0.0163	-0.0267**	0.0355***	0.0046	0.0007	-0.0100
	(0.0137)	(0.0131)	(0.0114)	(0.0081)	(0.0115)	(0.0126)
t+1	0.0146	-0.0246*	0.0346***	0.0006	0.0089	-0.0224
	(0.0153)	(0.0145)	(0.0133)	(0.0092)	(0.0127)	(0.0141)
t−2 × Robot	0.0646*	-0.0219	0.0547	-0.0248	0.0370	0.0269
	(0.0382)	(0.0286)	(0.0339)	(0.0393)	(0.0395)	(0.0427)
t−1 × Robot	0.0885*	0.0359	0.0166	-0.0769*	0.0979*	0.0401
	(0.0504)	(0.0416)	(0.0434)	(0.0459)	(0.0501)	(0.0484)
t × Robot	0.1281**	0.0790	0.0995*	-0.0914*	0.0973	0.1314**
	(0.0619)	(0.0558)	(0.0541)	(0.0539)	(0.0608)	(0.0524)
t+1 × Robot	0.1377*	0.1030	0.0761	-0.0355	0.1134	0.0737
	(0.0724)	(0.0703)	(0.0657)	(0.0568)	(0.0691)	(0.0550)

Notes: (i) This table reports the event-study results based on the estimation equation (1). The number of observations is 10,390 across all columns. (ii) The dependent variables are based on BeH data and rescaled by the inverse hyperbolic sine transformation. (iii) The plant fixed effect is included. (vi) Standard errors in parentheses are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 6: Middle-aged Employees (35−54 years old) by Occupation

	(1) simple manual	(2) qualified manual	(3) technician engineer	(4) manager	(5) service	(6) admin
t−2	-0.0188**	-0.0100	0.0051	0.0130**	-0.0030	-0.0008
	(0.0074)	(0.0075)	(0.0065)	(0.0056)	(0.0075)	(0.0074)
t−1	-0.0238**	-0.0111	0.0016	0.0093	-0.0080	0.0079
	(0.0102)	(0.0096)	(0.0086)	(0.0079)	(0.0099)	(0.0095)
t	-0.0084	-0.0293***	-0.0065	0.0136	-0.0140	0.0026
	(0.0120)	(0.0111)	(0.0104)	(0.0096)	(0.0117)	(0.0114)
t+1	-0.0128	-0.0409***	-0.0207*	0.0126	-0.0302**	-0.0159
	(0.0141)	(0.0128)	(0.0118)	(0.0113)	(0.0131)	(0.0130)
t−2 × Robot	0.0118	0.0192	0.0041	-0.0370	-0.0328*	0.0090
	(0.0227)	(0.0250)	(0.0256)	(0.0288)	(0.0194)	(0.0296)
t−1 × Robot	0.0118	0.0372	0.0393	-0.0120	-0.0511	-0.0125
	(0.0354)	(0.0383)	(0.0316)	(0.0391)	(0.0366)	(0.0398)
t × Robot	-0.0033	0.0866	0.1154***	0.0284	0.0265	0.0072
	(0.0528)	(0.0561)	(0.0387)	(0.0455)	(0.0500)	(0.0466)
t+1 × Robot	0.0121	0.0472	0.1078**	0.0193	-0.0024	0.0773
	(0.0579)	(0.0627)	(0.0478)	(0.0505)	(0.0585)	(0.0534)

Notes: (i) This table reports the event-study results based on the estimation equation (1). The number of observations is 10,390 across all columns. (ii) The dependent variables are based on BeH data and rescaled by the inverse hyperbolic sine transformation. (iii) The plant fixed effect is included. (vi) Standard errors in parentheses are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 7: Old Employees (55−65 years old) by Occupation

	(1) simple manual	(2) qualified manual	(3) technician engineer	(4) manager	(5) service	(6) admin
t−2	0.0415***	0.0417***	0.0266***	0.0097*	0.0183**	0.0314***
	(0.0079)	(0.0078)	(0.0064)	(0.0053)	(0.0078)	(0.0077)
t−1	0.0770***	0.0701***	0.0627***	0.0266***	0.0360***	0.0646***
	(0.0101)	(0.0100)	(0.0085)	(0.0072)	(0.0104)	(0.0100)
t	0.1081***	0.1076***	0.0910***	0.0335***	0.0570***	0.1120***
	(0.0118)	(0.0118)	(0.0104)	(0.0085)	(0.0120)	(0.0121)
t+1	0.1509***	0.1297***	0.1248***	0.0444***	0.0753***	0.1544***
	(0.0135)	(0.0138)	(0.0125)	(0.0102)	(0.0136)	(0.0137)
t−2 × Robot	0.0252	0.0310	0.0042	0.0772**	0.0026	0.0200
	(0.0257)	(0.0309)	(0.0297)	(0.0314)	(0.0329)	(0.0298)
t−1 × Robot	0.0729**	0.0640	-0.0331	0.0760*	-0.0002	0.0426
	(0.0358)	(0.0398)	(0.0366)	(0.0455)	(0.0470)	(0.0360)
t × Robot	0.0568	0.0865	0.0157	0.1212**	0.0527	0.0424
	(0.0477)	(0.0598)	(0.0435)	(0.0497)	(0.0609)	(0.0436)
t+1 × Robot	0.0584	0.0981	0.0164	0.1449***	0.0358	-0.0118
	(0.0516)	(0.0681)	(0.0520)	(0.0548)	(0.0669)	(0.0577)

Notes: (i) This table reports the event-study results based on the estimation equation (1). The number of observations is 10,390 across all columns. (ii) The dependent variables are based on BeH data and rescaled by the inverse hyperbolic sine transformation. (iii) The plant fixed effect is included. (vi) Standard errors in parentheses are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Appendix

A Proofs

Proof of Proposition 1: If firm i does not adopt robots, by symmetry across different tasks, its production function is simply given by $y_i = \phi_i \ell_i$, where ℓ_i is firm i's employment of human labor. Standard derivation based on the production function and the iso-elastic demand yields

$$\pi_i = \zeta \frac{(\eta-1)^{\eta-1}}{\eta^\eta} \left(\frac{\phi_i}{w}\right)^{\eta-1},$$

where π_i is firm i's profit. If firm i adopts robots, its production function is given by

$$y_i = \phi_i \left(\theta^{\frac{1}{\sigma}} (\lambda k_i)^{\frac{\sigma-1}{\sigma}} + (1-\theta)^{\frac{1}{\sigma}} \ell_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

where k_i firm i's robot input. Standard derivation yields

$$\pi_{k,i} = \zeta \frac{(\eta-1)^{\eta-1}}{\eta^\eta} \left(\frac{\phi_i}{P_k}\right)^{\eta-1},$$

where $\pi_{k,i}$ is firm i's operating profit (excluding the fixed cost) after robot adoption and P_k is the price index given by

$$P_k \equiv \left(\theta (r/\lambda)^{1-\sigma} + (1-\theta) w^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \tag{2}$$

Since $r < \lambda w$, $P_k < w$. Firm i chooses to adopt robots if and only if $\pi_{k,i} - F > \pi_i$, or equivalently,

$$\zeta \frac{(\eta-1)^{\eta-1}}{\eta^\eta} \left[\left(\frac{\phi_i}{P_k}\right)^{\eta-1} - \left(\frac{\phi_i}{w}\right)^{\eta-1}\right] > F,$$

which can be further simplified as

$$\phi_i > \left(\frac{F}{\zeta} \frac{\eta^\eta}{(\eta-1)^{\eta-1}}\right)^{\frac{1}{\eta-1}} \left(P_k^{1-\eta} - w^{1-\eta}\right)^{\frac{1}{1-\eta}} \equiv \bar{\phi}.$$

Since $w > P_k$ and $\eta > 1$, we have $\bar{\phi} > 0$. Thus, we have obtained the desired conclusion. $\square$

Proof of Proposition 2: If firm i does not adopt robots, its labor demand is given by

$$\ell_i = \zeta \left(1 - \frac{1}{\eta}\right)^\eta \phi_i^{\eta-1} w^{-\eta}.$$

If firm i adopts robots, its labor demand is given by

$$\ell_i' \;=\; \zeta\left(1-\frac{1}{\eta}\right)^{\eta}(1-\theta)P_k^{\sigma-\eta}\phi_i^{\eta-1}w^{-\sigma}$$

where P_k is defined in (2). To see how total employment changes, we consider

$$\frac{\ell_i'}{\ell_i}=(1-\theta)\left(\frac{P_k}{w}\right)^{\sigma-\eta}.$$

We know from the proof of Proposition 1 that $P_k < w$. If $\sigma \geq \eta$, then it immediately follows from $P_k < w$ that $\ell_i' \leq (1-\theta)\ell_i < \ell_i$. Thus, if $\sigma \geq \eta$, total employment falls after robot adoption.

However, if $\sigma < \eta$, we have $(P_k/w)^{\sigma-\eta} > 1$, and the overall employment change becomes ambiguous . To see the ambiguity, consider the limiting case of $\sigma \to 0 : \frac{\ell_i'}{\ell_i} \to (1-\theta)\left(\frac{P_k}{w}\right)^{-\eta}$. If $(1-\theta)\left(\frac{P_k}{w}\right)^{-\eta} > 1$, then it is straightforward to show that there exists $\bar{\sigma} \in (0,\eta)$ such that for any $\sigma < \bar{\sigma}$, $\frac{\ell_i'}{\ell_i} > 1$. In words, the employment effect can be positive for a sufficiently small σ. Thus, we have obtained the desired conclusion. □

Proof of Proposition 3: With the occupation dimension being incorporated, if firm i does not adopt robots, its production function is given by

$$y_i = \phi_i\left(\sum_{o\in\mathcal{O}}\mu_o^{\frac{1}{\sigma}}\ell_{i,o}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

and if firm i adopts robots, its production function is given by

$$y_i = \phi_i\left(\theta^{\frac{1}{\sigma}}(\lambda k_i)^{\frac{\sigma-1}{\sigma}} + \sum_{o\in\mathcal{O}}(\mu_o(1-\theta_o))^{\frac{1}{\sigma}}\ell_{i,o}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

where $\theta = \sum_{o\in\mathcal{O}}\mu_o\theta_o$. Following essentially the same argument as the proof of Proposition 2, we can show that the change in the employment of occupation o following robot adoption is given by

$$\frac{\Delta\ell_{i,o}}{\ell_{i,o}} = (1-\theta_o)\left(\frac{P_k}{w}\right)^{\sigma-\eta} - 1.$$

Clearly, the employment change decreases with θ_o. Thus, we have obtained the desired conclusion. □

We make a simplifying assumption in the model that the wage rate is the same across occupations, but note that the proof above can be easily extended to a setting with occupation-specific wage rates. Similarly, the proof in what follows can also be extended to a setting with age-specific wage rates.

Proof of Proposition 4: With the age dimension being incorporated, if firm i does not adopt robots, its production function is given by

$$y_i = \phi_i \left(\sum_{a \in \mathcal{A}} (\mu^a)^{\frac{1}{\sigma}} (\ell_i^a)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

If firm i adopts robots, because of the introduction of new tasks, firm i's production function is given by

$$y_i = \phi_i \left(\theta^{\frac{1}{\sigma}} (\lambda k_i)^{\frac{\sigma-1}{\sigma}} + \sum_{a \in \mathcal{A}} (\mu^a (1-\theta) + \nu^a)^{\frac{1}{\sigma}} (\ell_i^a)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

where we assume based on the empirical evidence that replaceability θ does not vary with age. The price index of the input bundle under robot adoption is now given by

$$P_k' \equiv (\theta (r/\lambda)^{1-\sigma} + (1-\theta+\delta) w^{1-\sigma})^{\frac{1}{1-\sigma}}.$$

Similarly, we can derive the change in the employment of age group a following robot adoption as

$$\frac{\Delta \ell_i^a}{\ell_i^a} = \left(1 - \theta + \frac{\nu^a}{\mu^a}\right) \left(\frac{P_k'}{w}\right)^{\sigma-\eta} - 1,$$

which increases with $\frac{\nu^a}{\mu^a}$. If $\frac{\nu^a}{\mu^a}$ decreases with a, then $\frac{\Delta \ell_i^a}{\ell_i^a}$ must also decrease with a. Thus, we have obtained the desired conclusion. □

B Survey Questions

We provide below a word-to-word English translation of the section on robot use in the 2019 IAB Establishment Survey.

Question 77.

a) Have you used robots over the last 5 years for operational performance or production? [*A robot is any automated machine with multiple axes or directions of movement, programmed to perform specific tasks (partially) without human intervention. This includes industrial robots but also service robots. This excludes machine tools, e.g., CNC-machines.*] Yes/No.

If so:

b) How many robots have you used in total over the last five years? An estimation will suffice. If more robots are used in one robot cell, please count them individually. An estimation will suffice. [Interviewer: If "none" enter "0". Please enter "XXXX" if there is no information available for single years.]

If in 2018 no use of any robot or no information available, go to question 81. If there was use of at least one robot in 2018, go to question 78.

Question 78.

If there was use of at least one robot in 2018: How many of the robots used in 2018 were purchased at a price of less than 50,000 Euros? Please — if possible -– consider only the purchase price, without any further costs for tools or the integration of the robots into your production circle.

Question 79.

How many of the robots used in 2018 are separated from employees during the regular operations with the help of a protection device, e.g., cage, fence, separate room, light barrier or sensor mat?

Question 80.

How many of the robots used in 2018 did you just purchase in 2018?

C Appendix Tables

Table A1: Summary Statistics: Further Details

	Robot Adopter (N=116)	Non-User (N=1962)
Hires by Occupation (%)		
Simple manual	4	4
Qualified manual	4	4
Technician/engineer	1	2
Manager	0	0
Service	1	2
Administrative	2	3
Separations by Occupation (%)		
Simple manual	3	3
Qualified manual	3	4
Technician/engineer	1	2
Manager	0	0
Service	1	1
Administrative	2	3
Hires by Age (%)		
Young (20−34)	6	6
Mid-age (35−54)	5	6
Old (55−65)	1	2
Separations by Age (%)		
Young (20−34)	5	5
Mid-age (35−54)	3	5
Old (55−65)	2	3
Occupation Structure (20−34) (%)		
Simple manual	7	6
Qualified manual	10	9
Technician/engineer	3	3
Manager	0	0
Service	1	2
Administrative	4	4
Occupation Structure (35−54) (%)		
Simple manual	17	13
Qualified manual	13	13
Technician/engineer	6	7
Manager	2	2
Service	5	5
Administrative	7	10
Occupation Structure (55−65) (%)		
Simple manual	9	6
Qualified manual	5	6
Technician/engineer	3	3
Manager	1	1
Service	3	3
Administrative	2	4

Notes: (i) Based on the BHP data we report the plant-level averages for the manufacturing sample as of $t-3$. (ii) All variables are measured as percentage shares of *total* employment. (iii) Occupational shares do not sum to 100% because we focus on the selected Blossfeld categories, excluding very small categories such as (semi-)professions. (iv) Age shares do not sum to 100% because we exclude workers younger than 20 years old.

Table A2: Worker Flows by Occupation

	(1) simple manual	(2) qualified manual	(3) technician engineer	(4) manager	(5) service	(6) admin
			Panel A: Hires by Occupation			
t−2	-0.0584***	-0.0413**	-0.0301**	-0.0118	-0.0147	-0.0147
	(0.0174)	(0.0178)	(0.0152)	(0.0108)	(0.0158)	(0.0168)
t−1	-0.0389**	-0.0483***	-0.0010	-0.0149	-0.0059	0.0085
	(0.0187)	(0.0179)	(0.0160)	(0.0108)	(0.0162)	(0.0169)
t	0.0185	-0.0038	0.0049	-0.0045	0.0136	0.0303*
	(0.0194)	(0.0185)	(0.0162)	(0.0110)	(0.0164)	(0.0174)
t+1	0.0351*	-0.0026	0.0043	-0.0072	0.0350**	0.0209
	(0.0199)	(0.0193)	(0.0161)	(0.0117)	(0.0176)	(0.0174)
t−2 × Robot	0.0096	-0.0311	-0.0208	0.1404**	0.0681	-0.1167
	(0.0880)	(0.0853)	(0.0821)	(0.0658)	(0.0760)	(0.0862)
t−1 × Robot	0.1231	0.0605	-0.0496	0.0964	0.0589	-0.1496*
	(0.0960)	(0.0900)	(0.0781)	(0.0601)	(0.0842)	(0.0816)
t × Robot	0.2151**	0.1529	0.1431*	0.1912***	0.2361***	0.0931
	(0.0937)	(0.1039)	(0.0853)	(0.0673)	(0.0912)	(0.0834)
t+1 × Robot	0.1351	0.0775	-0.0229	0.1252**	0.0726	-0.0485
	(0.1033)	(0.1079)	(0.0933)	(0.0633)	(0.0883)	(0.0872)
			Panel B: Separations by Occupation			
t−2	0.0566***	0.0297*	0.0165	-0.0145	0.0482***	0.0399**
	(0.0175)	(0.0178)	(0.0145)	(0.0106)	(0.0152)	(0.0161)
t−1	0.0250	0.0432**	0.0400***	-0.0014	0.0429***	0.0457***
	(0.0176)	(0.0182)	(0.0155)	(0.0104)	(0.0149)	(0.0165)
t	0.0662***	0.0595***	0.0645***	0.0014	0.0644***	0.0740***
	(0.0182)	(0.0188)	(0.0155)	(0.0108)	(0.0158)	(0.0170)
t+1	0.0985***	0.0678***	0.0786***	0.0149	0.0790***	0.0783***
	(0.0189)	(0.0189)	(0.0159)	(0.0109)	(0.0166)	(0.0174)
t−2 × Robot	-0.0217	-0.0357	0.0092	0.1356**	0.0994	-0.0686
	(0.0930)	(0.0818)	(0.0726)	(0.0569)	(0.0733)	(0.0803)
t−1 × Robot	0.0896	-0.0658	0.0505	0.0711	0.0578	0.0554
	(0.0831)	(0.0755)	(0.0768)	(0.0643)	(0.0780)	(0.0820)
t × Robot	0.1616*	0.0710	-0.0748	0.0306	0.0693	-0.0344
	(0.0945)	(0.0849)	(0.0741)	(0.0607)	(0.0810)	(0.0821)
t+1 × Robot	0.1761*	0.0485	-0.0117	0.1159*	0.1766**	0.0929
	(0.1002)	(0.0854)	(0.0807)	(0.0622)	(0.0852)	(0.0845)

Notes: (i) This table reports the event-study results based on the estimation equation (1). Panel A displays the results for hires by occupation, and Panel B does so for separations by occupation. The number of observations is 10,390 across all columns. (ii) The dependent variables are rescaled by the inverse hyperbolic sine transformation. (iii) The plant fixed effect is included. (vi) Standard errors in parentheses are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A3: Worker Flows by Age

	Hires			Separations		
	(1) young (20−34)	(2) mid-age (35-54)	(3) old (55−65)	(4) young (20−34)	(5) mid-age (35-54)	(6) old (55−65)
t−2	-0.0527***	-0.0507**	-0.0292	0.0090	0.0261	0.0376**
	(0.0190)	(0.0204)	(0.0179)	(0.0182)	(0.0199)	(0.0183)
t−1	-0.0409**	-0.0350*	-0.0176	0.0127	0.0074	0.0515***
	(0.0194)	(0.0207)	(0.0181)	(0.0191)	(0.0204)	(0.0182)
t	0.0161	-0.0060	0.0498***	0.0193	0.0611***	0.0867***
	(0.0200)	(0.0216)	(0.0186)	(0.0196)	(0.0203)	(0.0182)
t+1	-0.0010	0.0088	0.0827***	0.0454**	0.0845***	0.1072***
	(0.0209)	(0.0223)	(0.0187)	(0.0198)	(0.0215)	(0.0193)
t−2 × Robot	0.0425	-0.0447	0.1193	-0.1069	0.0982	0.0915
	(0.0842)	(0.0856)	(0.0944)	(0.0759)	(0.0748)	(0.0786)
t−1 × Robot	0.0683	0.0497	0.0828	-0.1044	0.1608*	0.0690
	(0.0897)	(0.0942)	(0.0997)	(0.0780)	(0.0849)	(0.0815)
t × Robot	0.2408***	0.2788***	0.1366	0.0020	0.1392	0.0883
	(0.0893)	(0.0981)	(0.0965)	(0.0812)	(0.0904)	(0.0837)
t+1 × Robot	0.1486	0.1870*	0.0572	0.0410	0.1969**	0.1551*
	(0.0909)	(0.1019)	(0.0895)	(0.0750)	(0.0842)	(0.0922)

Notes: (i) This table reports the event-study results based on the estimation equation (1). The number of observations is 10,390 across all columns. (ii) The dependent variables are rescaled by the inverse hyperbolic sine transformation. (iii) The plant fixed effect is included. (vi) Standard errors in parentheses are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A4: Robustness Checks for Employment and Worker Flows

	(1) Employment	(2) Hires	(3) Separations
	Panel A: Excluding Plants with <20 Employees		
t−2 × Robot	0.0138	0.0729	-0.0217
	(0.0105)	(0.0712)	(0.0608)
t−1 × Robot	0.0212	0.1106	0.0299
	(0.0157)	(0.0736)	(0.0646)
t × Robot	0.0494**	0.2506***	0.0168
	(0.0241)	(0.0778)	(0.0681)
t+1 × Robot	0.0618**	0.1655**	0.0549
	(0.0275)	(0.0805)	(0.0711)
	Panel B: Percentile Regressions		
t−2 × Robot	0.2822	1.4431	0.6803
	(0.2020)	(1.4548)	(1.4152)
t−1 × Robot	0.3399	2.3144	2.4795*
	(0.3025)	(1.6429)	(1.3790)
t × Robot	0.6178	3.9789***	1.6825
	(0.4078)	(1.4762)	(1.5084)
t+1 × Robot	0.6725	2.9155*	2.9470**
	(0.5188)	(1.7010)	(1.4993)
	Panel C: Log Transformed		
t−2 × Robot	0.0143	0.0066	0.0278
	(0.0103)	(0.0662)	(0.0584)
t−1 × Robot	0.0206	0.0676	0.0745
	(0.0153)	(0.0728)	(0.0588)
t × Robot	0.0480**	0.2035***	0.0855
	(0.0234)	(0.0757)	(0.0644)
t+1 × Robot	0.0512*	0.1170	0.1510**
	(0.0282)	(0.0780)	(0.0660)

Notes: (i) This table reports the event-study results based on the estimation equation (1). (ii) The dependent variables are based on BHP data. (iii) Panel A displays treatment effects for a sample that excludes plants with fewer than 20 employees, where the number of observations is 6950 across all columns. The dependent variables are rescaled by the inverse hyperbolic sine transformation. (iv) Panel B displays treatment effects for percentile regressions, where the dependent variable is measured in percentile $(0-100)$ based on the plant-level distribution of the original outcome variable for each time period. The number of observations is 10,390 across all columns. (v) Panel C displays treatment effects for log-transformed dependent variables, where the number of observations is 10,390 for employment, 9205 for hires, and 9306 for separations. (vi) The plant fixed effect is included. (vii) Standard errors in parentheses are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A5: Robustness Checks for Employment by Occupation and Age

	Occupation						Age		
	(1) simple manual	(2) qualified manual	(3) technician engineer	(4) manager	(5) service	(6) admin	(7) young (20−34)	(8) mid-age (35-54)	(9) old (55−65)
Panel A: Excluding Plants with <20 Employees ($N = 6950$)									
t−2 × Robot	0.0133	0.0148	0.0216	0.0138	0.0137	0.0071	0.0148	0.0107	0.0152
	(0.0202)	(0.0195)	(0.0210)	(0.0313)	(0.0222)	(0.0211)	(0.0195)	(0.0133)	(0.0190)
t−1 × Robot	0.0109	0.0610**	0.0086	0.0048	0.0206	-0.0293	0.0754***	0.0204	0.0007
	(0.0283)	(0.0295)	(0.0319)	(0.0363)	(0.0334)	(0.0271)	(0.0284)	(0.0193)	(0.0250)
t × Robot	-0.0030	0.0738	0.0640*	0.0748*	0.0729	0.0168	0.1140***	0.0545*	0.0005
	(0.0510)	(0.0470)	(0.0374)	(0.0414)	(0.0508)	(0.0319)	(0.0365)	(0.0280)	(0.0356)
t+1 × Robot	-0.0041	0.0918*	0.0842**	0.0906*	0.0756	0.0211	0.1359***	0.0825**	-0.0081
	(0.0565)	(0.0551)	(0.0412)	(0.0489)	(0.0572)	(0.0334)	(0.0415)	(0.0335)	(0.0378)
Panel B: Percentile Regressions ($N = 10390$)									
t−2 × Robot	0.4058	-0.0646	0.5886	1.3179	0.5690	0.3624	0.4619	-0.0003	0.9224**
	(0.4266)	(0.3184)	(0.4232)	(1.1142)	(0.5210)	(0.5550)	(0.3817)	(0.2730)	(0.4458)
t−1 × Robot	0.2397	0.8247*	-0.1722	1.4053	0.4477	-0.3974	0.9036*	0.1617	0.5300
	(0.5213)	(0.4995)	(0.6356)	(1.3729)	(0.7879)	(0.6424)	(0.5476)	(0.4030)	(0.5206)
t × Robot	-0.0155	0.6014	1.0668	2.4533	1.5607	0.4584	1.1822*	0.4489	0.2090
	(0.9031)	(0.7051)	(0.7484)	(1.5776)	(1.1200)	(0.7255)	(0.6771)	(0.5182)	(0.6626)
t+1 × Robot	0.1644	0.5539	1.3165*	3.5552*	1.9159	0.5356	1.3058	1.0568	0.0555
	(1.0480)	(0.9192)	(0.7833)	(1.8365)	(1.2008)	(0.7548)	(0.8016)	(0.6579)	(0.7296)
Panel C: Log Transformed									
t−2 × Robot	0.0003	0.0220	0.0307	-0.0265	0.0166	0.0128	0.0246	-0.0016	0.0380*
	(0.0217)	(0.0186)	(0.0230)	(0.0275)	(0.0225)	(0.0223)	(0.0196)	(0.0133)	(0.0196)
t−1 × Robot	0.0101	0.0601**	0.0048	-0.0310	0.0168	-0.0171	0.0727***	0.0171	0.0105
	(0.0295)	(0.0299)	(0.0351)	(0.0315)	(0.0286)	(0.0264)	(0.0280)	(0.0216)	(0.0255)
t × Robot	-0.0004	0.0762	0.0658	0.0328	0.0747	0.0311	0.1026***	0.0492*	0.0059
	(0.0436)	(0.0467)	(0.0404)	(0.0353)	(0.0515)	(0.0316)	(0.0357)	(0.0287)	(0.0330)
t+1 × Robot	0.0140	0.0946*	0.0686	0.0379	0.0600	0.0311	0.1132***	0.0712**	-0.0021
	(0.0492)	(0.0527)	(0.0429)	(0.0394)	(0.0582)	(0.0336)	(0.0411)	(0.0329)	(0.0350)
N	8027	8736	7723	5348	7634	9691	9716	10354	9739

Notes:(i) This table reports the event-study results based on the estimation equation (1). (ii) The dependent variables are based on BHP data. (iii) Panel A displays treatment effects for a sample that excludes plants with fewer than 20 employees, where the dependent variables are rescaled by the inverse hyperbolic sine transformation. (iv) Panel B displays treatment effects for percentile regressions, where the dependent variable is measured in percentile ($0-100$) based on the plant-level distribution of the original outcome variable for each time period. (v) Panel C displays treatment effects for log-transformed dependent variables. (vi) The plant fixed effect is included. (vii) Standard errors in parentheses are clustered at the plant level. (v) *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

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