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GS4S Working paper series (D7.3)
Working paper no. 7

Migration vs. automation as an answer to labour shortages: Firm-level analysis for Austria

This working paper is part of the Horizon Europe project GS4S - Global Strategy for Skills, Migration and Development (gs4s.eu).
Project deliverable: D7.3 in T3.4

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Language editor: Josh Ward

Suggested citation (APA): Tverdostup, M., Ghodsi, M., & Leitner, S. (2025). Migration vs. automation as an answer to labour shortages: Firm-level analysis for Austria. Global Strategy for Skills, Migration and Development (GS4S). https://doi.org/10.5281/zenodo.15115025

Migration vs. automation as an answer to labour shortages: Firm-level analysis for Austria

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Abstract:

Labour shortages in Europe have led firms to adopt two key strategies: automation and the employment of migrants. This study empirically examines the relationship between robot adoption and immigrant labour (differentiated by region of origin and education level) in Austrian firms using a novel dataset linking firm-level survey data on robotics adoption from Austria's Information and Communication Technologies (IKTU[1]) surveys (waves 2018, 2020 and 2022) with registry-based employment records. Employing Poisson pseudo-maximum likelihood (PPML) estimations, we analyse firm-level employment decisions while controlling for firm characteristics, industry and region. Our findings show that firms adopting robots tend to employ more workers overall, particularly those with low and medium education levels. Notably, robot-adopting firms employ a higher share of low-educated migrants who are not from the European Economic Area (EEA), suggesting complementarity rather than substitution. However, automation appears to reduce the employment of highly educated migrant workers relative to natives. Distinguishing between industrial and service robots, we find that service robots have a stronger association with employment growth than industrial robots. The impact of robot adoption also differs by sector and is most pronounced in manufacturing, whereas its effects vary in the private service sectors. Our findings suggest that while automation can alleviate labour shortages, it may reinforce labour market segmentation. For EU policy makers, targeted interventions are needed to support the transition of migrant workers into higher-skilled occupations and to ensure that the benefits of automation are equitably distributed. Given the EU-wide relevance of automation and migration dynamics, these results provide insights that are also applicable beyond Austria.

Keywords: Migration, automation, employment, firm- and worker-level analysis

JEL code: D22, J23, J24, J61, O33

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[1] In German: Einsatz von Informations- und Kommunikationstechnologien in Unternehmen (IKTU) 2018.

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Acknowledgement: This paper is part of the Horizon Europe project GS4S – Global Strategy for Skills, Migration and Development (gs4s.eu). The funding from the European Union (EU) is gratefully acknowledged. However, the views and opinions expressed herein are those of the authors only and do not necessarily reflect those of the EU, Horizon Europe or the Research Executive Agency. Neither the EU nor the granting authority can be held responsible for them. The broad line of inquiry in this paper had initially been suggested by Isilda Mara.

The authors would like to thank Pascal Beckers and Ciprian Panzaru for their extensive feedback and suggestions on the early drafts of this paper.

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1. Introduction

Europe is experiencing labour shortages (EURES 2023) in many sectors of activity due to demographic changes. To remain competitive in global markets and to be resilient to numerous and frequent shocks, such as the COVID-19 pandemic and geopolitical risks, European firms have two main strategies to circumvent labour shortages. One strategy is to automate and fill vacant positions with robots and artificial intelligence. Another option is to recruit migrants. In the face of looming labour and skills shortages, analysing the substitution versus complementarity effects between migrant labour and automation is of high political and societal relevance.

This paper provides a pioneering empirical analysis of Austrian firms' choices between these strategies. Specifically, it examines whether the adoption of robots by Austrian firms is correlated with the employment of foreign workers, differentiated by origin and education level. The adoption of robots and automation technologies may also pose significant challenges for employment, especially for low- and medium-skilled workers, who are most vulnerable to job displacement because they are employed in easily automatable jobs, which are often characterised by repetitive and predictable activities that can be effectively replicated by machines (Arntz et al. 2016; Acemoglu and Restrepo 2018a, 2020b; Graetz and Michaels 2018).

Moreover, the literature suggests that automation can lead to job polarisation, where middle-skill jobs decline and there is growth in both high-skill/high-wage jobs and low-skill/low-wage jobs that are less likely to be automated (Autor 2015; Goos et al. 2014). Low- and middle-skill routine tasks are particularly vulnerable to both full and partial automation, leading to significant employment declines within these skill groups as well as increasing employment and wage polarisation (Acemoglu and Restrepo 2022; Mandelman and Zlate 2022; Downey 2021; Cortes 2016; Goos et al. 2014; Autor 2013).

This polarisation further marginalises low- and medium-skilled workers, especially immigrants, who are disproportionately represented in low- and medium-skilled occupations – the very jobs most at risk from automation (see, among others, Biagi et al. 2018; Bisin et al. 2011) – and may find it difficult to move into the growing high-skilled sectors due to various barriers, such as limited access to education and training, language skills and discriminatory hiring and promotional practices. For instance, Mandelman and Zlate (2022) show for the US that the decline in medium-skilled occupations due to automation and off-shoring does not lead to employment and wage polarisation for native workers. As the supply of low-skilled immigrant labour fills employment needs in low-skilled jobs and depresses wages, native workers upgrade their skills and move into high-skilled jobs, leading to employment and wage growth. Similarly, Basso et al. (2020) show that routine task-replacing technological change attracts low-skilled immigrants, who cluster in low-skilled jobs. Low-skilled migration drives natives to upgrade their skills and move into higher level jobs that require stronger cognitive skills.

The adoption of robots may also have broader implications for the structure of labour markets and social welfare systems. For instance, Bessen (2019) suggests that while automation may lead to overall productivity gains, the distribution of these gains is uneven, often favouring capital

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owners and high-skilled workers, while low-skilled workers, including many immigrants, may see their job prospects decline. This uneven distribution of benefits raises important questions about the role of policy in mitigating the adverse effects of automation on vulnerable groups, including the need for retraining programmes, social safety nets, and inclusive economic policies that can help workers transition to new opportunities in an increasingly automated economy.

At the same time, empirical evidence on the relationship between immigrant labour and automation is limited. Ghodsi et al. (2024) is among the few empirical analyses presenting pioneering evidence on the relationship between technologies (measured in patents and robot adoptions) and immigrant employment. They show that while patents and robots in sectors across EU member states reduce total employment and the employment of migrants, they reduce the employment of native workers more than they reduce that of migrant workers. In fact, both the adoption of robots and patenting activities increase the share of immigrant workers in total employment. They also present heterogenous effects of different measures of technologies on migrant worker shares across different occupations and education levels. However, comprehensive empirical evidence on the relationship between automation and immigrant labour differentiated by levels of education at the firm level is missing in the literature.

Thus, this paper aims to fill this research gap by using a novel employer-employee database for Austria. In doing so, the paper has four main objectives. First, it analyses the relationship between automation (measured by the use of robots by firms) and the total number of workers as well as native and migrant workers, with the latter differentiated by region of origin in terms of whether or not the migrant workers were born in the EU or the European Economic Area (EEA) (referred to as 'EEA' and 'non-EEA') as well as by the level of educational attainment in terms of low, medium and high (based on the ISCED-2011 classification). It therefore sheds light on the substitution or complementarity between migrant labour of different education levels and robot use in addition to comparing the results for migrant workers with those for native workers to assess whether the supply of migrant and native labour is associated with automation differently and how this varies across education levels.

While the first objective focuses on the number of employees, changes in composition of employment is analysed for the second objective. Second, the paper analyses the effects of robot adoption on the share of migrant workers with low /medium/high education levels) relative to the total number of workers of firms with low /medium/high education level). In doing so, it sheds light on compositional changes of automation by origin and level of educational attainment.

Third, it analyses the relationship between the types of robots in use and changes in firm employment structures. Specifically, it identifies the relationship between the use of industrial and service robots and the share of EEA and non-EEA migrant workers in firms' workforces.

Fourth, the paper examines transitions into and out of employment in firms included in Statistics Austria's annual IKTU surveys on the use of information and communication technologies (ICT) in Austrian enterprises in the context of robot adoption, distinguishing between different types of transitions (job-to-job, unemployment-to-job and inactivity-to-job). In doing so, it focuses on

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disparities in the propensity to join and leave IKTU-surveyed firms and in the types of transitions across different groups of workers by origin and education level. It further investigates disparities in workers' propensity to join or leave firms surveyed by the IKTU, comparing transitions across groups defined by origin and education level. Moreover, it highlights wage disparities between groups of transitioning workers. This analysis aims to reveal whether robot-adopting firms exhibit distinct characteristics in terms of the employment dynamics of migrant workers compared to natives.

To achieve these objectives, the analysis uses several datasets that have been linked together. The information on employees and the financial data of firms are taken from registry data, while the data on the use of robotics are taken from the IKTU surveys. It focuses on the medium-term effect and identifies the relationship between automation and migrant labour for up to four years after the specific IKTU survey was conducted.

Our results indicate that, among responding firms, those that reported using either service or industrial robots generally have a larger workforce (particularly with low- and medium-educated workers) than firms that did not adopt robots. This suggests a complementarity between robots and employment despite labour shortages. While this relationship remains positive for highly educated workers in firms adopting robots, it is not statistically significant even when also controlling for other labour market conditions.

Furthermore, the ratio of non-EEA migrant workers to the total number of employees with low education levels is higher in firms that adopt robots than in those that do not. Additionally, firms that adopt robots employ more non-EEA migrant workers with medium education levels than EEA migrants or native workers. Among highly educated workers in robot-adopting firms, most come from EEA countries, followed by native workers. Our results underscore the importance of targeted policies to address the uneven impacts of automation and ensure that the benefits of technological advancements are more fairly distributed across the workforce. They suggest a complementary relationship between automation and certain types of migrant labour, particularly for manual, non-routine tasks that are less susceptible to automation. It is a nuanced result that highlights how robot adoption can reinforce existing labour market segmentation.

The remainder of the paper is organised as follows: Section 2 provides some theoretical considerations and discusses the related literature, Section 3 discusses the data used in the analysis, Section 4 discusses the empirical strategy, Section 5 presents the empirical results, and Section 6 provides concluding remarks.

2. Theoretical considerations and related literature

Theoretically, there are three main channels through which automation technologies can affect labour market outcomes (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018a, 2019). The first is a *displacement effect*, as automation technologies directly displace workers from tasks that they used to perform (Acemoglu and Restrepo 2020a; Autor 2015). In this context, since manual and cognitive routine tasks are particularly prone to being fully automated (Autor et al. 2003; Spitz-

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Oener 2006), the introduction of automation technologies is found to lead to decreased demand for labour in medium-skilled occupations (Autor and Dorn 2013; Goos et al. 2014). The second is a *productivity effect* stemming from a more flexible allocation of tasks, which increases productivity and, through a reduction in production costs, increases the demand for labour in non-automated tasks (Acemoglu and Restrepo 2019; Autor 2015), with employment effects also observed in up- and downstream industries (Bessen et al. 2020; Jiang et al. 2024). The third is a *reinstatement effect*, which arises because automation technologies create new labour-intensive tasks that increase labour demand (Acemoglu and Restrepo 2019; Fossen and Sorgner 2022). The net effect of automation on employment therefore depends on the strength of the displacement effect and the countervailing productivity and reinstatement effects, and it is negative if the displacement outweighs both the productivity and reinstatement effects.

The empirical literature is varied and inconclusive. Firm-level analyses on the employment effects of robots – the focus of our analysis[2] – have produced conflicting results. Some studies find that industrial robots are associated with higher employment (Acemoglu et al. 2020; Ballestar et al. 2020; Balsmeier and Woerter 2019; Bisio et al. 2025; Camiña et al. 2020; Wang et al. 2024), with the increase in employment occurring from the first year of adoption (Dixon et al. 2021) and being more pronounced in capital-intensive sectors, especially among Chinese firms (Huang et al. 2023; Zhu and Nie 2024). Others find that industrial robots decrease employment (Ballestar et al. 2021; Bonfiglioli et al. 2024; Jung and Lim 2020), where robot adoption occurs after periods of expansion in firm size and the associated initial increase in employment reverses soon after adoption, leading to lower employment in the longer term (Bonfiglioli et al. 2024).

Moreover, the negative employment effect of robot adoption appears to have accelerated more recently (Ballestar et al. 2021). In this context, an important role is also played by specific firm characteristics, such that employment reductions only occur in non-adopting firms due to a productivity-enhancing reallocation of labour from non-adopters to adopters, which tend to be larger and to grow faster (Acemoglu et al. 2020; Koch et al. 2019), or in small and medium-sized enterprises (SMEs) (Pellegrino et al. 2017).

Moreover, much of the empirical literature also finds support for the 'polarisation hypothesis', which posits that medium-skilled occupations are particularly at risk of being displaced by automation technologies that can take over manual and cognitive routine tasks (Autor et al. 2003; Autor and Dorn 2013; Goos and Manning 2007; Goos et al. 2014; de Vries et al. 2020), while employment of low- and high-skilled workers who respectively perform mainly non-routine manual and non-routine cognitive tasks increases (Dixon et al. 2021; Mandelman and Zlate 2022). Other studies also find a negative employment effect for low-skilled workers (Balsmeier and Woerter 2019; Borjas and Freeman 2018; Graetz and Michaels 2018; Jung and Lim 2020) and potentially stronger effects in the longer term (Balsmeier and Woerter 2019). However, according to projections of Vermeulen et al. (2018), only a few occupations are affected by automation technologies, which will result in a small loss of jobs. The occupations that will be most negatively affected regard production as well as office and administrative support occupations. Conversely,

[2] For an overview of the employment effects of automation at other levels of analysis, see Filippi et al. (2023).

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strong growth is expected in a number of occupations, notably in computer/mathematical, management and architecture/engineering occupations.

However, the impact of automation technologies is not only felt at the occupational level. In particular, due to their different *task specialisation*, migrant and native workers may also be affected differently. Specifically, less-educated migrants specialise in occupations requiring manual tasks (see Peri and Sparber 2009 for the US; Sebastian and Ulceluse 2019 for Germany), especially manual routine tasks (D'Amuri and Peri 2014 for 14 Western European countries), while less-educated natives specialise in more complex tasks requiring communication skills, among others.[3] Therefore, the displacement effect, (i.e. the tendency of automation technologies to replace manual and cognitive routine tasks) should affect migrant workers disproportionately more than natives, especially medium-skilled migrants who tend to specialise in manual routine tasks. However, workers in routine tasks could also *transition to perform non-routine tasks*, either cognitive or manual (Acemoglu and Autor 2011), and therefore profit from both productivity and reinstatement effects. In this context, the difference between native and migrant medium-skilled workers is again significant, as natives tend to move into high-skilled occupations in response to automation while migrants tend to move into low-skilled occupations (Mandelman and Zlate 2022), where they perform non-routine manual tasks, complementing and working alongside the automation technology (Downey 2021).

However, the region of origin of migrants makes a further difference. Due to the lower *transferability of their skills* from the home to the host country, migrants who are culturally and linguistically more distant from the native population may specialise even more in manual routine tasks than migrants who are culturally and linguistically closer to the native population. In addition to making the former more vulnerable to automation, it also makes them more likely to move into low-skilled occupations in response to automation.

The limited empirical literature seems to support the notion that migrants face a stronger displacement effect from automation than natives. For example, Javed (2023) studies the effect of industrial robot adoption on the employment of natives and migrants in US local labour markets between 1990 and 2014 and shows that employment in manual routine occupations has been more adversely affected for migrants than for natives: an increase of one robot per 1,000 workers is associated with a 0.19 percentage point (pp) decline in the routine manual employment ratio for natives and a 0.44 pp decline for migrants.

Moreover, cultural and linguistic distance also matters. For example, using large-scale Dutch employer–employee matched longitudinal data for the 2001-2014 period, ten Berge and Tomaskovic-Devey (2022) show that technology adoption reduces the likelihood of job termination. However, this technology-related job protection is lower (and sometimes even absent) for non-Western migrant workers, especially non-Dutch-speaking non-Western migrants, than for native workers, making non-Dutch-speaking non-Western migrant workers

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[3] A similar task specialisation is also found for skilled migrants and natives, where skilled native workers specialise towards interactive, language-intensive managerial tasks while skilled migrant workers specialise in analytical, technical research-oriented tasks (Mayda et al. 2022; Peri and Sparber 2011).

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more vulnerable to job loss through automation than both native workers and Dutch-speaking non-Western migrants.

Ghodsi et al. (2024) study the effect of various novel technologies, including robot adoption, on migrant employment for 18 EU member states in the 2005-2019 period. In contrast to other findings, they show that while robots replace workers, they more strongly replace native than migrant workers, leading to a 0.075% increase in the share of migrants in total employment in response to a 1% increase in the intensity of robots to employees in a sector. A further differentiation by occupation shows that while the migrant employment share increases in higher-skilled occupations (especially among technicians and associate professionals, ISCO-3), it decreases in the lower-skilled occupations (especially among craft and related trade workers (ISCO-7) as well as plant and machine operators and assemblers (ISCO-8)). The origin of migrants is important, but not as expected, as significant patterns are mainly observed for EU migrants, whose employment shares mainly decrease in lower occupations (including craft and related trades workers (ISCO-7), plant and machine operators and assemblers (ISCO-8), and elementary occupations (ISCO9)), while the employment share of non-EU migrants only decreases for craft and related trade workers (ISCO-7) but increases for high-skilled occupations (e.g. legislators, senior officials and managers (ISCO-1), professionals (ISCO-2), and technicians and associated professionals (ISCO-3)).

3. Data and database construction

We construct our dataset from several data sources that all stem from the Austrian Micro Data Center (AMDC) at Statistics Austria.[4] Specifically, we use the novel *register-based merged employer-employee data*, which provide firm and individual register data and allow us not only to construct an annual firm-level panel dataset but also to use individual-level register data to track changes in firm employment over time.

Moreover, we use three waves of the IKTU survey on the use of ICT in Austrian enterprises, which has been conducted annually by Statistics Austria since 2015. It is a random sample survey limited to enterprises in selected ÖNACE industries (i.e. C, D, E, F, G, H, I, J, L, M, N, S (95.1)) with 10 or more employees, with a sample size of around 3,000 per round. Participation in the survey is not mandatory. The survey is based on EU regulations[5] that require Austria (and all other EU member states) to report annual data on how enterprises use ICT. The stratification criteria used were the main economic activity of the enterprise (ÖNACE 2008 classification), firm size (approximated by the number of persons employed, divided into three size classes: small: 10-49 employees; medium: 50-249 employees; and large: 250 and more employees), and the main location (NUTS 2 region), with information taken from the business register of Statistics Austria. Topics of the survey include internet use, e-commerce, cloud services, data analytics, artificial intelligence and ICT security, among others. In 2018, 2020 and 2022, it also covered questions on the use of industrial

[4] See: www.statistik.at/en/services/tools/services/center-for-science/austrian-micro-data-center-amdc.

[5] See: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32017R1515 and https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32004R0808.

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and service robots by the surveyed firms, which we used in our analysis. Specifically, the surveys asked: '*Does your company use industrial robots (e.g. robot-controlled welding work, laser cutting, spray painting)?*'[6] and '*Does your company use service robots (e.g. for monitoring, cleaning, transport)?*'[7] with a binary answer option (yes/no). Companies were coded as 'robot users' if they answered in the affirmative. In the analysis, we use the use of robots in two different forms – (i) the use of any robots (when companies used either of the two types of robots) and (ii) by type of robot (industrial robots or service robots) – and constructed dummy variables accordingly. From the IKTU surveys, we also used information on the presence of ICT specialists in the firms' workforces. It is captured by the following question: '*Does your company employ ICT specialists?*' with a binary answer option (yes/no). We constructed a dummy variable that is equal to one if this question was answered in the affirmative. Given the cross-sectional nature of the IKTU data and the lack of information on the timing of the introduction of robots, it is not possible to determine exactly when the robots were introduced by the companies. However, further merging with register-based information makes it possible to construct a panel dataset on key characteristics, performance indicators and individual-level employee records for firms participating in the IKTU survey, thereby capturing a period following the survey.

We supplement the IKTU data with several additional register data from 2016, including the *structural business statistics* (*Leisungs- und Strukturstatistik*), the *integrated wage and income tax statistics* (*Integrierte Lohn- und Einkommensteuerstatistik*), and the *statistical business register* (*Statistisches Unternehmensregister*) as firm-level register data as well as the above-mentioned *merged employer-employee data* (*Abgestimmte Erwerbsstatistik und Registerzählung*) as individual-level register data. To analyse how the use of robots affects the skill structure of the native and immigrant labour forces as well as net changes in employment across skill levels, we construct a panel dataset for all firms participating in one of the three IKTU survey rounds mentioned above, following the two-step procedure described below:

First, we merge firm-level register data from (i) firm *performance and structural statistics* and (ii) the *statistical business register* for all firms covered by one of the IKTU surveys. The firm-level registers contain information on key firm characteristics and performance indicators, including firm ownership (domestic-, foreign-owned), the number of employees, revenue, turnover, total costs, personnel and wage expenses, and investments (in total and by asset type). Based on the register data, we construct an annual panel dataset for IKTU-surveyed firms covering the period from 2016 to 2021.

Second, we supplement the annual firm-level panel dataset with additional information derived from individual-level *merged employer-employee data*, which, in addition to a number of key socio-demographic characteristics, include a comprehensive list of employment-related variables that

[6] In the questionnaire, an industrial robot is defined as follows: 'An industrial robot is an automated, programmable machine that is used to handle, assemble or process objects in an industrial environment. Software robots (computer programmes) and 3D printers are excluded.'
[7] In the questionnaire, a service robot is defined as follows: 'A service robot is a machine that is autonomous to a certain degree. In a complex and dynamic environment, a service robot can interact with people, objects or other devices. Use in industrial automation applications is excluded. Software robots (computer programmes) and 3D printers are also excluded.'

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allow us to track individual employment transitions across firms and into unemployment/inactivity on an annual basis. From the merged employer-employee data, we use information on country of birth to differentiate native from migrant workers as well as to calculate for each firm the total number and the share in total firm employment of (i) Austrian-born workers, (ii) migrant EU-/EEA-born[8] workers, and (iii) migrant non-EEA-born workers, each with (i) low, (ii) medium, and (iii) high skill levels. The education level is approximated by the level of educational attainment according to the ISCED-2011 classification, with *low* referring to ISCED 0 to 2 (i.e. early childhood education, primary education, lower secondary education), *medium* to ISCED 3 and 4 (i.e. upper secondary education, post-secondary non-tertiary education) and *high* to ISCED 5 to 8 (short-cycle tertiary education, bachelor's or equivalent level, master's or equivalent level, doctoral or equivalent level). Employment variables at the firm level are calculated for the year of the IKTU survey to four years after the survey and used as dependent variables in our analysis (see below).[9] The variables derived from the individual-level data are further merged with the firm-level panel dataset to construct the final dataset for analysis.

Table B1 in Appendix B presents summary statistics for the data used in the analysis. While Panel A provides various indicators and summary statistics for robot-adopting firms, Panel B presents the same indicators for non-adopting firms. Panel C focuses on industry-robot-adopting firms, and Panel D on service-robot-adopting firms.

4. Empirical methodology

This paper conducts a two-step analysis relying on firm-level data. We use the following specification to identify the relationship between automation and the share of low-, medium- and high-skilled migrant and native workers in total employment at the firm level:

$$L^{os}_{ijrt+p} = \exp\left(\beta robot^{k}_{ijrt} + \gamma F'_{ijrt+p} + \theta_{t+k} \times \theta_j + \theta_{t+p} \times \theta_r + \varepsilon_{ijrt+p}\right),\ p \in \{0,1,2,3,4\} \quad (1)$$

where $L^{os}_{ijr\Delta t}$ refers to the number of workers, differentiated by their region of birth and skill level, and where $o \in \{AT, EU/EEA, non-EU/non-EEA\}$ and $s \in \{low, medium, high\}$ denote, respectively, the number of Austrian-born, EU-/EEA-born and non-EEA-born immigrant workers at the firm level with low, medium and high skill levels in year $t + p$ with $p \in \{0,1,2,3,4\}$, where t is the base year of the IKTU survey.[10] As the IKTU survey does not identify when the technology was adopted by the firm, we consider a time period of up to four years after the survey to allow for a sufficient post-adoption adjustment period. This introduces some temporal ambiguity, as the exact

[8] In our empirical analysis, 'EU' refers to the 27 member states of the post-Brexit EU.
[9] As the base year of the IKTU survey is always one year before the reference year, the period 2017-2021 is considered for the firms covered in the IKTU-2018 wave, the period 2019-2021 for the firms included in the IKTU-2020 wave, and only 2021 for the IKTU-2022 wave.
[10] The base year for IKTU-2018, IKTU-2020 and IKTU-2022 is 2017, 2019 and 2021, respectively.

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adoption year of robots in each firm, relative to the survey year, remains unclear. However, this ambiguity does not result in reverse causality issues for dependent variables measured in subsequent years, as these are clearly observed after the survey year. In the survey year, the adoption of robots could have occurred at any point $t - p, with\ p \in \{1,2,3, \dots\}$. The subscripts i, j, r and t denote firm, industry, region and time, respectively, with industry measured at the two-digit NACE level (according to the Austrian ÖNACE 2008 classification) and region measured at the NUTS 2 level (which, in the Austrian context, refers to the nine provinces).

$robot^{k}_{ijrt}$ captures the use of robots in firm i, industry j, NUTS 2 region r in year t. We consider three binary outcomes k, namely (i) the use of any robots, (ii) the use of industrial robots, and (iii) the use of service robots.

The vector $F'_{ijr\Delta t}$ contains a set of firm-level variables related to firm characteristics and performance, including being a subsidiary, firm productivity, profits, total investment, the share of software investments in total investments, the ratio of personnel costs in total expenditure, the value of property and equipment, having ICT specialists among employees, and the share of part-time contracts estimated for the year $t + p$. Finally, $\theta_{t+p} \times \theta_j$ and $\theta_{t+p} \times \theta_r$ refer to industry-year and region-year fixed effects, respectively. ε_{ijrt+p} is the error term. Equation (1) is estimated using the Poisson pseudo-maximum likelihood (PPML) estimator with high-dimensional fixed effects to be able to control for zero values in the dependent variables. Moreover, we use the 2018 IKTU survey (IKTU-2018) as the benchmark analysis while we combine all three IKTU waves as a robustness check (with results reported in the Annex).

4.1. Employee-level analysis

Entering employment in IKTU-surveyed firms

Furthermore, to analyse how transitions into firm employment vary for different origin groups in robot-adopting and non-adopting firms, we use a multinomial logit regression of the following form in samples of low-, medium- and high-educated workers:

$$P\left(y_{ki} = \{1,2,3\} \middle| robot_{ijr}, O'_{ki}, X'_{ki}, F'_{ijr}\right) \\ = \beta_1 robot_{ijr} + \beta_2 O'_{ki} + \beta_3 \left(robot_{ijr} \times O'_{ki}\right) + \delta X'_{ki} + \mu F'_{ijr} + \theta_j + \theta_r + \varepsilon_{ki}, \qquad (2)$$

where y_{ki} is a realisation of the random variable Y_{ki}, identifying three different transitions, namely, the transition of worker k (i) from employment in another firm to employment in firm i, (ii) from unemployment to employment in firm i, and (iii) from inactivity to employment in firm i over the 2017-2021 period. The binary variable $robot_{ijr}$ identifies the use of robots reported by firm i, operating in industry j, in NUTS 2 region r, which was surveyed in the IKTU-2018 wave. The vector O'_{ki} captures a set of origins of worker k, namely, being (i) Austrian-born, (ii) an EEA-born migrant, and (iii) a non-EEA-born migrant. The vector X'_{ki} contains several workers' demographic characteristics, including age and gender. The vector F'_{ijr} contains a set of firm-level characteristics related to the profile and performance of firm i, including productivity, profits, total investment, share of software investment in total investment, total expenses, ratio of

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personnel costs in total expenses, value of property and equipment, share of part-time contracts, whether it is a subsidiary, and whether it has ICT specialists among its employees. Apart from the latter two, all firm-level characteristics are measured as averages over the 2017-2021 period.[11] Specification (2) additionally includes industry fixed effects θ_j (according to the ÖNACE 2008 classification) and NUTS 2-level region fixed effects θ_r.

Exiting employment from IKTU-surveyed firms

Furthermore, we analyse how the probability of exiting employment in the firms surveyed in the IKTU-2018 wave differs by workers' origin and educational level as well as firms' adoption of robots. In doing so, we use a logit regression model of the following form:

$$P\left(z_{ki} = \{0,1\} \middle| robot_{ijr}, O'_{ki}, X'_{ki}, F'_{ijr}\right) \\ = \beta_1 robot_{ijr} + \beta_2 O'_{ki} + \beta_3 \left(robot_{ijr} \times O'_{ki}\right) + \delta X'_{ki} + \mu F'_{ijr} + \theta_j + \theta_r + \varepsilon_{ki}, \quad (3)$$

where z_{ki} is a realisation of the random variable Z_{ki}, which takes the value 1 if worker i left firm k at any point during the 2017-2021 period and the value 0 if the worker remained employed in firm k. To define the latter, we use two versions of the reference group. The first reference category takes as a reference group workers who (i) have been continuously employed by the firm over the 2017-2021 period or (ii) joined the firm during the observation period and remained employed until 2021 (i.e. the *total workforce as of* 2021). In the second version, the reference group only refers to those workers who have been continuously employed by the firm over the 2017-2021 period (i.e. the *long-term workforce as of* 2021). Hence, while the first version allows us to compare those workers who have left the firm with the firm's total workforce, the second version allows us to compare them with the long-term/permanent workforce. The remaining variables are defined as in specification (2).

5. Empirical results

5.1. Main figures: estimates based on the IKTU-2018 survey wave

In the first set of estimation results, we show how the number of employees from different origins and with different education levels correlates with the use of robots in the year in which the IKTU survey was conducted and in the following four years. Since the exact timing of robot adoption prior to the survey is not known, our results can be interpreted as a comparison between firms that adopt robots and those that do not. Therefore, we cannot interpret a direct causal relationship here.

Figure 1 shows the semi-elasticity of the robot-adoption coefficients derived from the PPML regressions on the number of employees with 95% confidence intervals. The first panel shows estimates for low-educated workers, the second panel for medium-educated workers, and the

[11] Being a subsidiary is a time-invariant characteristic and having ICT specialists among employees is only reported for the IKTU-2018 reference year (i.e. 2017).

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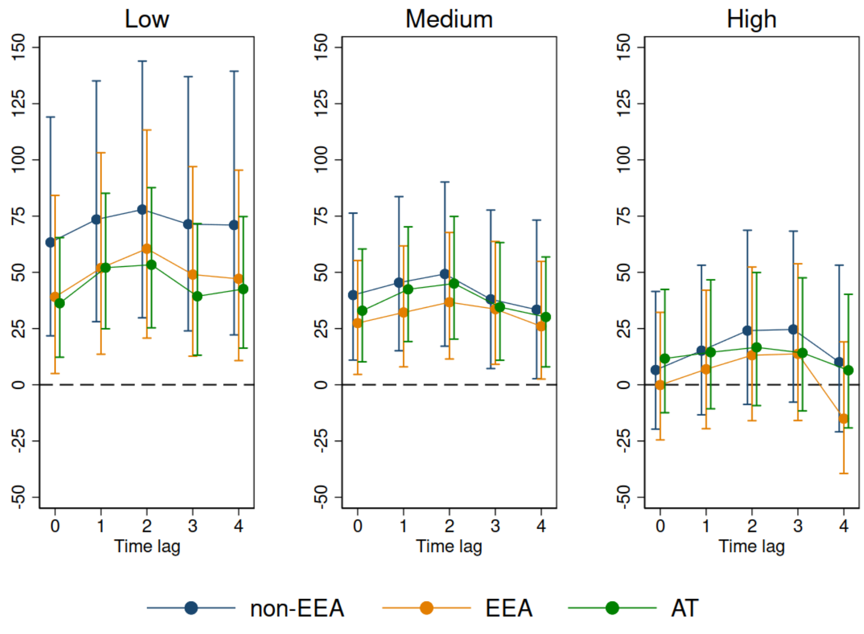
third panel for high-educated workers. In nearly all models, we observe a positive relationship between the number of workers and robot adoption. In general, firms that adopt robots tend to employ more workers with low and medium education levels than firms that do not adopt robots, while there is no statistically significant relationship between robot adoption and the number of employees with a high education level.

Moreover, for all models, the point estimates over the years following the survey exhibit a hump-shaped curve. Specifically, in the third and fourth years after the survey, the number of employees declines in robot-adopting firms. Notably, these two years correspond to 2020 and 2021, when several strict COVID-19 lockdowns disrupted labour markets. Therefore, the reduction in the point estimates for robot adoption may be attributable to the economic slowdown caused by the pandemic. Moreover, since we control for the turnover of companies in our estimations, this result may indicate that firms that adopted robots might have been better able to maintain production during the COVID years while laying off more employees than firms that did not adopt robots.

Figure 1 / Estimates of robot adoption – Percentage change in the *number* of employees (IKTU-2018 wave)



Notes: Exponentially transformed PPML regression coefficient for robot adoption with 95% confidence intervals are reported. The dependent variable is the number of firm employees of the respective education level and origin from the IKTU survey base year (2017) up to four years after the survey. The main independent variable takes the value 1 when the firm reports adopting robots in the survey base year. Therefore, the time lag refers to the years between the survey base year and the year of observing the dependent variable. All models control for firm productivity, profits, total investment, the share of investment in software, total expenses, the ratio of personnel costs in total expenses, the value of property and equipment, being a subsidiary, having ICT specialists among employees, and the share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with the respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

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Generally, our results suggest a complementarity between robot adoption and the employment of workers with low and medium levels of education, including plant and machine operators as well as assemblers or elementary occupations. Moreover, the magnitude of the coefficients is slightly larger for lower levels of education, indicating that robot-adopting firms employ a greater number of lower-educated workers than non-adopting firms. Workers with lower levels of education may be more involved in tasks related to robot operation, such as technical maintenance.

While the coefficients across different panels are not directly comparable, as they are derived from separate estimations, the point estimates within each panel and time interval are comparable. This allows us to assess differences in the number of workers according to their origin. For instance, in the first panel, during the survey year (or the following years), firms that adopt robots employ more low-educated workers from non-EEA countries, followed by those from EEA countries and, finally, those from Austria. This indicates a complementarity between migrant workers and robot adoption. However, for medium- and high-educated workers, automation does not have a statistically different effect according to origin. In other words, medium- and high-educated workers appear to be more homogeneous in their susceptibility to automation. By contrast, among lower-educated workers, non-EEA migrants appear to be more adaptable to automation, while native workers may be more vulnerable to job displacement.

Figure A1 in Appendix A shows the estimation results using all three waves of the IKTU survey. The results remain robust and similar to those in Figure 1, with the small difference that the number of highly educated employees becomes statistically significant for a few years after the survey.

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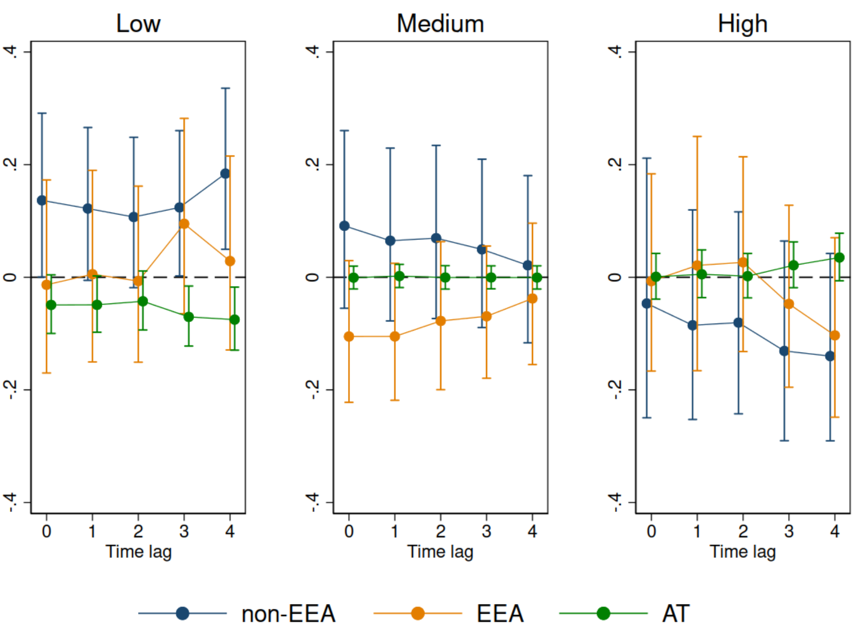
Figure 2 / Estimates of robot adoption – Percentage point change in the *ratio* of employees within education groups (IKTU-2018 wave)



Notes: Exponentially transformed PPML regression coefficient for robot adoption with 95% confidence intervals are reported. The dependent variable is the ratio of employees of the respective origin in low-, medium- and high-education groups from the IKTU survey base year (2017) up to four years after the survey. The main independent variable takes the value of 1 when the firm reports adopting robots in the survey base year. All models control for firm productivity, profits, total investment, the share of investment in software, total expenses, the ratio of personnel costs in total expenses, the value of property and equipment, being a subsidiary, having ICT specialists among its employees, and the share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with the respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

Figure 2 shows results that are similar to those in Figure 1, with the main difference being that the dependent variable is now the *share of workers* from different origins within each educational level relative to the total number of workers within that level. Except for low-educated workers, robot adoption does not appear to be significantly related to the share of workers from different origins. However, the share of low-educated workers from non-EEA countries relative to total low-educated employment is positive and statistically significant at the 1% level. This further supports the complementarity between automation and the employment of low-educated migrant workers, who may be more resilient to disruptive technologies or better suited to perform automated tasks than other groups of workers.

Although the coefficients for high- and medium-educated workers are statistically insignificant, they become negative in some models for migrant workers with high levels of education and, in some models, for EEA migrant workers with medium levels of education. Companies that adopt robots have a lower share of highly educated migrant workers than those that do not, but this is not statistically significant. Companies that adopt robots have a lower share of EEA migrant

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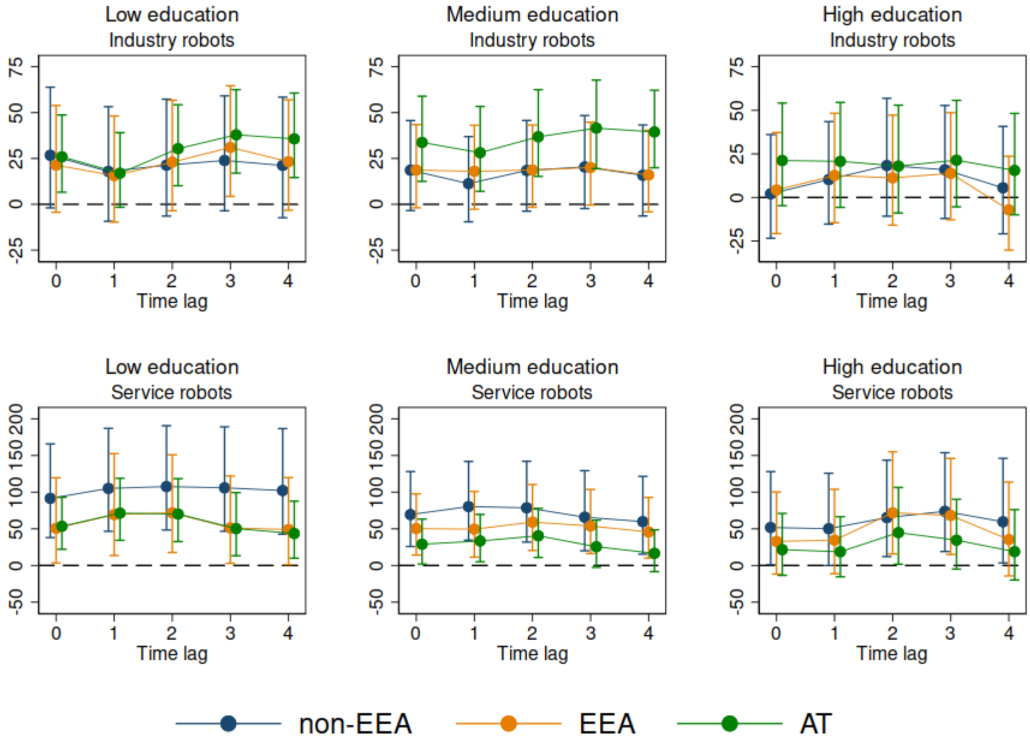
workers with medium levels of education than those that do not as well as a higher share of non-EEA migrant employees with medium levels of education than those that do not. However, these are only marginally significant.

The results presented in Figure A2 in Appendix A, using the three waves of the IKTU survey for the same specification, remain robust and consistent with those in Figure 2.

Figure 3 / Estimates of industry and service robot adoption – Percentage change in the *number* of employees (IKTU-2018 wave)



Notes: Exponentially transformed PPML regression coefficient for industry and service robot adoption with 95% confidence intervals are reported. The dependent variable is the number of firm employees of the respective education level and origin from the IKTU survey base year (2017) up to four years after the survey. The main independent variable takes the value 1 when the firm reports adopting industry or service robots in the survey base year. All models control for firm productivity, profits, total investment, the share of investment in software, total expenses, the ratio of personnel costs in total expenses, the value of property and equipment, being a subsidiary, having ICT specialists among its employees, and the share of part-time contracts. All control variables, except having ICT specialists among employees, are estimated with the respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

Figure 3 shows the same estimation results as Figure 1 but distinguishes between industrial robots and service robots. Therefore, the dependent variables are the number of employees with different levels of education in different panels as well as from different origins. As can be seen, the magnitudes of the coefficients for service robot adopters are much larger than for industrial

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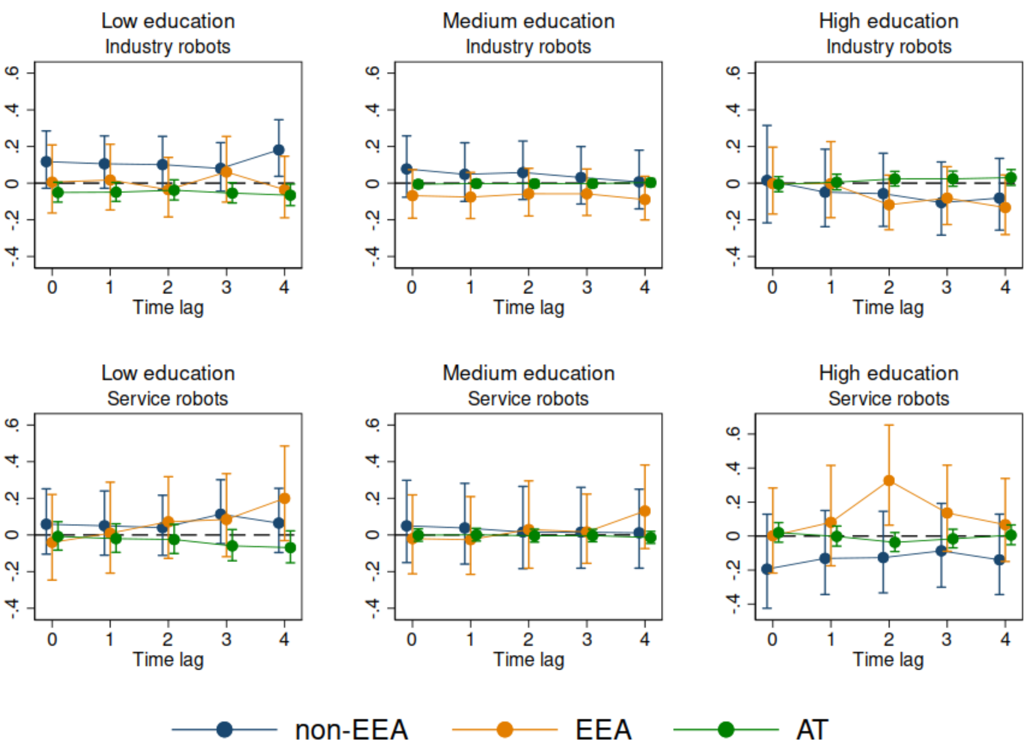
robot adopters. Service robot[12] adopters have a larger number of low- and medium-educated workers in the years following the IKTU survey than non-adopters of service robots. The results presented in Figure A3 in Appendix A, using the three waves of the IKTU survey for the same specification, have become more statistically significant and are consistent with those in Figure 3.

Figure 4 / Estimates of industry and service robot adoption – Percentage point change in the *ratio* of employees within education groups (IKTU-2018 wave)



Notes: Exponentially transformed PPML regression coefficient for industry and service robot adoption with 95% confidence intervals are reported. The dependent variable is the ratio employees of the respective origin in low-, medium- and high-education groups from the IKTU survey base year (2017) up to four years after the survey. The main independent variable takes the value 1 when the firm reports adopting industry or service robots in the survey base year. All models

[12] Here are some examples of service robots: **1. Retail & Hospitality** (e.g. Pepper – a humanoid robot used for customer service and interaction; Connie at Hilton Hotels – robotic concierge that provides hotel guests with information) **2. Health Care & Assistance (**e.g. Da Vinci Surgical System – assists surgeons in performing precise procedures; PARO – a therapeutic robot for elderly patients and those with dementia) **3. Logistics & Delivery** (e.g. Starship Robots – autonomous delivery robots for food and packages; Amazon's Kiva Robots – used in warehouses for sorting and transporting goods) **4. Cleaning & Maintenance** (e.g. Roomba – an autonomous vacuum cleaner; JetBot AI+ – a Samsung AI-powered robotic vacuum) **5. Security & Surveillance** (e.g. Knightscope K5 – a robot used for patrolling and surveillance; Anybots QB – a telepresence robot for remote security monitoring)

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control for firm productivity, profits, total investment, the share of investment in software, total expenses, the ratio of personnel costs in total expenses, the value of property and equipment, being a subsidiary, having ICT specialists among employees, and the share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with the respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

Figure 4 shows similar estimation results to Figure 2 but distinguishes between industrial robots and service robots. The different panels in Figure 4 show how the ratio of migrants from each origin (with each level of education) to the total number of employees with that level of education correlates with the adoption of industrial and service robots. For the low-education group, firms adopting both industrial and service robots have a lower share of native workers compared with migrant workers. For the medium level of education, the share of non-EEA migrant workers is higher in firms adopting both types of robots, whereas the share of EEA workers is particularly lower in firms adopting industrial robots. While the share of native workers at the medium-education level is not statistically significantly related to robot adoption, there is a substitution of non-EEA migrant workers for EEA migrant workers. For the high-education group, the estimations indicate a preference for native workers over migrant workers in firms adopting industrial robots. In contrast, firms adopting service robots have a larger share of EEA migrant workers than the other two groups: natives and non-EEA migrants. The results presented in Figure A4 in Appendix A, using the three waves of the IKTU survey for the same specification, remain consistent with those in Figure 4.

Figure 5 shows similar estimation results to Figure 1 distinguishes between manufacturing sectors (shown in the top panels) and private service sectors (shown in the bottom panels). Manufacturing sectors (NACE sectors starting with letter C) are the ones that produce goods, while private services are sectors (NACE sectors starting with letter D-U) are those that produce services excluding public services. As robot databases like the International Federation of Robotics (IFR) indicate, industrial robots predominantly operate within manufacturing sectors, with only a limited number of service sectors adopting robotics technology. According to the IFR, these robotised service sectors include electricity and water supply (DtE); construction (F); scientific research and development; other professional, scientific, and technical activities; veterinary activities; and education (MtN&P). Therefore, it is insightful to examine whether robot adoption differs between manufacturing and service sectors.

Interestingly, the effects of robot adoption are more pronounced in manufacturing sectors, as the coefficients in the top panels are positive and statistically significant. This indicates that the number of employees is significantly larger in manufacturing firms that adopt robots than in those that do not despite controlling for various firm characteristics, such as assets, productivity and profits. However, within the category of low- and medium-educated workers, there is no statistically significant difference in the origin of workers employed in manufacturing firms that adopt robots compared to those that do not.

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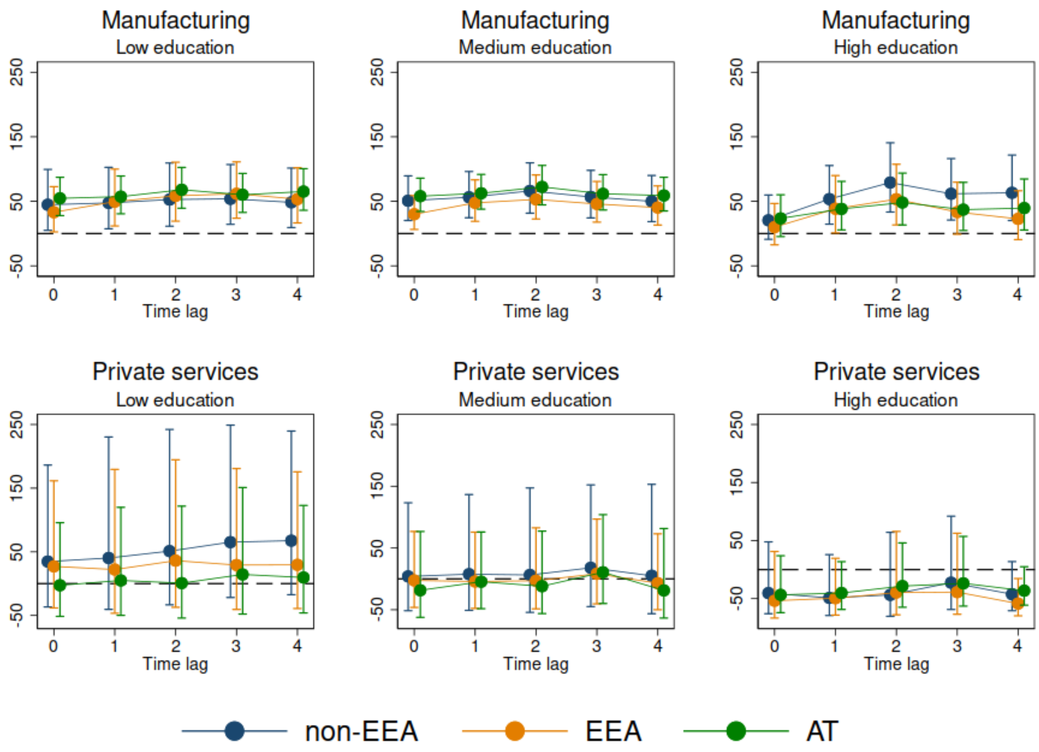
Figure 5 / Estimates of robot adoption – Percentage change in the *number* of employees, manufacturing and private service sectors (IKTU-2018 wave)



Notes: Exponentially transformed PPML regression coefficient for robot adoption with 95% confidence intervals are reported. Manufacturing includes NACE Rev 2 industry codes 10-33. The private service sectors include NACE Rev 2 industry codes 45-47, 49-53, 55, 56, 58-63, 64-66, 68-75, 77-82, 85-88 and 90-96. The dependent variable is the number of firm employees of the respective educational level and origin from the IKTU survey base year (2017) up to four years after the survey. The main independent variable takes the value of 1 when the firm reports adopting robots in the survey base year. All models control for firm productivity, profits, total investment, the share of investment in software, total expenses, the ratio of personnel costs in total expenses, the value of property and equipment, being a subsidiary, having ICT specialists among employees, and the share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with the respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

Figure 6 presents estimation results similar to those in Figure 2 but distinguishes between manufacturing sectors (shown in the top panels) and private service sectors (shown in the bottom panels). Although Figure 5 showed that the effects of robot adoption on the number of employees from different origins and with different educational levels were all positive and statistically significant for manufacturing firms, Figure 6 shows no significant effect of robot adoption in manufacturing firms on the share of migrant workers from different origins relative to the total number of employees at each educational level. This suggests that there is no clear distinction based on the origin of migrant workers, thus no compositional effects. Instead, manufacturing firms that adopt robots simply employ more workers overall than non-adopting firms.

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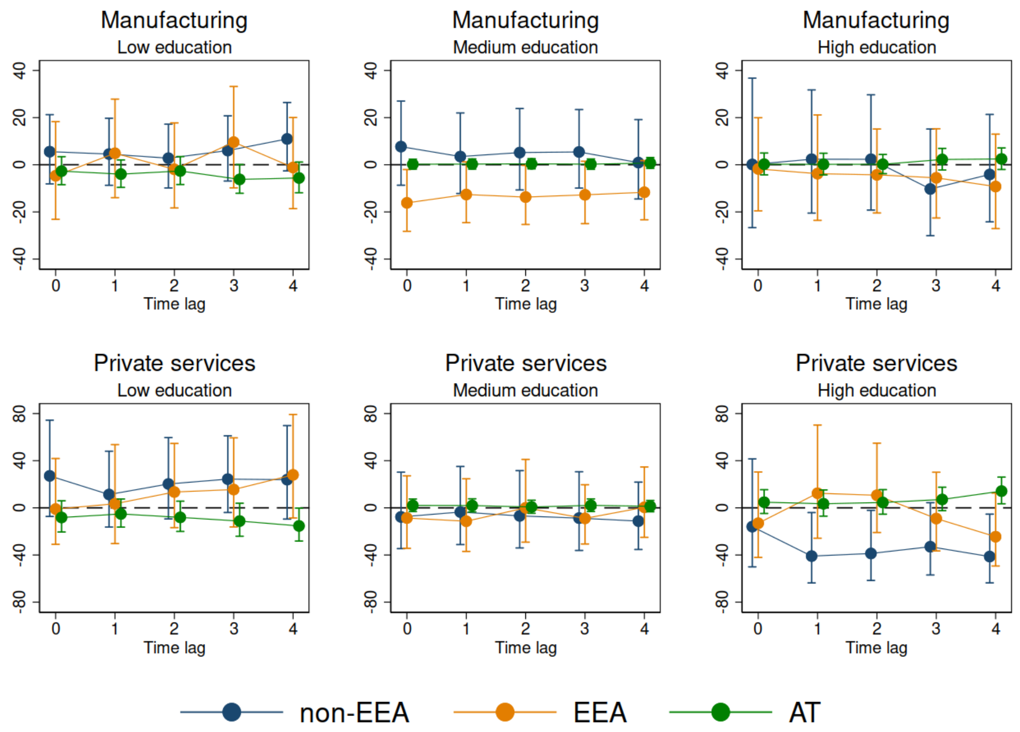
Figure 6 / Estimates of robot adoption – Percent change in the *ratio of employees within educational groups*, manufacturing and private service sectors (IKTU-2018 wave)



Notes: Exponentially transformed PPML regression coefficient for robot adoption with 95% confidence intervals are reported. Manufacturing includes NACE Rev 2 industry codes 10-33. The private service sectors include NACE Rev 2 industry codes 45-47, 49-53, 55, 56, 58-63, 64-66, 68-75, 77-82, 85-88 and 90-96. The dependent variable is the ratio of firm employees of the respective origin within low-, medium- and high-education groups from the IKTU survey base year (2017) up to four years after the survey. The main independent variable takes the value 1 when the firm reports adopting robots in the survey base year. All models control for firm productivity, profits, total investment, the share of investment in software, total expenses, the ratio of personnel costs in total expenses, the value of property and equipment, being a subsidiary, having ICT specialists among employees, and the share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

Figure 7 presents estimation results similar to those in Figure 1 but focuses mainly on industrial robots and distinguishing between manufacturing sectors (shown in the upper panels) and private service sectors (shown in the lower panels). Again, the effects of robot adoption are more pronounced in manufacturing sectors and for low- and medium-educated workers, as their coefficients in the upper panels are positive and statistically significant. This suggests that manufacturing firms that adopt robots employ more low- and medium-educated workers than those that do not. While the coefficients of robot adoption are statistically insignificant in the other models, they become negative for low-educated migrant workers employed by service firms that adopt robots. This could indicate that such service firms may rely more on native workers than on migrant workers.

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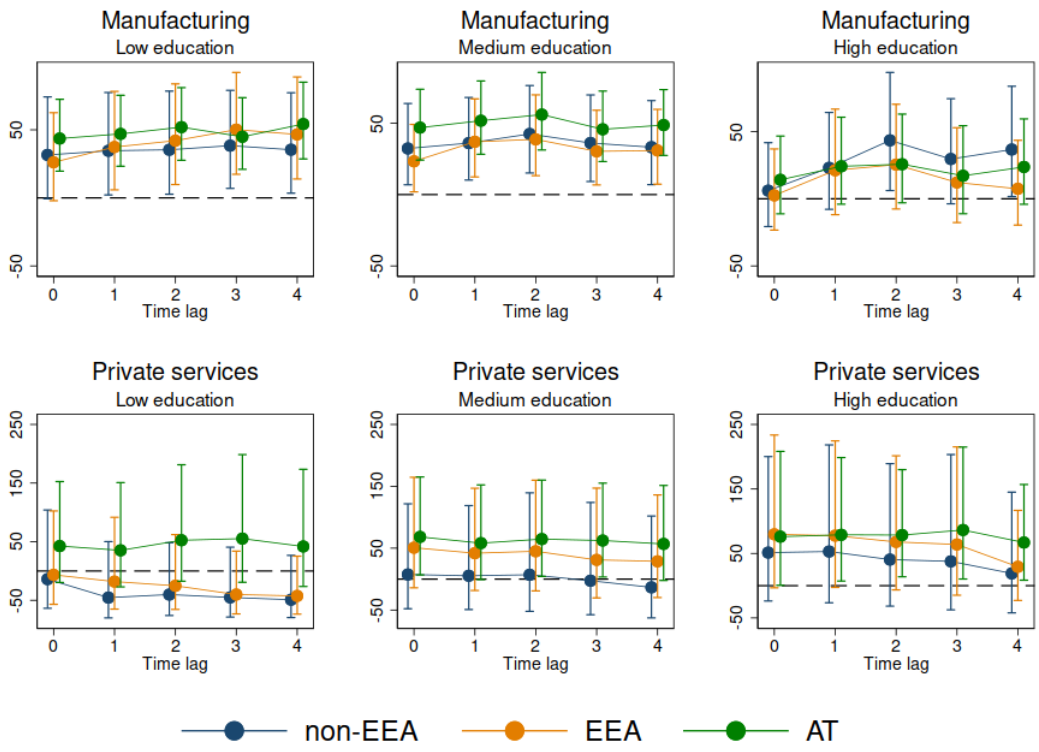
Figure 7 / Estimates of industry robot adoption – Percentage change in the *number* of employees, manufacturing and private service sectors (IKTU-2018 wave)



Notes: Exponentially transformed PPML regression coefficient for industry robot adoption with 95% confidence intervals are reported. Manufacturing includes NACE Rev 2 industry codes 10-33. The private service sectors include NACE Rev 2 industry codes 45-47, 49-53, 55, 56, 58-63, 64-66, 68-75, 77-82, 85-88 and 90-96. The dependent variable is the number of firm employees of the respective education level and origin from the IKTU survey base year (2017) up to four years after the survey. The main independent variable takes the value 1 when the firm reports adopting industry robots in the survey base year. All models control for firm productivity, profits, total investment, the share of investment in software, total expenses, the ratio of personnel costs in total expenses, the value of property and equipment, being a subsidiary, having ICT specialists among employees, and the share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

Figure 8 presents estimation results similar to those in Figure 2, but focuses exclusively on industrial robots and distinguishes between manufacturing sectors (shown in the upper panels) and private service sectors (shown in the lower panels). Although Figure 7 showed that the effects of industrial robot adoption on the number of employees from different origins with low and medium levels of education were all positive and statistically significant, Figure 8 shows that the adoption of industrial robots in manufacturing firms had no significant effect on the share of migrant workers from different origins in the total number of employees at each level of education. This suggests that there is no clear distinction based on the origin of the migrant workers. Instead, manufacturing firms that adopt industrial robots simply employ more workers overall than non-adopting firms. However, it is interesting to note that firms in the private service

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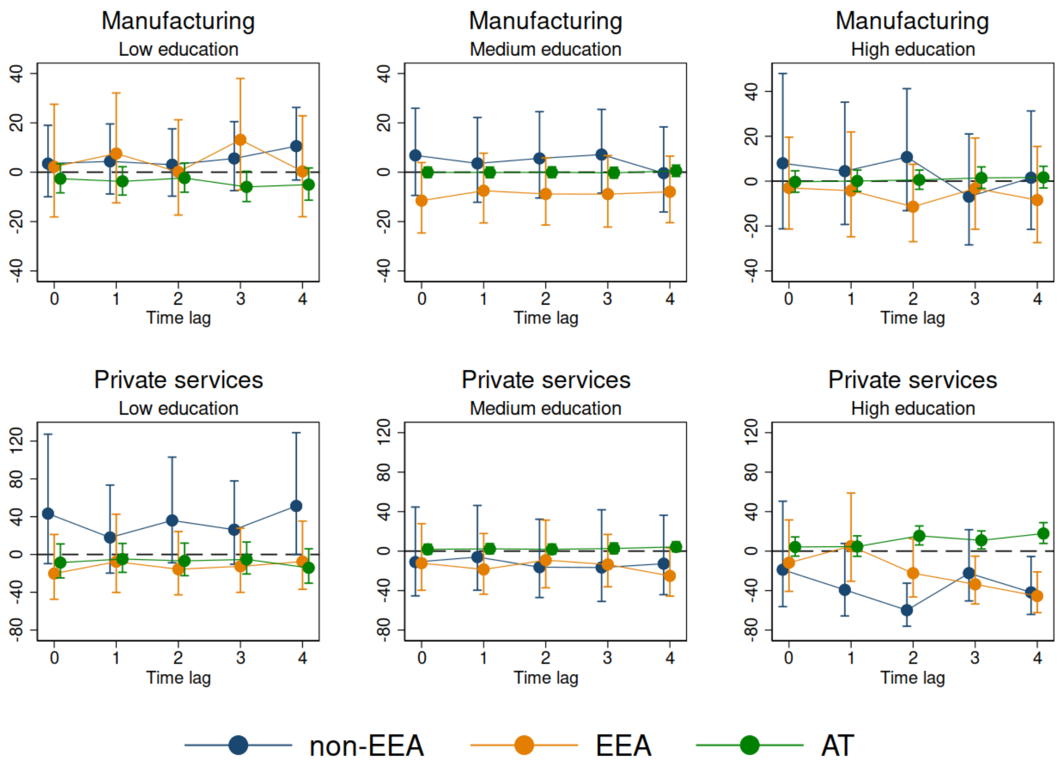
sectors that adopt industrial robots tend to gradually employ a larger share of highly educated native workers but a smaller share of highly educated migrant workers.

Figure 8 / Estimates of industry robot adoption – Percentage change in the *ratio of employees within education groups*, manufacturing and private service sectors (IKTU-2018 wave)



Notes: Exponentially transformed PPML regression coefficient for robot adoption with 95% confidence intervals are reported. Manufacturing includes NACE Rev 2 industry codes 10-33. The private service sectors include NACE Rev 2 industry codes 45-47, 49-53, 55, 56, 58-63, 64-66, 68-75, 77-82, 85-88 and 90-96. The dependent variable is the ratio of firm employees of the respective origin within low-, medium- and high-education groups from the IKTU survey base year (2017) up to four years after the survey. The main independent variable takes the value 1 when the firm reports adopting industry robots in the survey base year. All models control for firm productivity, profits, total investment, the share of investment in software, total expenses, the ratio of personnel costs in total expenses, the value of property and equipment, being a subsidiary, having ICT specialists among employees, and the share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with the respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

Figure 9 presents estimation results similar to those in Figure 1 but focuses primarily on service robots and distinguishes between manufacturing sectors (shown in the upper panels) and private service sectors (shown in the lower panels). Once again, the effects of robot adoption are more pronounced in manufacturing sectors across all education levels. Manufacturing firms that adopt service robots tend to employ a higher share of workers in all educational groups. However, in the service sector, firms that adopt service robots employ fewer medium- and high-educated workers than firms that do not adopt service robots.

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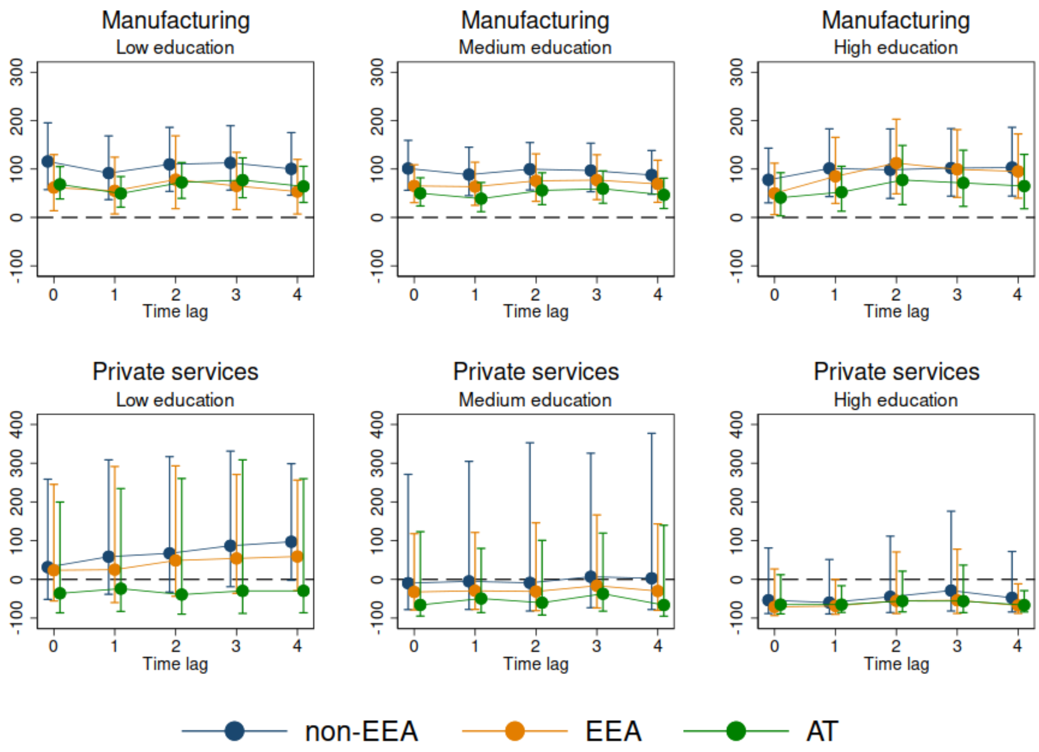
Figure 9 / Estimates of service robot adoption – Percentage change in the *number* of employees, manufacturing and private service sectors (IKTU-2018 wave)



Notes: Exponentially transformed PPML regression coefficient for service robot adoption with 95% confidence intervals are reported. Manufacturing includes NACE Rev 2 industry codes 10-33. The private service sectors include NACE Rev 2 industry codes 45-47, 49-53, 55, 56, 58-63, 64-66, 68-75, 77-82, 85-88 and 90-96. The dependent variable is the number of firm employees of the respective education level and origin from the IKTU survey base year (2017) up to four years after the survey. The main independent variable takes the value 1 when the firm reports adopting service robots in the survey base year. All models control for firm productivity, profits, total investment, the share of investment in software, total expenses, the ratio of personnel costs in total expenses, the value of property and equipment, being a subsidiary, having ICT specialists among employees, and the share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

Figure 10 presents estimation results similar to those in Figure 2 for firms adopting service robots but distinguishes between manufacturing sectors (shown in the upper panels) and private service sectors (shown in the lower panels). Although Figure 9 showed that the effects of service robot adoption on the number of employees from different origins and of different educational levels were all positive and statistically significant for manufacturing firms, Figure 10 shows that the adoption of service robots in manufacturing firms has no significant effect on the share of migrant workers from different origins in the total number of employees at each educational level. This suggests that there is no clear distinction based on the origin of migrant workers. Instead, manufacturing firms that adopt robots simply employ more workers overall than non-adopting firms.

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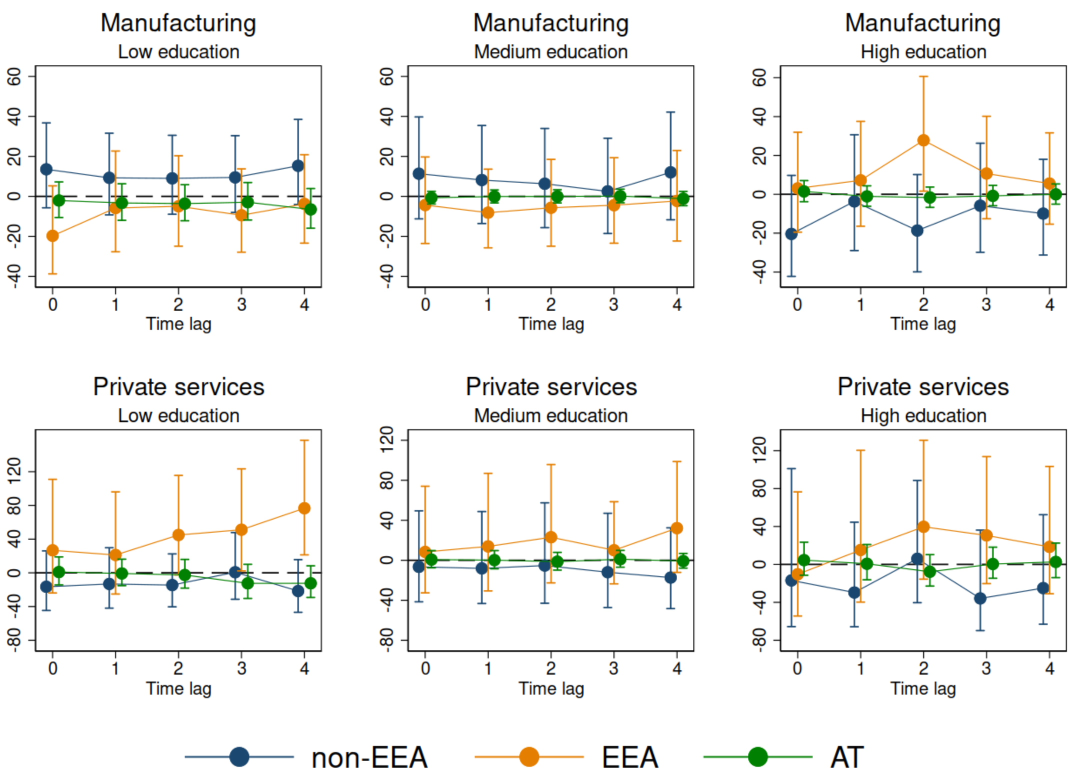
Figure 10 / Estimates of service robot adoption – Percentage change in the *ratio of employees within education groups*, manufacturing and private service sectors (IKTU-2018 wave)



Notes: Exponentially transformed PPML regression coefficient for robot adoption with 95% confidence intervals are reported. Manufacturing includes NACE Rev 2 industry codes 10-33. The private service sectors include NACE Rev 2 industry codes 45-47, 49-53, 55, 56, 58-63, 64-66, 68-75, 77-82, 85-88 and 90-96. The dependent variable is the ratio of firm employees of the respective origin within low-, medium- and high-education groups from the IKTU survey base year (2017) up to four years after the survey. The main independent variable takes the value 1 when the firm reports adopting service robots in the survey base year. All models control for firm productivity, profits, total investment, the share of investment in software, total expenses, the ratio of personnel costs in total expenses, the value of property and equipment, being a subsidiary, having ICT specialists among employees, and the share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

5.2 Individual-level transition analysis

5.2.1 Entering employment in firms in the sample of the IKTU-2018 survey

Figure 11 shows the probability of transitioning from employment in another firm, from unemployment, and from inactivity into employment in an IKTU-2018-surveyed firm based on the origin of the worker, their level of education, and firm robot adoption. The predicted probabilities from the multinomial logit estimation can be interpreted as percentage changes. As is evident from the results, the probability of finding employment in a surveyed firm is lowest for individuals

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who were unemployed compared to those who transition from employment in another firm or from inactivity across all educational levels, worker origins and types of firms (i.e. adopting and non-adopting firms). This suggests that unemployed individuals have greater difficulties in securing employment than those who were previously inactive. One possible explanation is that inactive individuals may have been engaged in education or training before entering the job market, making them more attractive candidates than those who were unemployed and actively seeking work. Additionally, individuals who are already employed have the highest probability of finding a job in another firm regardless of their educational level or the type of firm.

Furthermore, as indicated by the average wage of individuals reported alongside each point estimate, those entering a firm from inactivity generally receive lower wages than those entering from unemployment. This is true for individuals from the same origin and with the same level of education. Therefore, another important reason for the higher probability of employing individuals from the inactive pool rather than the unemployed pool is their lower wages.

Moreover, across all categories of individuals with medium and high levels of education – except for those with a high level of education who enter a firm from inactivity – we observe that natives earn the highest average wages, followed by EEA migrants, while non-EEA migrants receive the lowest average wages. This is true for both robot-adopting and non-adopting firms. However, among those with low levels of education, EEA migrant workers who join the surveyed companies earn the highest wages.

However, there is no clear pattern in terms of job positioning across different types of firms. The results are highly heterogeneous: for certain education levels and employment statuses, the coefficient is higher for adopting firms, while for others, it is higher for non-adopting firms. Therefore, no consistent trend can be identified in this regard.

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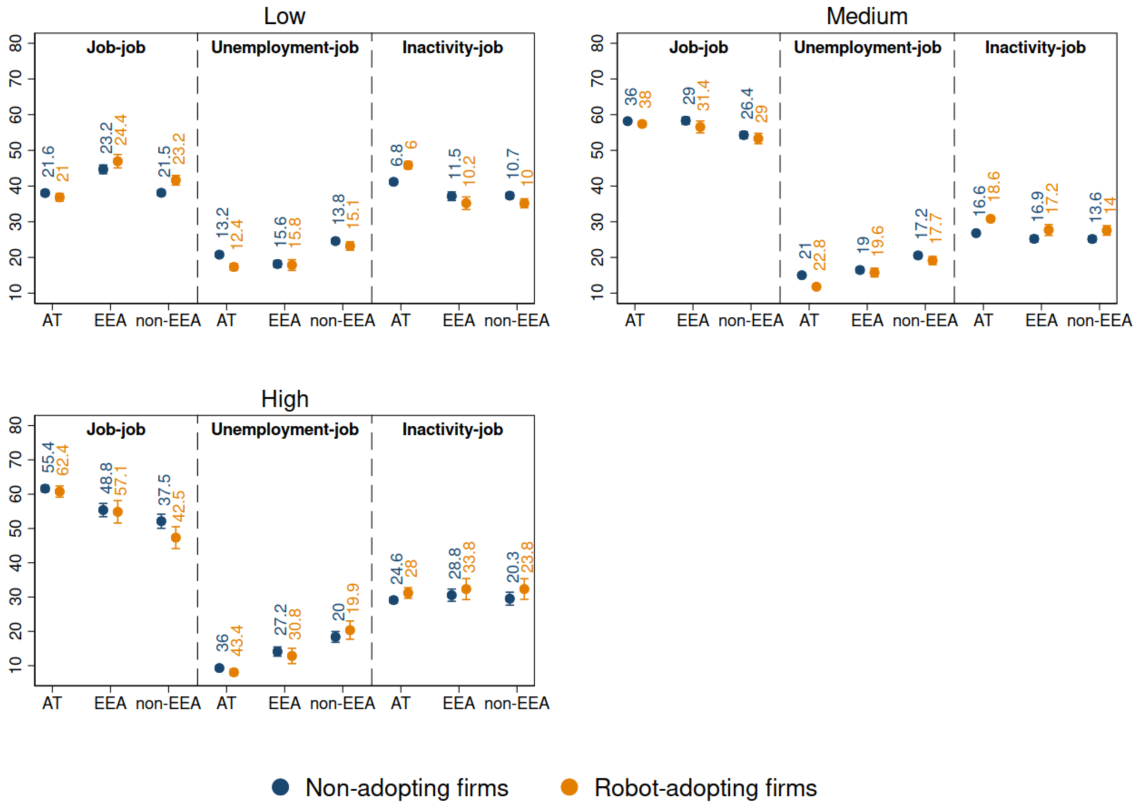
Figure 11 / Probability of transitioning from other employment, unemployment or inactivity to employment in an IKTU-2018-surveyed firm by worker origin, educational level and firm robot adoption – predicted probabilities from multinomial logit estimations (in %, dots) and average yearly gross wage upon transition (in thousands of euros, numbers)



Note: Results from multinomial logit regressions. Marginal effects with 95% confidence intervals are reported. The dependent variable is the transition from another employment, unemployment or inactivity to employment in a firm surveyed by the IKTU-2018 over the 2017-2021 period. The model follows specification (2) and is estimated across low-, medium- and high-educated worker samples.

Source: Statistics Austria; own calculations and illustration

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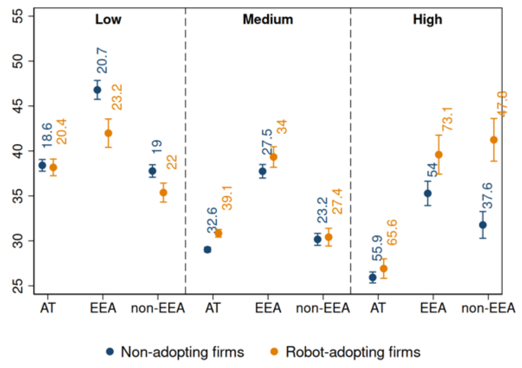
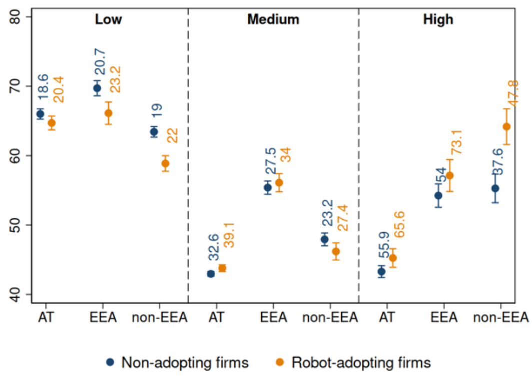
5.2.2 Exiting employment in firms in the sample of the IKTU-2018 survey

Figure 12 / Probability of transitioning out of employment in an IKTU-2018-surveyed firm by worker origin, educational level and firm robot adoption – predicted probabilities from binary logit estimations (in %, dots) and average gross yearly wage upon transition (in thousands of euros, numbers)

(i) Refernce group: firm total workforce as of 2021



(ii) Reference group: firm long-term workforce as of 2021



Note: Reference category 1 assumes workers who (i) were continuously employed at the firm over the 2017-2021 period or (ii) joined the firm during the observation period and stayed employed up until 2021 as a reference group of the dependent variable. Reference category 2 assumes only workers who were continuously employed at the firm over the 2017-2021 period as a reference group. Binary logit regression estimates. Marginal effects with 95% confidence intervals are reported. The dependent variable is withdrawing from employment in the IKTU-2018-surveyed firm over the 2017-2021 period. The model follows specification (3) and is estimated across low-, medium- and high-educated workers samples.

Source: Statistics Austria; own calculations and illustration

Figure 12 presents the probability of transitioning out of employment in the surveyed firm across different origins, education levels, and robot-adopting versus non-adopting firms. The results suggest that low-educated individuals have the highest probability of exiting employment across all models compared to medium- and high-educated individuals. Furthermore, among those with a low level of education, employment in robot-adopting firms is associated with a lower probability of job loss than in non-robot-adopting firms. This aligns with the earlier findings that robot-adopting firms employ a larger number of individuals with low levels of education.

In contrast, individuals with medium and high levels of education face a higher probability of exiting employment in robot-adopting than in non-adopting firms. The higher probability of unemployment for highly educated individuals in robot-adopting firms compared to non-adopting firms is more pronounced for migrant workers than for native workers. Thus, although entry into firms does not significantly differ by worker origin, highly educated natives are less susceptible to automation-driven job loss or firm exits than their migrant counterparts. This disparity may be attributed either to differences in abilities and skills or to structural discriminatory practices by firms favouring highly educated native workers over migrants.

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Moreover, as indicated by the wages reported alongside each point estimate, individuals who leave robot-adopting firms earn higher average wages than those leaving non-adopting firms regardless of their origin or educational level. This may suggest that robot-adopting firms are optimising costs by introducing automation and laying off higher-paid employees.

5.2.3 Exiting employment in firms in the sample of the IKTU-2018 survey versus changing jobs

Next, we analyse how transitions from employment in IKTU-2018-surveyed firms to employment in another firm, to unemployment or to inactivity differ by worker origin, educational level and firm robot adoption. We employ a specification similar to (2) but with the dependent variable being the transition of worker k (i) from employment in firm i to employment in another firm, (ii) from employment in firm i to unemployment, or (iii) from employment in firm i to inactivity. Estimated predicted probabilities are shown in Figure 13.

It shows that job-to-job transitions are the most likely to occur at all three levels of education. However, there are no significant differences between firms that adopt robots and those that do not. In fact, workers who leave a firm tend to find jobs in another firm regardless of their educational level. The probability of job loss leading to unemployment is the lowest across all three education levels.

Moreover, within each category and across all origin groups and educational levels, the average wage of individuals leaving robot-adopting firms is higher than that of those leaving non-adopting firms.

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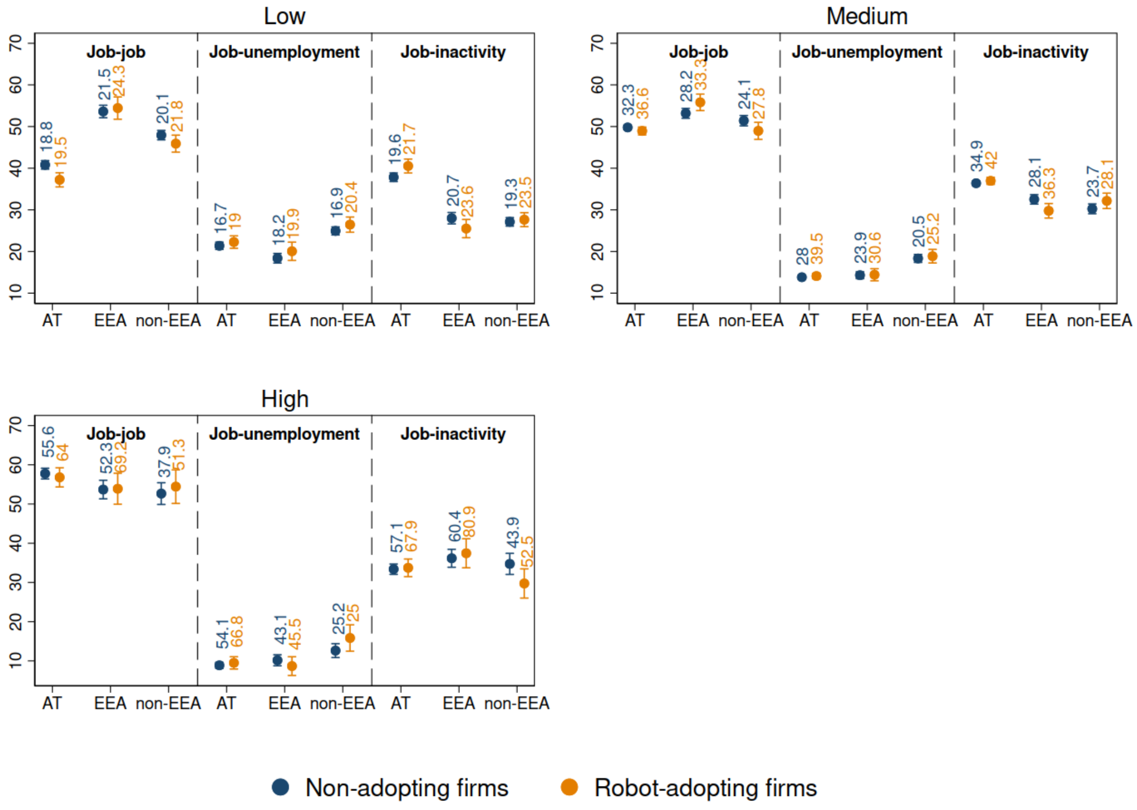
Figure 13 / Probability of transitioning out of employment in an IKTU-2018-surveyed firm to employment in another firm, unemployment or inactivity by worker origin, education level and firm robot adoption – predicted probabilities from multinomial logit estimations (in %, dots) and average yearly gross wage upon transition (in thousands of euros, numbers)



Note: Multinomial logit regression estimates. Marginal effects with 95% confidence intervals are reported. The dependent variable is transition from employment in an IKTU-2018-surveyed firm to employment in another firm, unemployment or inactivity over the 2017-2021 period. The model follows specification (2) and is estimated across low-, medium- and high-educated worker samples.

Source: Statistics Austria; own calculations and illustration

6 Summary and conclusions

This paper provides empirical evidence on the interplay between automation and migrant employment using comprehensive firm-level data from Austria. Our analysis yields several important findings:

First, we find a clear complementarity between robot adoption and employment, especially for low- and medium-educated workers. Firms that adopt robots tend to have larger workforces, suggesting that instead of largely displacing labour, automation complements it. Specifically, the

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employment of non-EEA migrants in low-skilled jobs increases significantly with robot adoption, highlighting their important role in maintaining firms' operations alongside automation technologies.

Second, our results show different effects depending on the origin and educational level of migrants. Non-EEA migrants, especially those with low and medium levels of education, experience positive employment outcomes in robot-adopting firms. Conversely, highly educated migrants appear to be somewhat disadvantaged relative to natives, suggesting potential barriers or mismatches in their integration into automated workplaces.

The observed complementarity between automation and employment for low- and medium-educated workers suggests that, rather than displacing labour, robots enhance job stability and demand within the secondary labour market (Doeringer and Piore 1971), in which non-EEA migrants are often concentrated. This supports the theory's concept of structural segmentation, implying that migrants play a crucial role in sustaining firms' operations, particularly in low-skilled roles, despite technological advancements. Furthermore, the differential impact based on migrants' educational levels reinforces the structural barriers characteristic of the dual labour market. While low- and medium-educated non-EEA migrants benefit from automation, highly educated migrants face relative disadvantages, indicating a potential mismatch between their qualifications and the demands of automated workplaces or a preference for native workers in high-skilled roles. These findings suggest that robot adoption may reinforce labour market segmentation while also creating opportunities for upskilling and mobility within the secondary labour market.

Third, a further distinction between industrial and service robots showed that service robots are more strongly correlated with employment growth than industrial robots. Moreover, positive effects of robot adoption are stronger in manufacturing sectors, highlighting sectoral disparities in the automation-employment nexus. This suggests that robots have greater potential to create jobs in goods manufacturing than in services, after controlling for output, despite the fact that industrial manufacturing typically involves routine tasks that are susceptible to automation. Some services require non-routine tasks that robots cannot easily replicate, whereas automated industrial production lines can readily reproduce goods from a given set of materials. Thus, in service sectors, the effects are more heterogeneous. Furthermore, within manufacturing sectors, the adoption of service robots generates employment growth across all three educational levels, whereas industrial robots do not significantly increase employment for highly educated workers. This implies that service robots may require highly educated employees to operate sophisticated software systems, such as those used in laboratories. In contrast, industrial robots, performing repetitive and routine tasks (e.g. assembly lines), often demand technical skills attainable at lower education levels. Policy interventions could facilitate the employment of highly educated workers by supporting the adoption of service robots rather than industrial robots within manufacturing sectors. However, policy measures could encourage the employment of workers with low and medium educational levels through the adoption of any type of robot in manufacturing.

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Fourth, the individual-level transition analysis highlights heterogeneous outcomes in the probability of employment transitions influenced by robot adoption. The unemployed face greater barriers to employment compared to previously inactive individuals, partly due to the lower wage demands of the latter. Furthermore, while low-educated workers have a lower probability of job exit in robot-adopting firms, highly educated workers, especially migrants, face increased risk of job exit in such firms. Notably, workers leaving robot-adopting firms generally earn higher average wages, suggesting that automation may induce firms to optimise labour costs by reducing higher-paid positions. These dynamics highlight the importance of policies that address wage and skill disparities to mitigate the uneven labour market impacts of automation.

In policy terms, these findings underline the importance of targeted interventions by EU and national policy makers. Policies should focus on promoting skills and retraining initiatives to enable workers, especially highly educated ones, to better integrate into technologically advanced roles. Moreover, there is a need for proactive labour market policies to reduce segmentation and ensure a fair distribution of the productivity gains from automation.

To conclude, if complemented with effective integration and education policies, automation can substantially alleviate labour shortages and improve productivity. However, policy makers must address the emerging inequalities and support migrants' transitions to higher-skilled, less vulnerable employment segments so as to ensure inclusive benefits from technological advancements.

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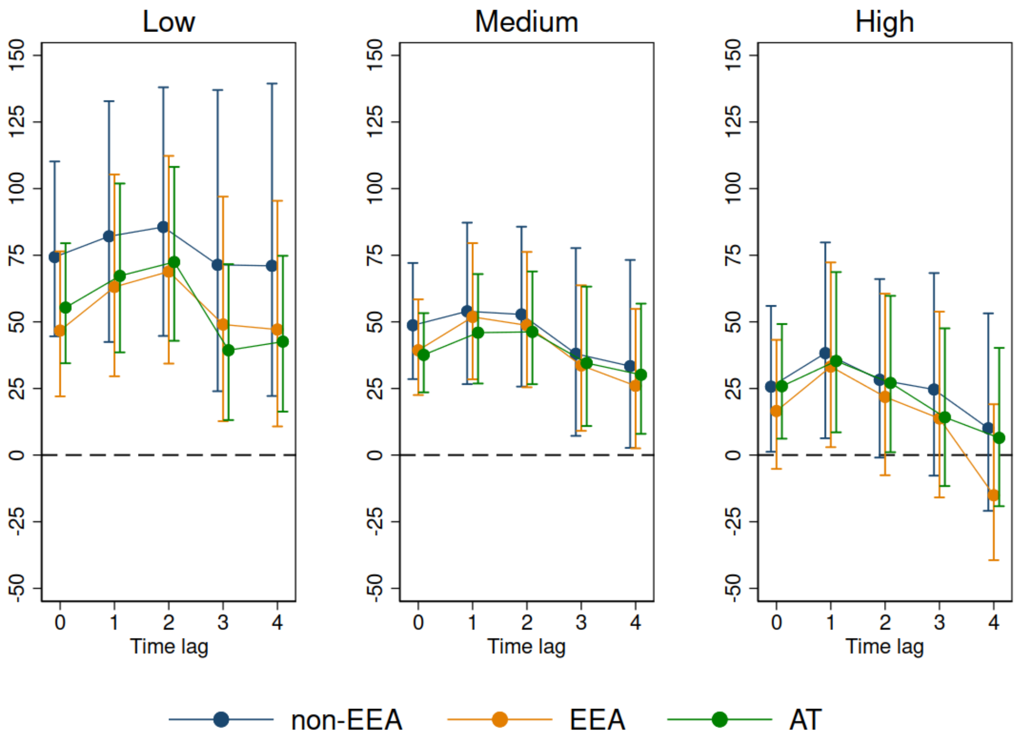
Appendix A

Supplementary figures: Estimates based on the pooled IKTU-2018, IKTU-2020 and IKTU-2022 sample

Figure A1 / Estimates of robot adoption – Percent change in the *number* of employees (all IKTU waves)



Notes: Exponentially transformed PPML regression coefficient for robot adoption with 95% confidence intervals are reported. The dependent variable is number of firm employees of respective educational level and origin from the IKTU survey base year (2017, 2019 and 2021 for IKTU-2018, IKTU-2020 and IKTU-2022, respectively) up to four years after the survey. The main independent variable takes a value of 1 when firm reports adopting robots in the survey base year. All models control for firm productivity, profit, total investment, share of investment in software, total expenses, ratio of personnel costs in total expenses, value of property and equipment, being a subsidiary, having ICT specialists among employees, and share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

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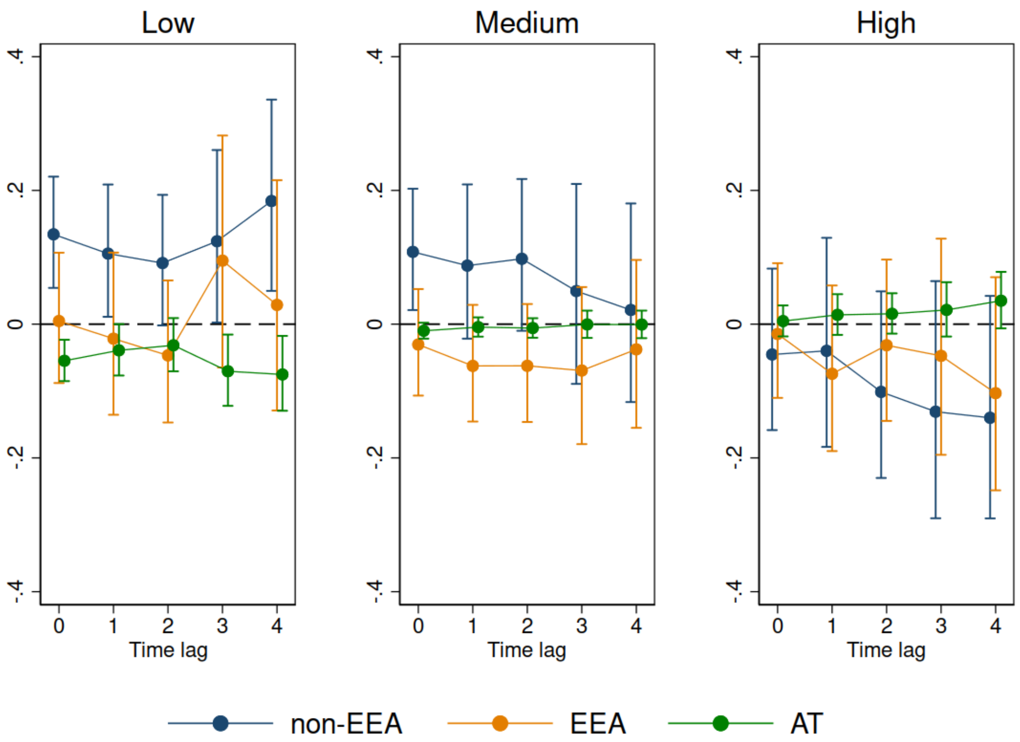
Figure A2 / Estimates of robot adoption – Percentage point change in the *ratio* of employees within educational groups (all IKTU waves)



Notes: Exponentially transformed PPML regression coefficient for robot adoption with 95% confidence intervals are reported. The dependent variable is a ratio of employees of respective origin in low-, medium- and high-education groups from the IKTU survey base year (2017, 2019 and 2021 for IKTU-2018, IKTU-2020 and IKTU-2022, respectively) up to four years after the survey in firm total employment. The main independent variable takes value of 1 when firm reports adopting robots in the survey base year. All models control for firm productivity, profit, total investment, share of investment in software, total expenses, ratio of personnel costs in total expenses, value of property and equipment, being a subsidiary, having ICT specialists among employees, and share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

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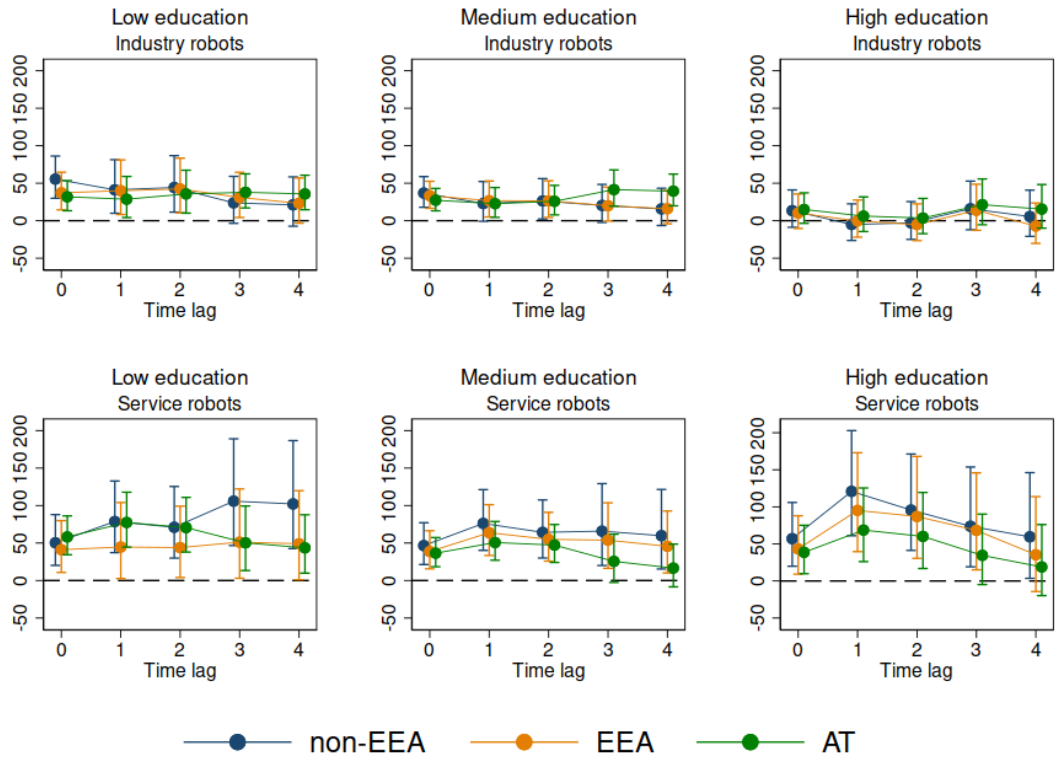
Figure A3 / Estimates of industry and service robot adoption – Percent change in the *number* of employees (all IKTU waves)



Notes: Exponentially transformed PPML regression coefficient for industry and service robot adoption with 95% confidence intervals are reported. The dependent variable is number of firm employees of respective education level and origin from the IKTU survey base year (2017, 2019 and 2021 for IKTU-2018, IKTU-2020 and IKTU-2022, respectively) up to four years after the survey. The main independent variable takes value of 1 when firm reports adopting industry or service robots in the survey base year. All models control for firm productivity, profit, total investment, share of investment in software, total expenses, ratio of personnel costs in total expenses, value of property and equipment, being a subsidiary, having ICT specialists among employees, and share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

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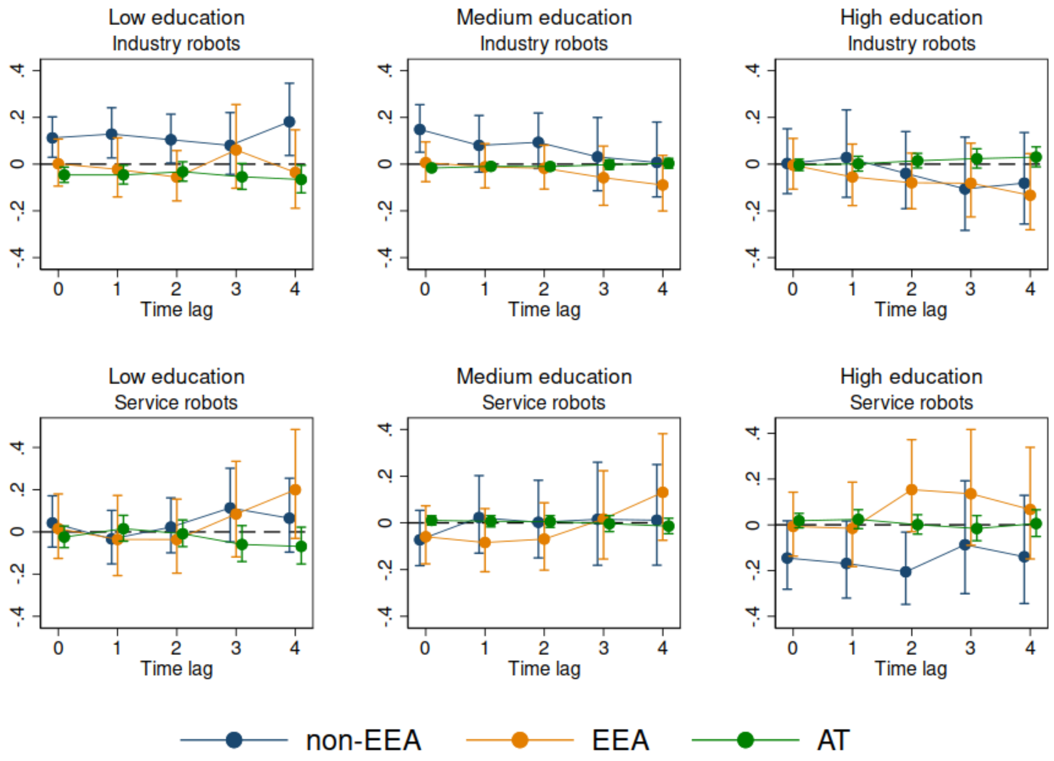
Figure A4 / Estimates of industry and service robot adoption – Percentage point change in the *ratio* of employees within educational groups (all IKTU waves)



Notes: Exponentially transformed PPML regression coefficient for industry and service robot adoption with 95% confidence intervals are reported. The dependent variable is a ratio of employees of respective origin in low-, medium- and high-education groups from the IKTU survey base year (2017, 2019 and 2021 for IKTU-2018, IKTU-2020 and IKTU-2022, respectively) up to four years after the survey in firm total employment. The main independent variable takes value of 1 when firm reports adopting industry or service robots in the survey base year. All models control for firm productivity, profit, total investment, share of investment in software, total expenses, ratio of personnel costs in total expenses, value of property and equipment, being a subsidiary, having ICT specialists among employees, and share of part-time contracts. All control variables, except having ICT specialists among employees, are estimates with respective time lag. All models account for interaction year and industry as well as for industry and NUTS 2 region fixed effects.

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Appendix B

Table B1 / Descriptive statistics – IKTU-2018 wave

Panel A: Robot-adopting firms	Δt=0	Δt=1	Δt=2	Δt=3	Δt=4
Firm workforce:					
Non-EEA, low education (% in education group)	23.47	22.98	23.63	24.05	24.22
EEA, low education (% in education group)	10.93	12.38	12.65	13.35	14.48
AT, low education (% in education group)	65.60	64.64	63.72	62.60	61.30
Non-EEA, medium education (% in education group)	7.12	7.40	7.45	7.29	7.64
EEA, medium education (% in education group)	6.55	6.80	7.43	7.48	7.70
AT, medium education (% in education group)	86.33	85.81	85.12	85.23	84.66
Non-EEA, high education (% in education group)	8.32	8.95	9.01	9.07	8.97
EEA, high education (% in education group)	12.65	12.62	12.85	12.10	12.00
AT, high education (% in education group)	79.03	78.43	78.15	78.83	79.03
Firm profile and performance:					
Productivity (in tsd. Euro)	339.9	342.6	345.2	320.5	369.6
Profit (in tsd. Euro)	18375.9	15662.7	20052.3	15396.6	18874.2
Property and equipment (in tsd. Euro)	9422.9	9240.2	10222.5	10280.7	11194.1
Investment (in tsd. Euro)	10066.3	10218.5	11007.8	11071.2	12256.6
Investment in sofrware (% of total)	5.3	4.2	4.4	5.8	6
Personnel costs (% of total)	27.7	27.9	28.2	29.1	27.1
Total expenses (in tsd. Euro)	192200.	210019.2	215794.6	205114.8	228405.2
Share of parttime workers (%)	11.2	11.2	12.1	12.2	12.7
ICT professionals among employees (%)			82.7		
Manufacturing sector (%)			80.9		
Private services sector (%)			14.7		
Transitions into and out of firm employment:					
Job-to-job in transition (%)			51.9		
Unemployment-to-job in transition (%)			14.1		
Inactivity-to-job in transition (%)			34		
Job-to-job out transition (%)			45.4		
Job-to-unemployment out transition (%)			15.3		
Job-to-inactivity out transition (%)			39.3		
N			382		

Note: In and out transitions refer to the 2017-2021 period.

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Panel B: Non-adopting firms	Δt=0	Δt=1	Δt=2	Δt=3	Δt=4
Firm workforce:					
Non-EEA, low education (% in education group)	24.32	24.86	24.54	24.29	24.71
EEA, low education (% in education group)	16.04	16.53	17.38	17.41	18.28
AT, low education (% in education group)	59.64	58.61	58.08	58.30	57.00
Non-EEA, medium education (% in education group)	9.30	9.73	9.73	9.57	9.97
EEA, medium education (% in education group)	10.68	10.42	10.71	10.80	11.18
AT, medium education (% in education group)	80.02	79.86	79.56	79.63	78.85
Non-EEA, high education (% in education group)	12.99	14.26	14.41	13.88	15.18
EEA, high education (% in education group)	15.95	15.80	16.00	15.67	15.88
AT, high education (% in education group)	71.06	69.95	69.58	70.45	68.94
Firm profile and performance:					
Productivity (in tsd. Euro)	274.9	439.3	365.4	343.6	307.6
Profit (in tsd. Euro)	2899.6	3445.1	3303.7	2660.3	4647.6
Property and equipment (in tsd. Euro)	2176.7	2301.8	2509.6	2337.5	2714.8
Investment (in tsd. Euro)	2334.8	2477.6	2752.1	2642	2939
Investment in sofrware (% of total)	5.2	5.2	4.9	5.5	5.5
Personnel costs (% of total)	37.6	38	37.5	38	36.9
Total expenses (in tsd. Euro)	43685.8	47078.28	48454.63	45884.97	50319.09
Share of parttime workers (%)	24.8	25.1	24.9	25.1	25.3
ICT professionals among employees (%)			38.2		
Manufacturing sector (%)			19.2		
Private services sector (%)			66		
Transitions into and out of firm employment:					
Job-to-job in transition (%)			52.3		
Unemployment-to-job in transition (%)			17.4		
Inactivity-to-job in transition (%)			30.3		
Job-to-job out transition (%)			54.2		
Job-to-unemployment out transition (%)			15.5		
Job-to-inactivity out transition (%)			30.3		
N			2437		

Note: In and out transitions refer to the 2017-2021 period.

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Panel C: Industry-robot-adopting firms	Δt=0	Δt=1	Δt=2	Δt=3	Δt=4
Firm workforce:					
Non-EEA, low education (% in education group)	23.10	22.66	23.31	23.52	24.05
EEA, low education (% in education group)	11.02	12.22	12.40	13.12	14.07
AT, low education (% in education group)	65.88	65.12	64.29	63.36	61.88
Non-EEA, medium education (% in education group)	7.06	7.24	7.30	7.10	7.28
EEA, medium education (% in education group)	6.26	6.48	6.90	6.96	7.20
AT, medium education (% in education group)	86.67	86.28	85.80	85.94	85.52
Non-EEA, high education (% in education group)	8.30	8.93	8.61	8.83	8.71
EEA, high education (% in education group)	12.18	11.98	11.66	11.40	11.15
AT, high education (% in education group)	79.52	79.10	79.73	79.77	80.14
Firm profile and performance:					
Productivity (in tsd. Euro)	318.1	328	329.9	307.1	353.4
Profit (in tsd. Euro)	13781.7	12645.5	16184.6	12604.2	15344.7
Property and equipment (in tsd. Euro)	8670.9	8669.2	9493.8	8950.4	9829.7
Investment (in tsd. Euro)	9288.5	9303	10075.8	9551.4	10807
Investment in sofrware (% of total)	5.1	4.2	4	5.6	5.8
Personnel costs (% of total)	27.8	28	28.3	29.2	27.1
Total expenses (in tsd. Euro)	179692.2	196162.6	200921.6	185976.4	205994
Share of parttime workers (%)	10	10	10.7	11	11.4
ICT professionals among employees (%)			84.5		
Manufacturing sector (%)			86.3		
Private services sector (%)			10.2		
Transitions into and out of firm employment:					
Job-to-job in transition (%)			52.5		
Unemployment-to-job in transition (%)			11.8		
Inactivity-to-job in transition (%)			35.7		
Job-to-job out transition (%)			44.9		
Job-to-unemployment out transition (%)			12.9		
Job-to-inactivity out transition (%)			42.2		
N			343		

Note: In and out transitions refer to the 2017-2021 period.

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Panel D: Service-robot-adopting firms	Δt=0	Δt=1	Δt=2	Δt=3	Δt=4
Firm workforce:					
Non-EEA, low education (% in education group)	25.55	24.90	26.03	27.47	26.23
EEA, low education (% in education group)	10.24	13.29	13.56	14.18	17.09
AT, low education (% in education group)	64.21	61.81	60.40	58.35	56.68
Non-EEA, medium education (% in education group)	7.54	7.91	7.95	8.01	8.74
EEA, medium education (% in education group)	7.91	8.23	9.70	9.57	9.76
AT, medium education (% in education group)	84.55	83.86	82.35	82.43	81.51
Non-EEA, high education (% in education group)	7.98	8.52	9.76	9.87	9.85
EEA, high education (% in education group)	14.39	14.79	17.00	15.27	15.02
AT, high education (% in education group)	77.64	76.69	73.24	74.86	75.14
Firm profile and performance:					
Productivity (in tsd. Euro)	454.6	442.9	442.7	411	477.1
Profit (in tsd. Euro)	34516.9	29466.5	40660.6	29376.5	36280.5
Property and equipment (in tsd. Euro)	15645	15674.7	18255.2	20219.9	23155.4
Investment (in tsd. Euro)	1673857	1777239	1966241	2157461	2464200
Investment in sofrware (% of total)	5.3	3.9	5.5	6.1	6.5
Personnel costs (% of total)	25.3	25.8	26.3	26.4	24.6
Total expenses (in tsd. Euro)	314577.1	363445.5	372927.1	361708.4	410468.6
Share of parttime workers (%)	15.8	15.0	16.2	15.8	16.3
ICT professionals among employees (%)			82.1		
Manufacturing sector (%)			64.3		
Private services sector (%)			29.5		
Transitions into and out of firm employment:					
Job-to-job in transition (%)			50.1		
Unemployment-to-job in transition (%)			16.3		
Inactivity-to-job in transition (%)			33.6		
Job-to-job out transition (%)			44.6		
Job-to-unemployment out transition (%)			17.2		
Job-to-inactivity out transition (%)			38.2		
N			112		

Note: In and out transitions refer to the 2017-2021 period.

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