Post-Automation Workforce Dynamics in (Non-)Multinationals

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Abstract

We estimate the impact of automation on worker separations and wages across Multinationals (MNEs) and domestic firms within the matched employer-employee dataset of the Netherlands. In MNEs, spikes in automation costs lead to a 24% separation rate, with the remaining workforce experiencing 2% wage growth. Higher-educated workers, those with a background in ICT and Sciences, and managers gain 5-8% wage growth. In contrast, domestic firm automation spikes lead to a 11% separation rate, with remaining workers experiencing a 1.4% wage decline, mostly confined to lower-educated workers. The difference is not explained by flexible contracts in MNEs, exports, imports, or industry. Firm-level hires reduce in both types of firms. Additionally, we document that firms' spikes in ICT investments raise MNE wage growth, while they lower wage growth in domestic firms. Machinery investments show no differential impact between MNEs and domestic firms.

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1 Introduction

Globalization has accelerated the integration of automation technologies such as industrial robots, machine learning, and artificial intelligence into business operations, raising concerns about increasing inequalities in job opportunities and wages driven by skill-biased technological change (e.g., Autor et al., 2013; Helpman et al., 2017). At the same time, the global technological shift prompts governments to extend large budgets towards attracting and retaining Multinational Enterprises (MNEs), in the hope that these firms benefit local workers. Yet, systematic evidence on how automation in MNEs affects local workers is lacking.

While some studies indicate productivity gains and employment growth from automation (e.g., Koch et al., 2021), others highlight concerns about worker displacements and growing wage disparities (e.g., Acemoglu and Restrepo, 2019). Persistent differences in productivity levels across firms (Syverson, 2011) suggest that firm-specific characteristics, such as workforce composition (Bender et al., 2018) and management practices (Bloom and Van Reenen, 2007; Giorcelli, 2019) relate to the firm's capacity to adopt and benefit from new technologies (Acemoglu et al., 2022). MNEs, which are characterized by higher productivity and a more skilled workforce (e.g., Girma and Görg, 2007; Koch and Smolka, 2019), often adopt more standardized production processes than domestic firms (e.g. Bircan, 2019), potentially leading to distinct automation impacts on their workers. In this paper, we explore the differential impact of automation on worker separations and wages within MNEs and domestic firms, documenting that automating MNEs separate more and pay higher wages.

We employ unique employer-employee matched data from the Netherlands, which allows us to track the employment and hourly wage trajectories of workers in automating firms for the years 2010 to 2021. Our measure of firm-level automation derives from a survey by Statistics Netherlands, which specifically collects details on firms' costs for third-party automation services. Compared to automation measures based on imports, automation costs offer a broad measure of automation across all industries and firm sizes. Drawing on additional administrative records, we comprehensively identify foreign and Dutch multinationals within the data. Our dataset covers approximately 22,000 firms and 2.1 million workers annually, capturing about 30% of the Dutch labor market. This extensive coverage allows us to discern the nuanced effects of automation on workers in MNEs and domestic firms.

We study the impact of significant, lumpy investments in firms' automation costs on worker separations and wages. Extending the methodology from Bessen et al. (2023), we identify an automation event as the initial substantial spike in a firm's automation costs relative to its usual operational costs. Exploiting the automation event, we employ a triple difference-in-differences regression model that isolates the effects of automation simultaneously for MNEs and domestic firms. Our approach compares the change within incumbent workers at automating firms to the change within their matched counterparts in firms that automate later, with matching based on 2-digit industries, employer size, and wage trajectories before automation.

Our results highlight distinct differences in the automation response of MNEs and domestic firms. In MNEs, automation leads to about 10% of the incumbent workforce separating in the automation year and 24% by the fourth year. This represents a 70% increase in separations, compared to the baseline separation rate of one third among matched control workers in later-automating firms. Workers who remain in the MNE accumulate a 1.6% wage premium over the same time, equating to around 16% higher wage growth than the control workers. In stark contrast, domestic firms separate less after automation, with about 11% of incumbents leaving eventually. Furthermore, the wage trajectory of non-separated workers diverges negatively, as they experience a 1.4% wage decrease in domestic firms by the fourth year post-automation. These trends are consistent across both manufacturing and service sectors and broadly extend to hiring practices. In a complementary firm-level analysis, we show the number of new hires contracts by about half in both MNEs and domestic firms post-automation, while new hires in domestic firms earn up to 6% less on average.

Several plausible differences between MNEs and domestic firms do not account for the differential automation effect. Higher flexibility in MNE workers' contracts offers one possible explanation, as temporary contracts are easier to terminate than permanent contracts under Dutch labor regulations. Yet, only 1.5% of the MNE workforce exits under temporary contracts, accounting for just 6% of total MNE separations, whereas domestic firm workers experience temporary contract separations at a rate of 3.4%, representing about a third of their total separations. Furthermore, we test whether firms' international trade activity, the intensity of automation investments, and 2-digit industry explain the difference. However, controlling for these factors in our estimation produces quantitatively similar results on the differential impact of automation on separations and wages in MNEs and domestic firms.

In dissecting the automation effect within MNEs and domestic firms, we document that automation impacts different segments of the workforce. The stylized facts for domestic firms align with skill-biased technological change theories that predict productivity and labor demand increases for high-skilled workers relative to lower-skilled workers (Katz and Murphy, 1992; Autor et al., 2006). We find that domestic firms separate less from their high-educated workers relative to their lower-educated workers, and pay high-educated workers about 2.7% more wage growth over time.

In contrast, automation-induced separations in MNEs are uniformly distributed among high- and low-educated workers, suggesting greater organizational change in MNEs than domestic firms. Aligning broadly with studies that highlight organizational change around automation (e.g., Dixon et al., 2021; Dauth, Findeisen, Suedekum and Woessner, 2021; Humlum, 2022), we find that high-educated workers and those with a technical background reach up to 5% higher wage growth post-automation in MNEs, while workers of lower education see no change in wage growth. Moreover, managers in MNEs benefit from up to 8% higher wage growth and relatively lower separation rates post-automation than non-managers, contrasting domestic firm automation, which leaves managers noticeably unaffected.

Within an additional dataset on firms' investments in Information and Communications Technology (ICT) and Machinery, we contrast the impact of general firm-level investments in such technologies to the investments in automation costs. While spikes in firms' ICT investments lead to a slight increase in wage growth in MNEs, they decrease wages in domestic firms, analogous to the overall differential wage dynamics of automation costs. However, ICT investments impact separations less, as they remain comparably low and similar between MNEs and domestic firms. Spikes in Machinery investments show a uniform effect across both types of firms, raising worker separations slightly, without significantly affecting wage trajectories.

Only few studies document the impact of automation on individual workers, often focusing on the effects of industrial robots within manufacturing (e.g., Dauth, Findeisen, Suedekum and Woessner, 2021; Acemoglu et al., 2023; Humlum, 2022). For instance, Acemoglu and Restrepo (2019) find modest wage increases and stable separation rates among a small sample of Dutch workers in robot-adopting firms, highlight wage compression for directly-affected blue-collar workers and increases for indirectly-affected workers. Similarly, Dauth, Findeisen, Suedekum and Woessner (2021) observe that German workers transition to higher-wage positions within their firms post-robot adoption, rather than separating.

Our paper extends these findings by exploring a broader range of automation technologies beyond just industrial robots, using comprehensive matched employer-employee data from the Netherlands. We identify higher separation probabilities across all workers and document significant differences in the impacts of automation on workers in MNEs and domestic firms. The broad spectrum of technologies captured in automation costs may partially explain the higher separation rates that we find. In complementary analyses, we show that firms' investments in Machinery lead to lower separation rates than automation costs. The discrepancy may also stem from the related studies' counterfactual of workers in non-automating firms. Instead, we closely match incumbent workers in automating firms to those in firms that automate later, recognizing that the trajectories of automating and non-automating firms diverge significantly. Moreover, by employing the full matched employer-employee data of the Netherlands, we track all workers of automating firms. This allows for a novel examination of the distinct distributional consequences of automation within and across firm types. Our findings show that automation in MNEs leads to substantial worker separations but also higher wage gains for remaining high-skilled employees, including managers. Conversely, domestic firms experience fewer separations but wage declines, especially among lower-skilled workers.

Most related to our study is Bessen et al. (2023), who examine the broad labor market implications of automation cost spikes in Dutch firms, highlighting important general effects such as total earnings losses and increased non-employment. Building on this, our paper employs newer, more detailed employer-employee matched data, enabling us to dissect within-firm impacts on hourly wages, a more direct measure of productivity effects than workers' total earnings. Our within-firm perspective reveals that while remaining workers in MNEs experience wage growth, potentially reflecting productivity increases, those in domestic firms face wage declines, indicating less favorable adjustments. Particularly, automation in MNEs disproportionately benefits managers, suggesting significant organizational changes in response to automation. Moreover, our findings uncover that separation rates in domestic firms align with those found by Bessen et al. (2023), but MNEs exhibit substantially higher separations of up to 24%. In an additional firm-level analysis, we show that these elevated separations are not offset by corresponding increases in hiring.

Our findings on automation in MNEs also contribute to the literature on technological change within multinationals (e.g., Guadalupe et al., 2012; Koch et al., 2021). Guadalupe et al. (2012) show that foreign-acquired firms in Spain increase innovation and adopt foreign technologies. Using a similar sample, Koch et al. (2021) document that foreign acquisitions raise the level of technology and average skill of the firms' workforce. By leveraging variations in firms' automation events, we provide causal evidence at the worker level, indicating that automation leads to job displacement but also productivity increases, as evident in the higher wages that MNEs pay to managers and high-skilled workers post-automation.

2 Data

We construct a yearly employer-employee matched dataset for the Netherlands covering the period from 2010 to 2021. Our dataset merges a firm-level survey on firms' investments in automation with detailed administrative databases from Statistics Netherlands at both the firm and worker levels. It allows us to track worker movements in and out of employment across all firms, combined with the employers' MNE and domestic firm status, and importantly, their investments in automation.

Data on firm-level automation derives from the "Production Statistics" (Productiestatistiek), an annual survey of non-financial private firms that is available from the year 2000. This survey captures all firms with more than 50 employees and a sample of smaller firms, including a question on automation costs. Automation costs refer to payments for external automation services, including equipment and software not recorded as assets on the firm's balance sheet. While the exact automation technologies are not directly observed, automation costs serve as an official book-keeping entry that allows us to accurately identify firms' investments in automation. Using data from another small firm-level survey by Statistics Netherlands, Bessen et al. (2023) demonstrate that these costs correlate with process innovations within firms.[1] This includes a wide-range of technologies such as Customer Relationship Management (CRM) and Enterprise Resource Planning (ERP), as well as technologies for electronic data processing and big data analysis. Importantly, automation costs contrast with measures based on the import of automation technologies, which only capture imports of physical automation technologies.

The design of the automation cost survey implies that larger firms are sampled more frequently. We focus on firms that report automation costs at least every third year over the period 2010 to 2021, mitigating the influence of reporting differences when we compare lumpy investments in automation costs between MNEs and domestic firms. In addition, we remove firms that automated for the first time before 2010 (see Section 3.1). We link automation costs with other firm-level information, such as ownership structure, total exports, imports, and industry classification, using firms' unique identifiers. We define a firm as an MNE if a non-Dutch entity controls it or if it reports foreign affiliates. In addition, we omit firms affected by events like mergers, spin-offs, or changes in MNE status that could lead to inconsistent firm-worker linkages over time.

At the worker level, we draw our primary data from the Polisadministratie, which is a comprehensive dataset compiled from all Dutch employers' mandatory reports to the Employee Insurance Agency (Uitvoeringsinstituut Werknemersverzekeringen) and tax authorities. Alongside workers' contract type (temporary or permanent), the dataset provides details on total income and hours worked, allowing us to calculate hourly wages that include base, overtime, and bonus pay. We augment the worker data with information on demographics, socio-economic status, and highest education. Education is observed for about 60% of workers, providing details on education level and broad field according to the International Standard Classification of Education (ISCED) 2013 framework.[2] We identify workers that are ever employed at a firm with recorded automation costs and select their full earnings history across all firms, including those without recorded automation costs. For workers with multiple employers

[1] Bessen et al. (2023) provide detailed descriptive statistics on automation costs. We discuss differences between MNEs and domestic firms in Section 3.1.

[2] Availability of education data is skewed towards younger and Dutch workers.

within a year, we determine the primary employer based on continuous employment at a firm with observed automation cost, highest income, most hours worked, and whether the workers holds a permanent contract. We exclude any firm-worker relationships with gaps, instances where workers' socio-economic status indicates they are students, and the full earnings history of workers with annual log hourly wage changes outside the -1 to 1 range.

The final dataset includes 22,344 firms that employ around 2.1 million workers annually, covering roughly 30% of the Dutch labor market. Although MNEs constitute only about 20% of these firms, they account for approximately 50% of the annual employment captured in the data. Table A1 in Appendix A shows that MNEs not only pay higher hourly wages - approximately 37% more on average than domestic firms - but also employ a higher proportion of workers with a University degree. Despite similar shares of automation costs relative to total costs between MNEs and domestic firms (around 0.55%), MNEs spend nearly 50% more on automation per worker. About 40% of MNEs operate in industries such as Manufacturing, Transportation and Storage, and Construction that often employ physical automation technologies, while 60% operate in Service industries that more often focus more on software-based automation technologies. For domestic firms, the share of firms in Manufacturing- or Service-related industries is similar at 35% and 65%, respectively.

3 Difference-in-differences framework

We employ a triple difference-in-differences regression to assess the effects of automation within MNEs and domestic firms on two worker-level outcomes: the probability of firm separation and the trajectory of hourly wages among those remaining with the firm. The main empirical challenges include identifying automation events and estimating the unobserved counterfactual outcomes for individual workers had their employer not automated, while distinguishing between MNEs and domestic firms. Extending the approach of Bessen et al. (2023), our regressions leverage lumpy investments in automation costs, so-called automation cost spikes, to closely compare incumbent workers at automating firms to their matched counterparts at firms that automate later. Sections 3.1 and 3.2 detail the definition of spikes and the matching procedure in our setting. Our empirical specification is

$$y_{igt} = \alpha_i + \alpha_{gt} + \sum_{c \in C} \sum_{s=-3, s\neq -1}^{4} \delta_s^c \times auto_{igs}^c \times treated_i + \sum_{c \in C} \sum_{s=-3, s\neq -1}^{4} \gamma_s^c \times auto_{igs}^c + \mathbf{x}_{it}\beta + \epsilon_{igt}, \tag{1}$$

where i, g, and t denote worker, matched group, and calendar year, respectively; y_{igt} is the outcome of interest (worker separation and log hourly wage of non-separated workers). The indicators $auto_{igs}^c$ identify the relative timing s from three years before to four years post the automation year, separately by firm type c: MNE or domestic. The year before the automation year serves as the reference. Similarly, the indicator $treated_i$ identifies treated workers. Vector $\mathbf{x}_{it}$ includes the control variables age and its square, delineated by the workers' contract type in the year before automation. Finally, ϵ_{igt} is an error term.

We employ specification (1) to isolate the impact of automation relative to the control workers by the type of the firm c: MNE or domestic. The coefficients δ_s^{MNE} measure the automation effect on MNE workers, while the $\delta_s^{Domestic}$'s measure the impact on domestic firm workers. The differential effect on MNE workers compared to domestic firm workers is $\delta_s^{MNE} - \delta_s^{Domestic}$. We prevent these estimates from capturing variations in outcome developments unrelated to automation between the two types through the coefficients γ_s^c (Olden and Møen, 2022; De Chaisemartin and D'haultfœuille, 2023).

We use two distinct outcomes: an indicator whether worker i in year t has left employment at the automating firm, and the log hourly wage of workers who stay with the firm over the whole post-automation period. The former examines the cumulative probability of worker separation due to automation, while the latter captures changes in wage growth.

The difference-in-differences comparison is conditional on two fixed effects: First, α_i is a worker-specific effect that accounts for unobserved, time-invariant differences between workers. Second, α_{gt}, a time-varying effect for each group g of matched treated and control workers. With this fixed effect, treated workers' outcome developments are estimated relative to the developments in the matched control workers. This prevents biases from time-varying omitted variables, such as common demand shocks, from contributing to the identification of the impact of automation. As we match workers from firms undergoing automation to those in firms that automate later, the fixed effect also avoids "forbidden comparisons" between workers treated at different times (De Chaisemartin and d'Haultfoeuille, 2020). The matching procedure is detailed in Section 3.2.

When estimating specification (1), our interest lies in the effect of automation on treated workers. To account for many-to-many matching in our matching strategy, we assign weights to control workers according to the ratio of treated to control workers within group g (Stuart, 2010).[3] Additionally, we cluster standard errors at the level of the firm where a worker is employed before the automation event.

3.1 Automation events

Specification (1) requires the definition of an automation event. We adapt the concept of automation cost spikes of Bessen et al. (2023) to the comparison between MNE and domestic firm workers. According to their approach, a firm experiences an automation cost spike in a given year τ if its real automation costs AC, relative to its average operating costs across all years $\overline{TC}$ (excluding the automation costs), are at least three times the firm's average ratio of automation costs to total operating costs across all other years. As such a spike is defined as

$$spike_{j\tau} = \mathbb{1}\left\{\frac{AC_j}{\overline{TC}_j} \geq 3 \times \frac{1}{T-1}\sum_{t\neq\tau}\frac{AC_j}{\overline{TC}_j}\right\}, \tag{2}$$

where $\mathbb{1}$ is the indicator function.

Leveraging automation cost spikes in the difference-in-differences comparison assumes that equation (2) captures the timing of firms' automation events. We focus on a firm's first automation spike by identifying its spikes on the full automation cost data, which ranges from 2000 to 2021.[4] As additional firm- and worker-level data is only available starting in 2010, we use the pre-2010 data to filter out firms that had an automation event before

[3]The distribution of OLS weights among control workers is shown in Table C3 in Appendix C.

[4]Figure B1 in Appendix B shows a visual depiction of the average spike in automation cost shares.

2010. Furthermore, the automation cost survey captures larger firms more frequently, whereby the timing of MNEs' automation events may be estimated more precisely. To mitigate the influence of reporting frequency on our estimates, we include only those MNEs and domestic firms that report automation costs at least every third year over the period 2010 to 2021.[5] This strategy ensures that we observe a firm's automation costs at least three times during the eight-year event window in specification (1).

About 40% of the 22,343 firms in the post-2010 data spike at least once. Table B1 in Appendix B shows the distribution of spikes, differentiated by MNEs and domestic firms. While the share of automating firms is similar, there are differences in the distribution of serial spikes between the two firm types. Within the group of domestic firms, 29% spike exactly once and 11% feature more than one spike. In contrast, MNEs exhibit a higher frequency of serial spikes, with only 22% of MNEs exhibiting a single spike and 18% featuring multiple spikes in the data. This complicates the event study design in specification (1) if firms with serial spikes respond differently to automation. Hence, when estimating the specification, we difference out the common automation effect for workers that experience multiple spikes during the event window.

MNEs and domestic firms also differ in automation expenditures and industry at the automation event. The average ratio of MNEs' automation cost to their usual automation costs of 10.4 (SD = 40.8) significantly exceeds the average ratio of 8.2 (SD = 18.7) among domestic firms; $t(2144) = 2.2$, $p = 0.03$. Similarly, Figure B2 in Appendix B depicts the automation cost shares and expenditures per worker. While the distributions of automation cost shares in Panel (a) largely overlap, the distribution of automation costs per worker, depicted in Panel (b), is clearly rightward shifted. This suggests that MNEs may invest more heavily in automation than domestic firms.

Regarding industry, most automation events occur in Wholesale and Retail Trade for both MNEs and domestic firms (see Figure B3 in Appendix B). Manufacturing also shows a considerable number of automation events in MNEs, while domestic firms' automation events are more skewed towards the Construction and Administrative and Support Activities industries. In Section 4.4, we show that differences in automation intensity and 2-digit industry do not impact our findings.

3.2 Causality and event data

The causal interpretation of the difference-in-differences estimates in specification (1) relies on the assumptions that workers do not anticipate automation and that, without automation, outcomes for treated and control workers would have followed parallel trends.

To mitigate anticipation bias, we focus on incumbent workers who have been with their current firm for at least three years prior to an automation event, excluding recent hires. Recent hires might have selected into the firm in anticipation of the automation event, while anticipatory effects are less likely for incumbents, as their employment predates the firm's decision to automate by a significant margin (Bessen et al., 2023).

We address parallel trends in several ways. First, in Appendix D we show that automating and non-

[5]Roughly 63% of MNEs report automation costs yearly, 91% at least every second year, and 97% at least every third year. For domestic firms, the shares are 18%, 63%, and 86%.

automating firms are on different growth paths, similar to the results in Bessen et al. (2023). Consequently, workers in non-automating firms are not a good counterfactual for workers in automating firms. Instead, we rely on incumbent workers in firms that automate later as a more suitable proxy for the counterfactual, whereby our difference-in-differences approach leverages only the variation in the timing of automation events for identification. By fixing the comparisons, this approach also circumvents issues of negative weights in difference-in-differences regressions with staggered adoption of treatment, such as ours (for an overview see e.g., Roth et al., 2023).

To operationalize the approach, we construct a stacked dataset that aligns incumbent workers by automation year cohorts (Baker et al., 2022): Firms (and workers) undergoing an automation event in year p are matched with those that will automate in years $p + c$ (where $c \geq 5$). We require treated and control firms to be observed over the entire event period, from three years before to four years after the automation year. In addition, we require the firms to survive in the fifth year to avoid picking up firm closures with our estimates. Given the potential for workers to be included in the dataset multiple times due to their presence in different automation year cohorts, we introduce unique identifiers for each worker-cohort combination. The inclusion of a time-invariant fixed effect at the worker-cohort level, α_i, in specification (1) adjusts for repeated observations across different treatment cohorts.

Second, we match incumbent workers on pre-automation outcomes, combining exact and coarsened exact matching (Iacus et al., 2012). Different from earlier literature, we employ specification (1) to estimate the adjustment within firms in response to automation, requiring a close counterfactual at both the firm- and worker-level. At the firm-level, we control for business cycle fluctuations and industry-specific automation technologies by matching on calendar year and 2-digit NACE industry. To control for firm-size related differences in wages and employment, we also match on every 10th percentile of the firm employment size distribution, including a separate group specifically for the 99th percentile. Within each group of matched firms, we further refine the control group by matching individual workers on every 10th percentile and the 99th percentile of the log hourly wage distribution and its two preceding years. As specification (1) includes matched-group-year fixed effects, our strategy closely compares workers who are on similar wage trajectories in comparable firms prior to automation.

The descriptives of the matched data are in Table C1 in Appendix C. Table C2 in the same Appendix additionally shows descriptive statistics for treated MNE and domestic firm workers separately. The table highlights that MNEs and domestic firms differ in their involvement in international trade, automation costs, and industry distribution. In Section 4.4, we check whether these observable differences explain differences in the impact of automation on MNE and domestic firm workers.

4 Main Results

In our main set of results, we estimate the impact of automation on MNE and domestic firm workers' probability to separate, and their hourly wages, conditional on staying in the firm. We also document heterogeneity by broad sectors. We further examine the potential influences of workers' contract flexibility and firms' international trade activities, automation investment intensity or industry in Sections 4.3 and 4.4. Finally, Section 4.5 presents estimates on the number of new hires and their average wage at the firm-level.

4.1 Separations and wages

Figure 1 depicts the results of a difference-in-differences comparison (as specified in equation (1)) on the impact of automation on workers' cumulative separation probability and hourly wages, compared with the matched control workers. Black estimates depict a difference-in-differences comparison for workers employed at an MNE before the automation event, while gray estimates show those for workers at domestic firms. Full regression results, including estimates on the difference between MNE and domestic firm workers, are in Table E1 in Appendix E.

Panel (a) of Figure 1 depicts the cumulative separation probability after the automation event, differentiated by firm type (MNE or domestic). The estimates reveal an increase in separations of MNE workers post-automation compared to the matched controls. Specifically, in the year of automation, the probability for MNE workers to separate is about 10 percentage points higher than for the control worker.[6] Across the first to fourth year post-automation, this gap stabilizes at about 24 percentage points, implying nearly immediate separations due to automation of about 24% of the MNE workforce. In contrast, the estimates for domestic firm workers are about half the size of those for MNE workers: They rise from 3 percentage points in the automation year to 11 percentage points by the fourth year.[7] All estimates are statistically significant. Given that 34% of control workers separate by the fourth year, these results suggest that automation in MNEs leads to about a 70% increase in separations over five years, while automation in domestic firms leads to an increase in separations by about a third.

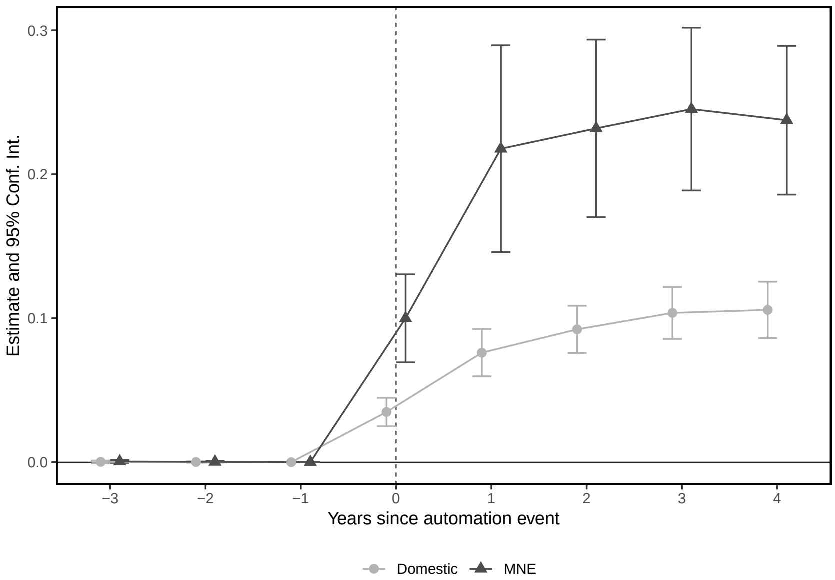
Panel (b) of Figure 1 examines the effect of automation on hourly wages for workers remaining with the firm post-automation. The estimates for MNE workers are positive and statistically significant in the third and fourth year post-automation, where they indicate that automation leads to about 1.6% ($\approx exp(0.016) - 1$) higher wage growth in MNEs, compared to the control group. For domestic firm workers, wage growth declines after an automation event. Specifically, there is a 0.5% reduction in wage growth in the automation year, deepening to a 1.4% decrease by the fourth year post-automation. Over the same period, control workers' wages increase by about 10%, suggesting that automation in MNEs increases wage growth by 16%, while it decreases wage growth in domestic firms by about 14%.

Taken together, these results imply MNEs and domestic firms adjust to automation differently: MNEs separate from a larger part of the incumbent workforce, while workers that stay within the MNE experience higher wage growth. On the other hand, domestic firms separate less but staying workers experience declining wage growth. Table E1 in Appendix E confirms statistically significant differences, amounting to a 13 percentage-point higher probability of separation in MNEs (Column one) and a 3% wage difference (Column two) by the fourth year post-automation.

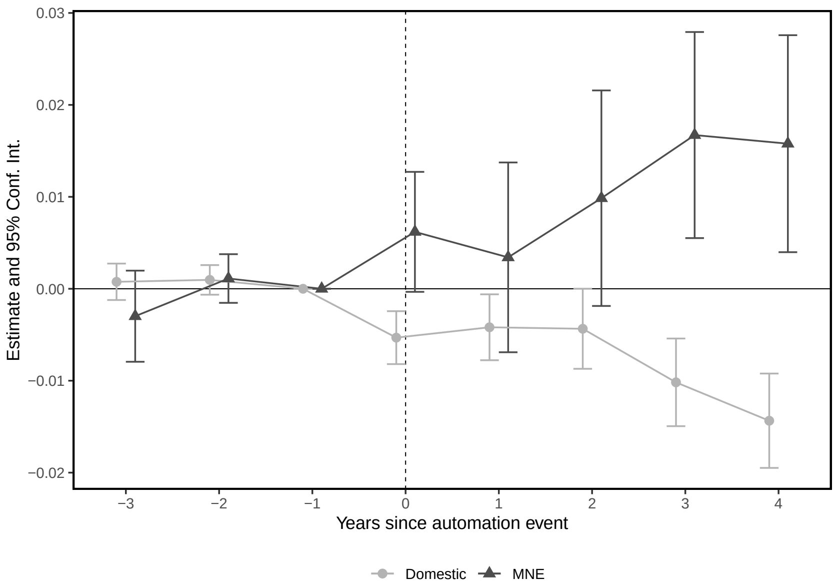
[6] This estimate could capture a partial treatment effect as we do not observe the exact timing of the automation event within the automation year.

[7] This trend is consistent with Bessen et al. (2023)'s findings, which imply a similar cumulative separation rate of about 8% by the fourth year for a sample of automation spikes between 2003-2011 in the Netherlands. Bessen et al. (2023) do not distinguish between MNEs and domestic firms.

Figure 1: Separations and staying workers' wages.



(a) Separation probability.



(b) Log hourly wages of staying workers.

Notes: This plot presents difference-in-differences coefficients for MNE and domestic firm workers, see eq. (1). Full regression results are in Table E1 in Appendix E. Dependent variables are an indicator whether a worker has left the automating firm (Panel (a)) and the log hourly wage of stayers (Panel (b)). MNEs include foreign firms and domestic firms with foreign subsidiaries. The regressions compare incumbent workers at automating firms with matched controls at firms that automate later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Automation events are based on firms' costs on third-party services; see Section 2. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

4.2 Sector level heterogeneity

We document that the impact of automation on MNE and domestic workers differs within Manufacturing and Service industries. We adopt a broad definition for the Manufacturing sector that includes the NACE industries Manufacturing, Construction, and Transport and Storage (Acemoglu et al., 2023). Automation within this sector typically involves physical technologies, such as industrial robots, aiming to enhance production efficiency. Conversely, the Service sector leans towards software-based automation technologies, focusing on automating administrative tasks, information processing, and customer service interactions.[8]

Panel (a) of Figure 2 highlights a common trend across both sectors: MNE workers face higher separation probabilities after automation compared to workers in domestic firms. Specifically, in Manufacturing, MNE workers face a separation probability of about 20 percentage points over the control workers, contrasted with approximately 13 percentage points for domestic firm workers. Similarly, in the Service sector, MNE workers face a separation probability of around 27 percentage points, significantly higher than the roughly 9 percentage points for workers in domestic firms.

The wage developments in Panels (b) and (c) of Figure 2 also reflect divergent impacts of automation. In both sectors, MNE workers experience wage increases after automation that range from approximately 1.3 to 2.0%, with a notable delay in wage increases within the Service sector. Automation in domestic firms within the Manufacturing sector does not result in significant wage adjustments (Panel (b)). Conversely, in the Service sector, wages decrease for workers in domestic firms post-automation by about 2%, aligning with the overall trends depicted in Figure 1.

These results highlight two insights: First, the differential impact of automation in MNEs compared to domestic firms persists across sectors. Second, this differential effect is more pronounced in the Service sector, which more often employs software-based automation.

4.3 Separations of temporary and permanent contract workers

Dutch labor market regulations tightly control the termination of permanent contracts, leaving most flexibility in separations for temporary contracts.[9] This regulatory environment suggests that MNEs might leverage a more flexible workforce to adjust after automation, explaining their higher separation rates in Figure 1.

We decompose separations by workers' temporary or permanent contract before automation by scaling the contract-type-specific separation probabilities by the respective share of contracts across MNE and domestic firm

[8]Service sectors include the NACE industries Wholesale and Retail Trade; Administrative and Support Activities; Information and Communication; Accommodation and Food Services; Professional, Scientific and Technical activities.

[9]Temporary contracts in the Netherlands are usually set for a period of a maximum of two years and, depending on the collective labor agreement of the industry, can be terminated under a 30-day notice. For permanent contracts, obtaining approval from the Employee Insurance Agency (UWV) is a required step for terminations based on economic reasons, including organizational or technological changes like automation, see: https://www.uwv.nl/werkgevers/werkgever-en-ontslag/ik-wil-ontslag-aanvragen/detail/ontslag-via-uwv/ontslagaanvraag-wegens-bedrijfseconomische-redenen/onderbouwen-redenen-ontslag.

workers.[10] As a result, the estimates in Figure 3 measure the share of the workforce leaving with a particular contract type, and they add up to the total separation rates depicted in Figure 1 by construction.

The estimates in Panel (a) of Figure 3 imply that about 1.5% of MNE workers separate with a temporary contract, explaining only 6% ($\approx 1.5/24$) of total separations in MNEs in Figure 1. This contrasts with the 3.4% of domestic firm workers, implying that separations of temporary contract workers explain about one third of total domestic firm separations. Conversely, the estimates in Panel (b) show higher separations of permanent contract workers in MNEs than in domestic firms: While 22% of MNE workers separate under a permanent contract, only 7% of domestic firm workers do so.

These findings rule out flexibility in workers' contract types as an explanation for the overall higher separation rates after automation in MNEs. This is not entirely surprising, as only about 4% of MNE workers in the matched sample are on temporary contracts, compared to 20% in domestic firms (see Table C2 in Appendix C).

4.4 International trade, automation intensity and industries

We test three plausible explanations for the varying impacts of automation between MNEs and domestic firms in Figure 1: firms' international trade activities, the intensity of automation investments, and industry-specific automation technologies.

The related literature suggests that firms exposed to stronger competition in export and import markets invest more in automation (Kromann and Sørensen, 2019). Similarly, firms that adopt automation technologies are often more integrated into global supply chains, sometimes increasing offshoring activities to lower-income countries (Stapleton and Webb, 2020). Such dynamics, along with the distinct patterns of automation investment intensity and industry-specific deployment discussed in Section 3.1, might explain why MNEs exhibit distinct automation effects.

To difference out these related automation effects, we apply a variation of specification (1) that estimates the differential effect of automation in MNEs conditional on these common automation effects among MNEs and domestic firms. The adjusted specification is

$$\begin{aligned} y_{igt} = {} & \alpha_i + \alpha_{gt} \\ & + \sum_{s=-3, s\neq -1}^{4} \delta_s^{MNE} \times auto_{igs}^{MNE} \times treated_i + \sum_{s=-3, s\neq -1}^{4} \gamma_s^{MNE} \times auto_{igs}^{MNE} \\ & + \sum_{g\in G} \sum_{s=-3, s\neq -1}^{4} \delta_s^{g} \times auto_{igs}^{g} \times treated_i + \sum_{g\in G} \sum_{s=-3, s\neq -1}^{4} \gamma_s^{g} \times auto_{igs}^{g} \\ & + \mathbf{x}_{it}\beta + u_{igt}, \end{aligned} \tag{3}$$

where the definitions in Section 3 apply.

Specification (3) includes a group-specific automation effect δ_s^g. This effect captures the impact of automation according to different groupings of all workers (and firms) in the data. We apply three types of groupings across

[10]We drop the interaction between age and contract type for this analysis.

different estimations. In a first set, we assign groups according to every 10th percentile of the export and import distributions before the automation event. In a second set, we assign groups according to every 10th percentile of the automation cost per worker and automation cost share distributions in the automation year. The final grouping captures automation effects at the granular 2-digit NACE industry level. If the MNE effect differs from the common automation effects captured by these groups, we should see this reflected in the MNEs' differential treatment effect δ_s^{MNE}.

We present aggregated automation effects across the trade and automation intensity groups in Tables E4 and E5 in Appendix E. For expositional ease, we separately aggregate the estimates of groups below the median and those of groups above the median. Overall, the results in both tables show increased separations and declining wages. Moreover, these results suggest that higher trade volumes before the automation event associate with relatively lower separations and wage declines. Conversely, higher automation intensities associate with higher separations and wage declines.

Tables E2 and E3 in Appendix E show the automation effect on separations and wages in MNEs, conditional on the related automation effects. In each table, Column one presents the main difference estimate using only domestic firms as reference. Columns two and three correct the difference estimate for automation effects related to firms' exports and imports. Columns four and five control for differences in automation intensity, and Column six for 2-digit industry effects.

The estimates show positive and significant differences for the MNE effect across all groupings. Controlling for treatment effects related to firms' imports and automation cost expenditures per worker leads to marginally smaller estimates on separations, while the difference estimates for wage growth of staying workers are very similar to the main estimate. Controlling for treatment effects related to firms' exports, automation cost shares, and 2-digit industry does not impact the estimates for both separations and wages.

4.5 Firm-level hires

Increased separations of incumbent workers may coincide with changes in firms' hiring practices. In particular, automating firms may increase their hires, potentially replacing incumbent workers with new workers of higher skill levels (Humlum, 2022). Moreover, adjustments in hiring may happen in anticipation of automation, or following automation. In this section, we provide descriptive evidence on the change in the count of new hires and their average wage around the automation event.

To examine hiring dynamics, we apply difference-in-differences specification (1) at the firm level within the matched data, with the reference year set to three years prior to the automation event to evaluate pre-automation adjustments in hiring. We exclude firms that automate in 2013 from this analysis, as we cannot identify their hires three years prior to automation. We account for zeros in the firm-level hiring data by estimating the model using Poisson regression.

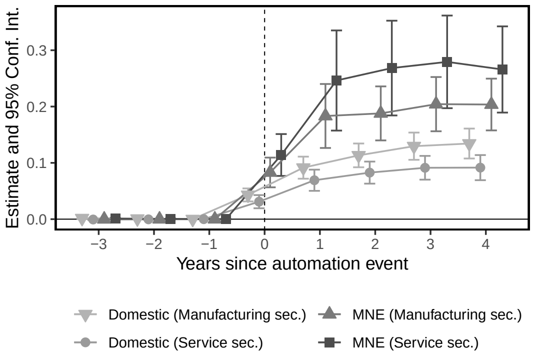
Figure E1 in Appendix E shows estimates on the change in the number of hires and their average wage at firm entry, relative to the levels three years before automation. The results on the numbers of hires in Panel (a) suggest a small increase in hires just before the automation event in MNEs, although the standard errors are large. This is followed by a substantial decline that amounts to about 50% fewer hires by the fourth year post-automation.

Domestic firms show no sign of increased hiring before automation and a similar decline post-automation.

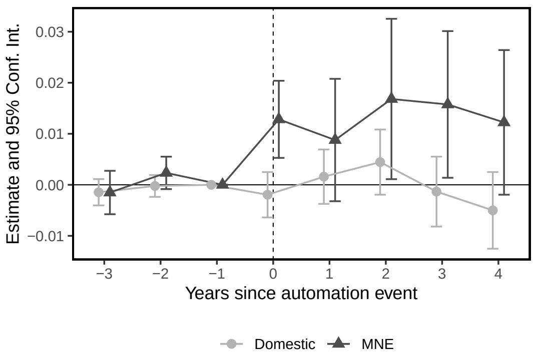
The wage trends for new hires in Panel (b) do not show significant trends in MNEs, indicating that wages for workers hired before and after the automation event are similar. However, in domestic firms, there is a notable decline in the average wages of new hires by about 6% post-automation. This wage reduction could result from overall wage adjustments within domestic firms, as evidenced by the wage decline of incumbent workers in Figure 1, or it may indicate a shift towards hiring lower-productivity workers.

Overall, these results do not indicate that separated incumbent workers are replaced by new hires. Three years before automation, treated MNEs average 21 new hires, compared to 12 in domestic firms, implying an overall modest influence of hiring on workforce dynamics within automating firms.

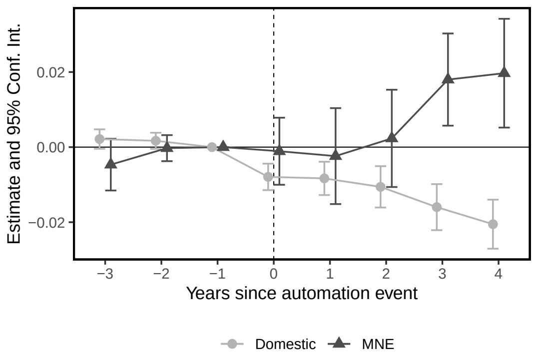
Figure 2: Manufacturing vs Service Sectors.



(a) Separations.



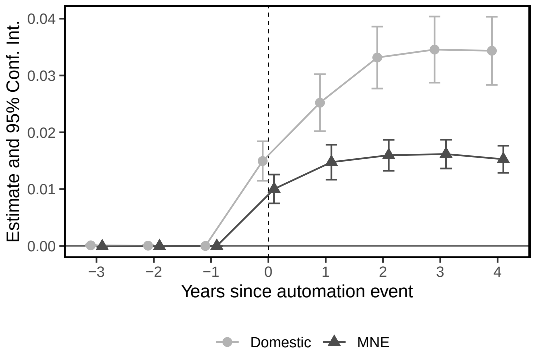
(b) Manufacturing sector: Stayer log wage.



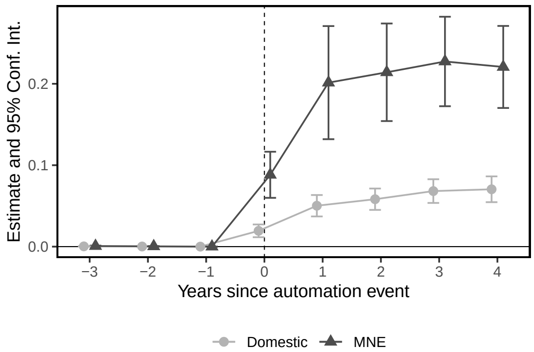
(c) Service sector: Stayer log wage.

Notes: This plot presents difference-in-differences coefficients for MNE and domestic firm workers, based on eq. (1) with interactions for sectors. Manufacturing includes the NACE industries Manufacturing, Construction, and Transport and Storage. Service includes the NACE industries Wholesale and Retail Trade; Administrative and Support Activities; Information and Communication; Accommodation and Food Services; Professional, Scientific and Technical activities. Dependent variables are an indicator whether a worker has left the automating firm (Panel (a)) and the log hourly wage of stayers (Panels (b) and (c)). MNEs include foreign firms and domestic firms with foreign subsidiaries. The regressions compare incumbent workers at automating firms with matched controls at firms that automate later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Automation events are based on firms' costs on third-party services; see Section 2. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

Figure 3: Separations by contract type.



(a) Temporary contracts.



(b) Permanent contracts.

Notes: This plot presents difference-in-differences coefficients for MNE and domestic firm workers, based on eq. (1) with interactions for workers' contract types (temporary or permanent) at 'Years since automation event' = -1. The dependent is both panels is an indicator whether a worker has left the automating firm. MNEs include foreign firms and domestic firms with foreign subsidiaries. The regressions compare incumbent workers at automating firms with matched controls at firms that automate later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Automation events are based on firms' costs on third-party services; see Section 2. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

5 Dissecting the automation effects

While automation costs closely identify firms' expenditures on third-party automation services, the specific technologies used and their integration into the production processes of MNEs and domestic firms are unobserved. To address this, we analyze how automation impacts workers differently based on observed characteristics, such as managerial status and educational background. In Section 5.3, we employ a complementary dataset on firms' investments in ICT and Machinery to compare the impact of such investments with those inferred from the broader automation costs.

5.1 Firm hierarchy

Internationally-oriented firms are likely to adopt more standardized organizational structures (Caliendo and Rossi-Hansberg, 2012). Such standardization might come through automation and disproportionately benefit managers by enhancing their role in coordinating standardized processes (Mariscal, 2020). Hence, automation could lead to wage disparities and a shift towards higher hierarchical levels within firms, potentially affecting workers in MNEs more than those in domestic firms. We dissect the impact of automation on workers based on their managerial status to understand these dynamics.

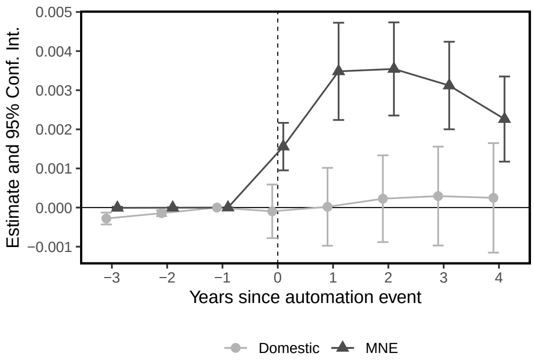
We employ two distinct sources to identify managers. First, through the firm's Chamber of Commerce listing, we comprehensively identify members of the board of directors, owners, and upper management of each firm. Second, for a small sample of workers in each year, we observe ISCO08 occupations, which we use to complement the identification of managers. We classify a worker as a manager if, at any point in the firm-worker match, the worker is identified as a manager by either source. Only a few workers in the data are classified as managers: About 2% of MNE workers and 3% of domestic firm workers (see Table C2 in Appendix C).

Figure 4 segments the impact of automation by workers' managerial status. Panels (a) and (b) show the separation rates of managers and non-managers, respectively. Both managers and non-managers separate from MNEs after automation. Compared to the share of 23% of workers with a non-manager status separating from an MNE, separations of managers are small at about 0.23%, reflecting the small share of managers in the MNEs workforce. The estimates imply that managers face a 12% risk of separation ($\approx 0.23/2$), while non-managers face a substantially higher separation risk of 23%. In domestic firms, no impact of automation on separations of managers is visible, suggesting that separations in domestic firms are fully driven by non-managers.

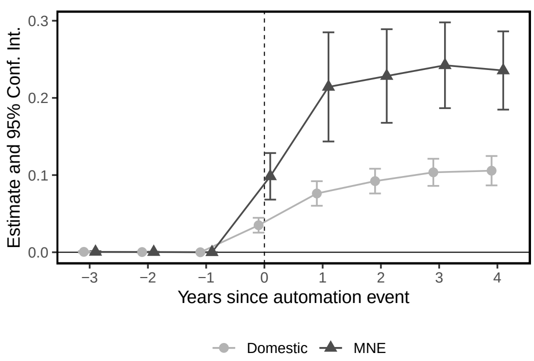
Panels (c) and (d) of Figure 4 highlight clear differences in the impact of automation on managers' hourly wages in MNEs as compared to domestic firms. Post-automation in MNEs, managers that stay experience immediate and increasing wage growth, reaching 8% by the fourth year post-automation. There is a role for non-managers in MNEs, too. Wage effects of non-managers are visibly delayed but reach about 1.4% higher wage growth in third and fourth year. In domestic firms, managers' wages are unaffected by automation, suggesting that overall wage growth decline in domestic firms is driven by non-managers (see Panel (d)).

In sum, automation in MNEs benefits those higher up in the organizational hierarchy, through enhanced wage growth and relatively lower separation rates. Non-managerial workers, on the other hand, face higher layoff risks and see little wage growth. Domestic firms exhibit a different pattern, where automation impacts are largely confined to non-managerial workers.

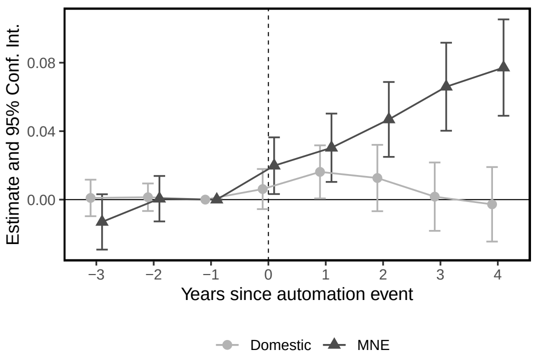
Figure 4: Managers vs. Non-managers.



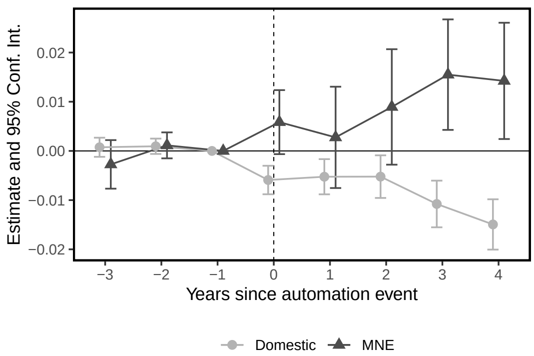
(a) Managers: Separations.



(b) Non-Managers: Separations.



(c) Managers: Stayer log wage.



(d) Non-Managers: Stayer log wage.

Notes: This plot presents difference-in-differences coefficients for MNE and domestic firm workers, based on eq. (1) with interactions for workers' manager status. Manager status is determined based on firm's Chamber of Commerce listing and workers' ISCO08 occupations; see Section 5.1 for details. Dependent variables are an indicator whether a worker has left the automating firm (Panels (a) and (b)) and the log hourly wage of stayers (Panels (c) and (d)). MNEs include foreign firms and domestic firms with foreign subsidiaries. The regressions compare incumbent workers at automating firms with matched controls at firms that automate later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Automation events are based on firms' costs on third-party services; see Section 2. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

5.2 Education level and background

Theories of skill-biased technological change imply that automation improves the productivity of higher-skilled workers, while it lowers that of lower-skilled workers. As workers' occupations and their skill content are unobserved in our data, we proxy skill level by educational attainment, which is observed for 50% of the workers in the matched data. We begin by analyzing the impact of automation on separation and wages, categorizing workers based on whether they hold a University degree. Subsequently, we categorize workers by their broad educational backgrounds in ICT and Sciences, Engineering, or non-technical fields. Following theories of skill-biased change, we expect that workers with university degrees and in technical fields experience fewer separations and higher wage growth post-automation (Katz and Murphy, 1992; Dauth, Findeisen, Suedekum and Woessner, 2021; Acemoglu et al., 2023).

Separation rates, depicted in Panels (a) and (b) of Figure 5, vary by education level. To compare the relative impact on MNE and domestic firm workers with and without a university degree, we scale the separation probabilities by the respective share of workers with observed education. The estimates reveal a stark contrast: While about 12% of MNE workers with a University degree separate, the share is only about 3% for domestic firm workers. For those without University degrees, the separation rates are closer, at 12% for MNEs and 10% for domestic firms, suggesting a uniform distribution of separations across educational levels in MNEs, whereas in domestic firms, separations are tilted towards workers without a University degree.

The wage impacts of automation also show significant variation by education and firm type, as indicated in Panels (d) and (c) of Figure 5. Post-automation, workers with a University degree experience higher wage growth of up to 5% at an MNE, while those in domestic firms see a modest 1% increase. Conversely, the negative wage impact of automation is predominantly felt by workers without a University degree, who face a 1.7% decline in wage growth in domestic firms, but no change in MNEs.

We further classify workers' educational backgrounds into ICT and Sciences, Engineering, or non-technical, following the International Standard Classification of Education (ISCED) 2013 framework.[11] Figure 6 details the automation effect differentiated by these educational backgrounds.

Panels (a), (c), and (e) present scaled separation rates per educational background.[12] They show that MNEs have higher separations across all educational backgrounds compared to domestic firms. The distribution of separations by education background within each firm type reveals similar shares relative to total separations: ICT and Sciences workers constitute 9% of total separations in MNEs (5% in domestic firms) and Engineering workers make up 23% (26% in domestic firms).

We examine wage impacts in Panels (b), (d), and (f). MNE workers with an ICT and Sciences background experience a significant wage growth of about 4.6% by the fourth year post-automation. Workers with Engineering or non-technical backgrounds in MNEs also see wage increases of 2.2% and 1.6% respectively. Conversely, domestic firm workers in non-technical fields face a wage growth decline of about 1%, with minimal impacts on the wages of workers with ICT and Sciences or Engineering backgrounds.

These insights suggest that automation in MNEs predominantly benefits high-skilled workers, particularly those with a background in ICT and Sciences. This is reflected in higher wage growth of staying workers, but not separation rates, implying that skill-biased automation does not fully explain the impact of automation on MNE workers. Conversely, the evidence for domestic firms aligns more closely with theories of skill-biased technological

[11]Specifically, we categorize the ISCED2013 groups "Natural Sciences, Mathematics, and Statistics" and "Information and Communication Technologies" as "ICT and Sciences"; "Engineering, Manufacturing, and Construction" as "Engineering"; and the remaining groups as "non-technical". See https://www.cbs.nl/nl-nl/onze-diensten/methoden/classificaties/onderwijs-en-beroepen/standaard-onderwijsindeling–soi–/standaard-onderwijsindeling-2021 for an overview of the groups.

[12]The distribution of educational backgrounds is similar between MNE and domestic firm workers, with 8% (6%) of MNE (domestic firm) workers in ICT and Sciences, and 27% (26%) in Engineering.

change, as domestic firm automation displaces low-educated workers and benefits high-educated workers, both in relative wages and separations.

5.3 ICT and Machinery investments

The discussion in Section 4.2 indicates that the impact of automation on workers in MNEs and domestic firms differs most in the Service sector, which often employs ICT- rather than Machinery-related automation technologies. Although our automation cost data provides a comprehensive measure of automation, it does not distinguish between ICT and Machinery investments at the firm level. To gauge the differential effect of ICT and Machinery automation in MNEs and domestic firms, we analyze firms' investments in these technologies.

We employ another firm-level survey from Statistics Netherlands, which for the years 2012 to 2020 details firms' investments in Machinery, Computers, Communication equipment, and Software. The items include newly acquired, second-hand and in-house manufactured assets, as well as, standard, custom and self-developed software. This survey encompasses approximately two-thirds of the firms from the automation cost dataset, with a skew towards larger firms. We group investments in Computers, Communication assets, and Software as ICT investments, while investigating Machinery investments separately.

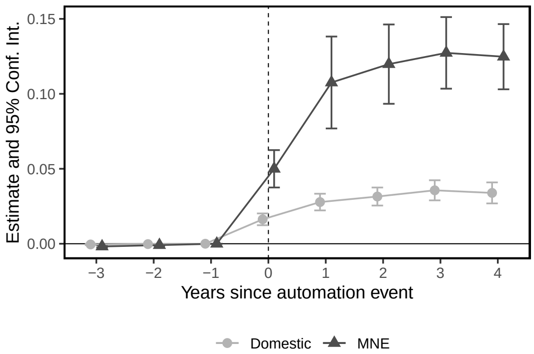
Following the methodology outlined in Section 3, we identify spikes in ICT and Machinery investments when a firm's investment share in these areas exceeds three times its average investment share in other years. We construct matched samples of incumbent workers at firms with investment spikes compared to those at firms that spike later. Then, we employ difference-in-differences specification (1) to assess the impact of these investment spikes on worker separations and hourly wages, focusing on spikes during the years 2013 to 2015.

The results in Figures 7 and 8 show the dynamics of worker separations and wage growth surrounding ICT and Machinery investment spikes, differentiated by MNE and domestic firms. Specifically, ICT investments are associated with an approximate 6% increase in worker separations by the fourth year post-investment for both MNE and domestic firm workers. However, the impact on wage growth diverges between the two firms: ICT investments in domestic firms decrease hourly wage growth by about 1%, whereas in MNEs, the investment spikes lead to a 1% increase in wage growth. The difference is statistically significant, as shown in Table E6 in Appendix E.

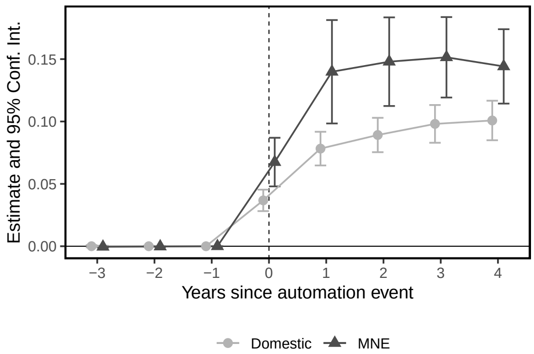
Conversely, spikes in Machinery investments do not exhibit a significant differential impact between MNEs and domestic firms (Table E7 in Appendix E). Both firm types show similar separation rates, with around 5% of the workforce separating by the fourth year post-investment, and no notable effect on the hourly wages of remaining workers.

These findings indicate that ICT investments, unlike Machinery investments, are closely associated with the divergent wage dynamics between MNEs and domestic firms, echoing the broad pattern observed in automation costs in Figure 1. However, these investments do not account for the differing separation rates. In contrast, Machinery investments uniformly impact worker separations across both MNEs and domestic firms, while leaving wage trajectories largely unaffected.

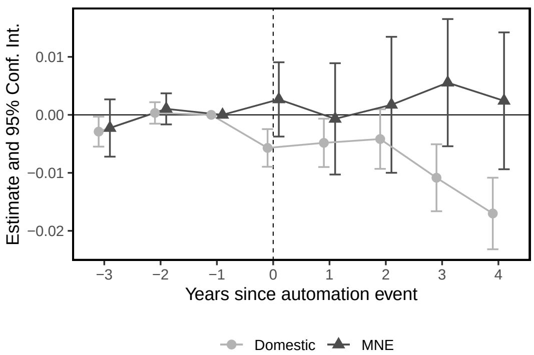
Figure 5: University vs. non-University educated workers.



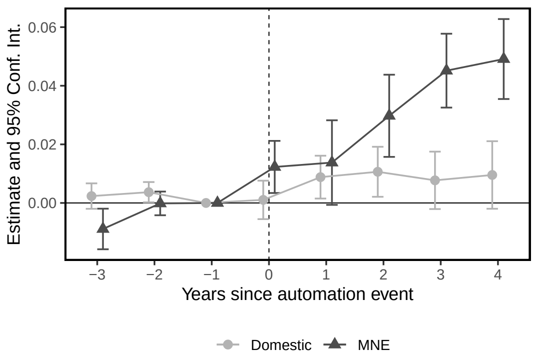
(a) University degree: Separations.



(b) No University degree: Separations.



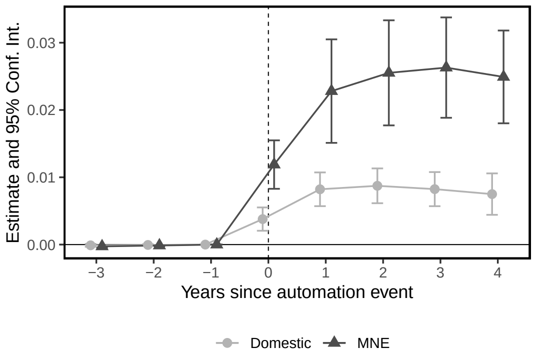
(c) No University degree: Stayer log wage.



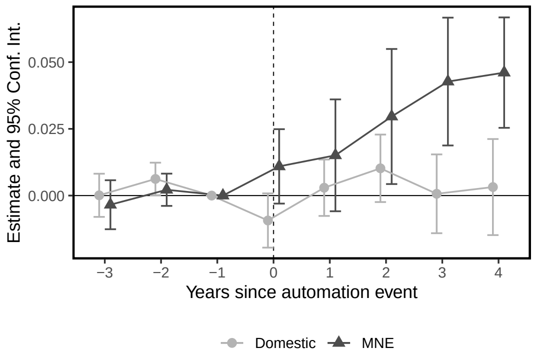
(d) University degree: Stayer log wage.

Notes: This plot presents difference-in-differences coefficients for MNE and domestic firm workers, based on eq. (1) with interactions for workers' education level (University, no University or unobserved). Estimates for workers' with unobserved education are omitted from the plot. Dependent variables are an indicator whether a worker has left the automating firm (Panels (a) and (b)) and the log hourly wage of stayers (Panels (d) and (c)). MNEs include foreign firms and domestic firms with foreign subsidiaries. The regressions compare incumbent workers at automating firms with matched controls at firms that automate later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Automation events are based on firms' costs on third-party services; see Section 2. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

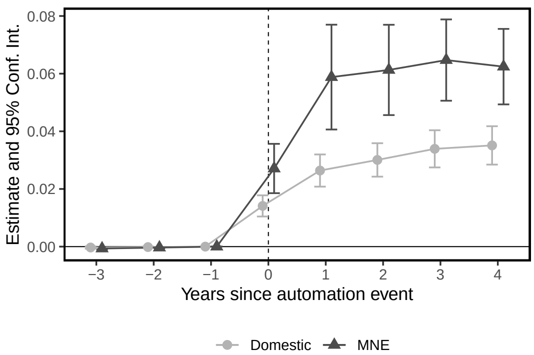
Figure 6: Technical vs. non-technical educational backgrounds.



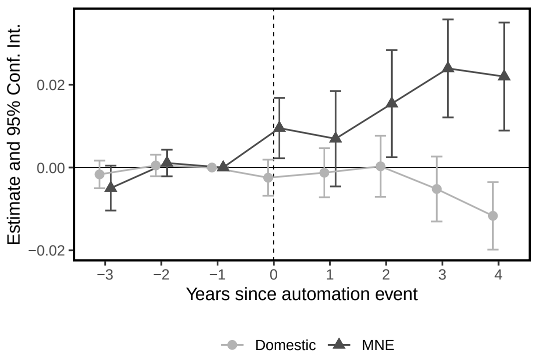
(a) ICT and Sciences: Separations.



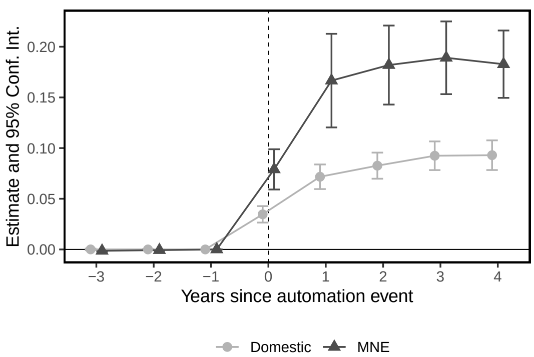
(b) ICT and Sciences: Stayer log wage.



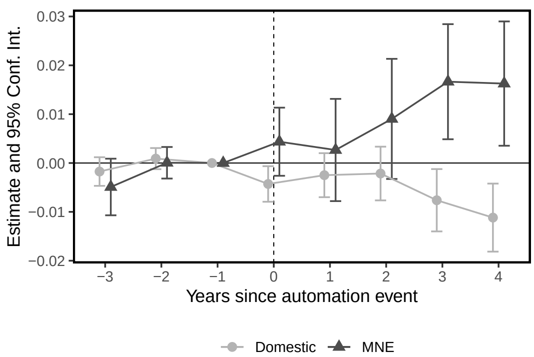
(c) Engineering: Separations.



(d) Engineering: Stayer log wage.



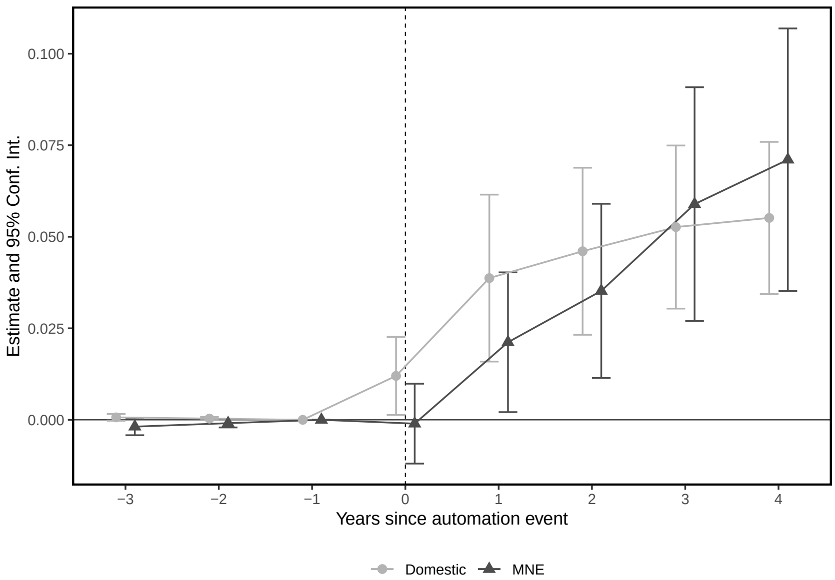
(e) Non-technical background: Separations.



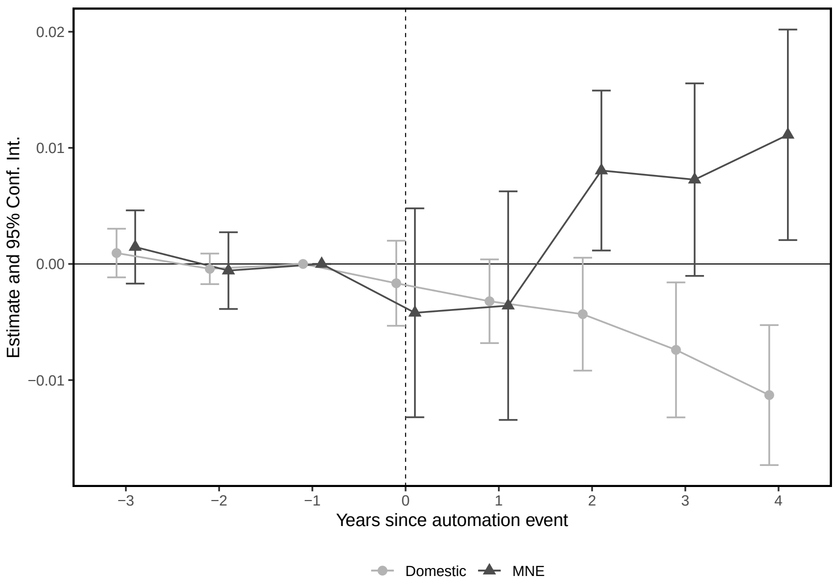
(f) Non-technical background: Stayer log wage.

Notes: This plot presents difference-in-differences coefficients for MNE and domestic firm workers, based on eq. (1) with interactions for workers' educational background (ICT and Sciences, Engineering, Non-technical or unobserved). Estimates for workers' with unobserved educational background are omitted from the plot. "ICT and Sciences" comprises the ISCED2013 groups "Natural Sciences, Mathematics, and Statistics" and "Information and Communication Technologies (ICTs)"; "Engineering" comprises the ISCED2013 group "Engineering, Manufacturing, and Construction"; and "non-technical" all remaining ISCED2013 groups. Dependent variables are an indicator whether a worker has left the automating firm (Panels (a), (c) and (e)) and the log hourly wage of stayers (Panels (b), (d) and (f)). MNEs include foreign firms and domestic firms with foreign subsidiaries. The regressions compare incumbent workers at automating firms with matched controls at firms that automate later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Automation events are based on firms' costs on third-party services; see Section 2. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

Figure 7: Spikes in ICT investments: Separations and staying workers' wages.



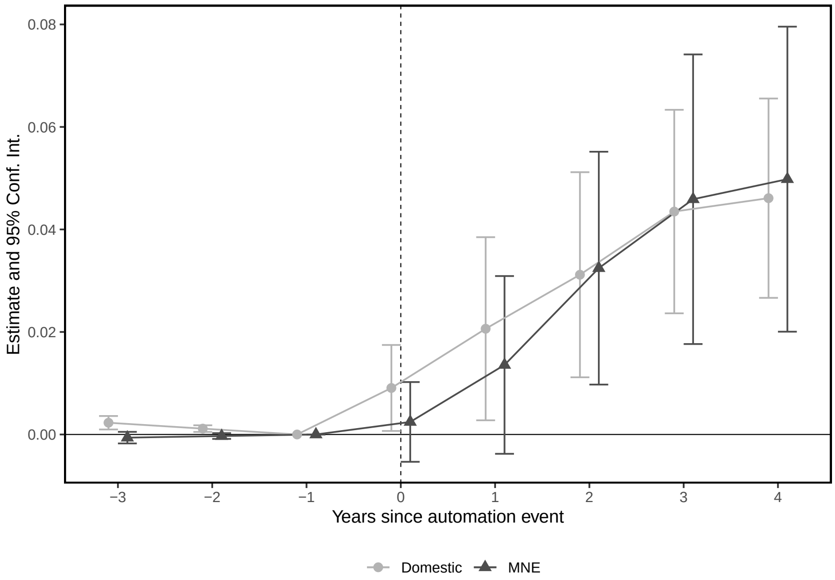
(a) Separation probability.



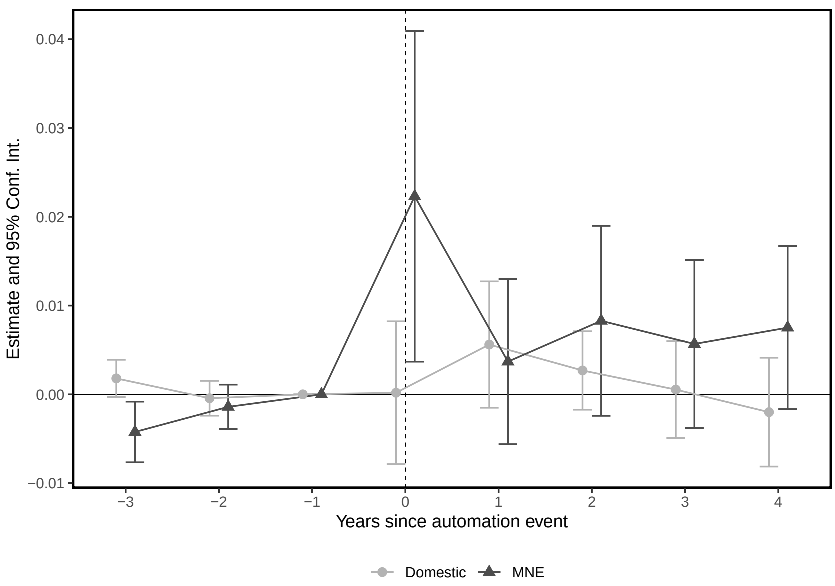
(b) Log hourly wages of staying workers.

Notes: This plot presents difference-in-differences coefficients for MNE and domestic firm workers, see eq. (1). Full regression results are in Table E6 in Appendix E. ICT refers to Information and Communications Technology. Dependent variables are an indicator whether a worker has left the automating firm (Panel (a)) and the log hourly wage of stayers (Panel (b)). MNEs include foreign firms and domestic firms with foreign subsidiaries. The regressions compare incumbent workers at firms with an ICT investment spike with matched controls at firms that spike later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. ICT investment spikes are based on firms' investments in ICT-related technologies: Computers, Communication equipment, and Software; see Section 5.3. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

Figure 8: Spikes in Machinery investments: Separations and staying workers' wages.



(a) Separation probability.



(b) Log hourly wages of staying workers.

Notes: This plot presents difference-in-differences coefficients for MNE and domestic firm workers, see eq. (1). Full regression results are in Table E7 in Appendix E. Dependent variables are an indicator whether a worker has left the automating firm (Panel (a)) and the log hourly wage of stayers (Panel (b)). MNEs include foreign firms and domestic firms with foreign subsidiaries. The regressions compare incumbent workers at firms with a Machinery investment spike with matched controls at firms that spike later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Machinery investment spikes are based on firms' investments in Machinery; see Section 5.3. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

6 Conclusion

We examine the role of a firm's multinational or domestic identity in shaping the consequences of automation for its workforce. Tracking workers within the matched employer-employee data of the Netherlands from 2010 to 2021, we leverage spikes in firms' third-party automation costs for identification (Bessen et al., 2023). Our triple difference-in-differences regressions compare incumbent workers at automating firms to their matched control workers at firms that automate later.

Our findings highlight that MNEs and domestic firms respond distinctly to automation. Specifically, automation in MNEs leads to a substantial increase in worker separations post-automation, with 24% of the incumbent workforce separating due to automation by the fourth year. This rate is significantly higher than the 11% separation rate among domestic firm workers. In addition, the remaining workforce in MNEs benefits from a wage premium of up to 1.6% on average, contrasting with the 1.4% wage decreases experienced by non-separated workers in domestic firms. We show that these patterns persist across Manufacturing and Service industries and are not offset by increased hiring in automating firms.

Our results resonate with those documented by Bessen et al. (2023) on the Dutch data, which imply a separation rate of around 8% over four years, similar to our estimate for domestic firms. The higher separation rate of 24% in MNEs aligns more closely with the literature on mass layoffs that highlights substantial separations rates in some firms (e.g., Davis and Von Wachter, 2011; Dauth, Findeisen and Suedekum, 2021). However, they contrast those of studies on foreign acquisitions, which often find negligible impacts on separations (e.g., Hijzen et al., 2013; Roesch et al., 2022), suggesting complex interactions between a firm's MNE status, its automation strategy, and labor market outcomes.

Domestic firms' responses to automation largely mirror the patterns predicted by theories of skill-biased technological change: The firm lays off relatively more lower educated workers and remaining workers' wages decline. In turn, high-educated domestic firm workers experience wage increases and relatively lower separations rates. In contrast, the adjustment process in MNEs is more complex, as they pay higher wages to high-educated workers but also separate from them frequently.

The distinct separation rates and wage adjustments in MNEs may hint at stronger selection effects within the MNE. MNEs may retain only a more productive subset of their workforce that complements the automation technology. This select group, in turn, is possibly in a better position to negotiate higher wages. In line with this, a plausible explanation for the observed divergence is that MNEs automate to standardize the organization of production (Caliendo and Rossi-Hansberg, 2012). Particularly in the context of ICT technologies, technological change may expand managers' span of control, raising relative demand for their skills within the firm (Mariscal, 2020). Within subsamples, we indeed document that managers wages rise disproportional compared to non-managers wages in MNEs, while managers' separation probabilities are relatively lower. The results also imply increased demand for ICT-related skills within the MNEs, as the wage of workers with an educational background in ICT and Sciences increases sharply. Finally, we find that spikes in firms' ICT investments increase wages in MNEs, while they decrease wages in domestic firms, suggesting that ICT investments lead to different adjustment mechanisms between MNEs and domestic firms.

There are various other possible explanations. One explanation is that MNEs may leverage a more flexible workforce. We find no evidence for this hypothesis, as only a minor fraction of the MNE workforce exits under temporary contracts, in stark contrast to domestic firms, which use temporary contracts more frequently for workforce adjustments. Another set of explanations suggests that MNEs may offshore more, invest more intensely in automation or are more active in industries that employ disruptive automation technologies. However, controlling for firms' exporter-, importer-, automation-intensity- or industry-specific automation effects does not account for the differential automation effect in MNEs and domestic firms. A related explanation is that MNEs may leverage their global value chains to offshore services around automation, which is unobserved in our data.

Finally, the size of MNEs offers another layer of explanation. The presence of strong unions and collective labor agreements in larger firms in the Netherlands, such as MNEs, implies standardized salary scales and wage increases. While MNEs may not be able to downgrade workers to lower salary scales, productive workers can ascend quicker to higher levels. Unfortunately, our data does not allow us to test this hypothesis either.

Our findings highlight how globalisation associates with inequalities in local workers' job opportunities and wages, particularly in the context of automation. MNEs tend to offer higher wages but retain fewer workers post-automation, primarily benefiting highly skilled workers, whereas domestic firm automation mostly affects low skilled workers. These observations suggest that policies aimed at attracting MNEs should not only focus on expected technology transfers, but also consider strategies to protect less-skilled workers when firms automate, such as through enhanced training programs. Furthermore, we find that observable differences between MNEs and domestic firms do not fully account for their differential response to automation. Data that details the application of different automation technologies within firms would be invaluable for discerning the nuanced effects of automation on workforce dynamics and firm organization in relation to globalisation.

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Appendix

A Summary statistics of the data

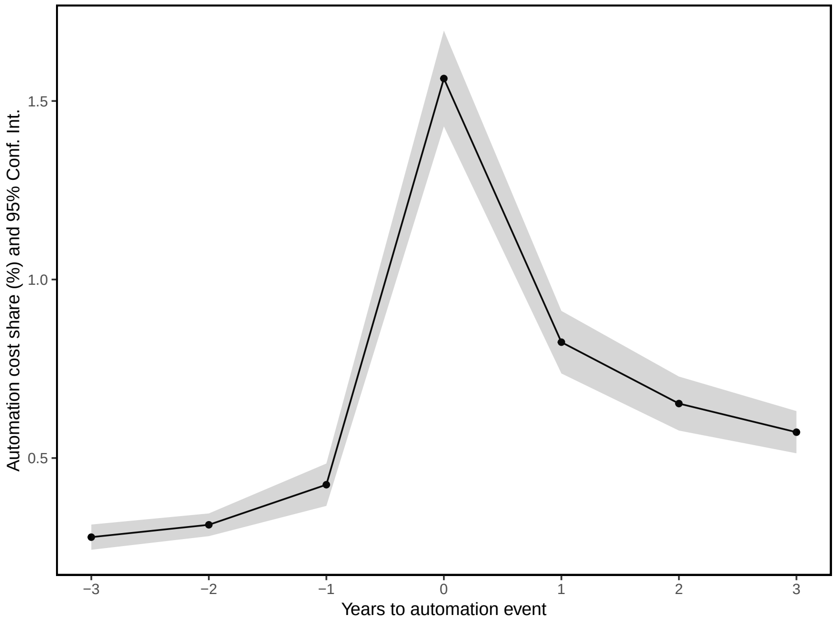
Table A1: Firm-level summary statistics by MNE and domestic firm status.

	MNE		Domestic	
	Mean	SD	Mean	SD
Firms	4,921		17,423	
Automation adopter	0.41	0.49	0.41	0.49
Automation cost share	0.61	1.12	0.52	0.77
Automation cost per worker real (1,000 EURs)	2.57	29.54	1.70	100.19
Sales per worker real (1,000 EURs)	1,264.84	13,014.28	267.35	449.00
Employment (full time equivalent)	234.24	1,140.36	58.56	201.62
Mean hourly wage real	32.05	11.50	23.45	6.06
Mean worker age	42.62	4.43	40.62	5.17
University Education Level (%)	18.86	14.32	10.96	15.31
Medium Education level (%)	19.21	9.86	21.19	13.12
Low Education level (%)	6.32	6.14	7.69	7.73
Unobserved Education level (%)	42.51	15.81	38.94	19.58
Wholesale and Retail Trade (%)	39.99		31.09	
Manufacturing (%)	25.91		11.47	
Information and Communication (%)	7.86		7.40	
Transportation and Storage (%)	8.92		7.51	
Prof., Scientific and Technical Activities (%)	7.01		10.78	
Administrative and Support Activities (%)	5.39		11.84	
Construction (%)	3.92		16.29	
Accommodation and Food Service (%)	1.00		3.61	

Notes: This table shows summary statistics of the full data; see Section 2 for details. Real values refer to 2021 EURs.

B Automation spikes

Figure B1: Automation cost share spike.



Notes: This plot depicts the average spike in the automation cost share in data. Automation cost shares are calculates as firms' real automation in a given year relative to its total operations costs (excluding automation costs) averaged across all years. Automation cost share spikes identify years that exceed three times the average cost share across all years; see Section 3.1 for details.

Table B1: Distribution of automation spikes in MNEs and domestic firms.

Domestic firms

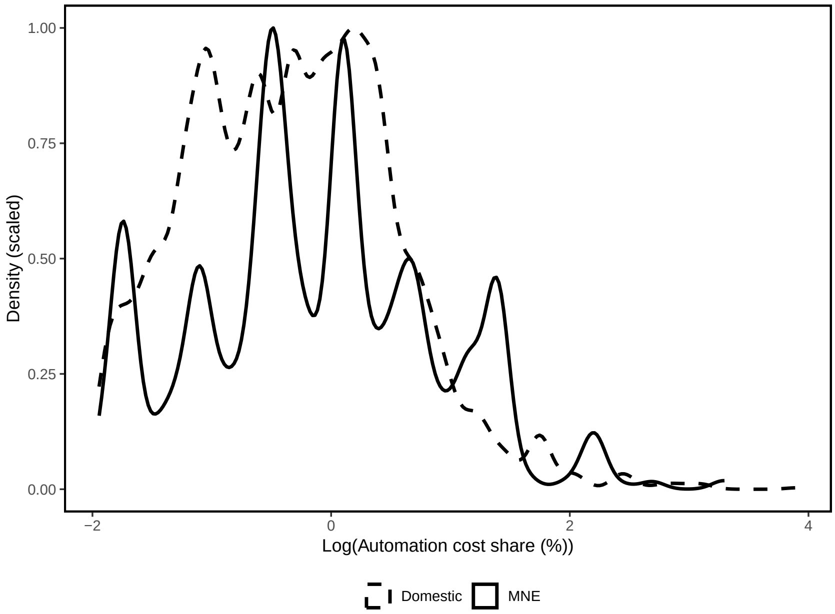
Automation spikes	Firms	Share of firms
0	10,335	59.32
1	5,063	29.06
2	1,590	9.13
3	355	2.04
≥ 4	80	0.46

Multinationals

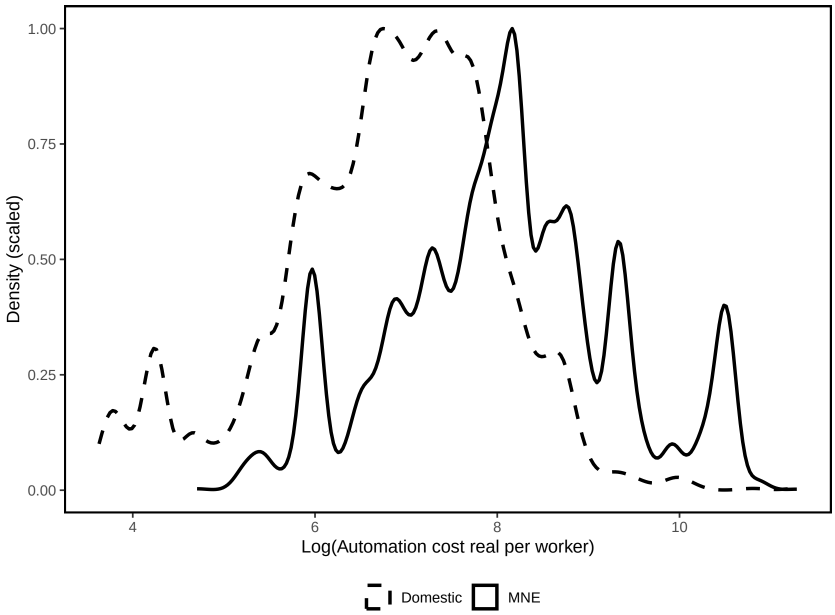
Automation spikes	Firms	Share of firms
0	2,912	59.17
1	1,100	22.35
2	619	12.58
3	223	4.53
≥ 4	67	1.36

Notes: The tables shows the distribution of the number of automation cost share spikes, differentiated by firms' MNE and domestic status. Automation cost shares are calculates as firms' real automation in a given year relative to its total operations costs (excluding automation costs) averaged across all years. Automation cost share spikes identify years that exceed three times the average cost share across all years; see Section 3.1 for details.

Figure B2: Automation costs at the automation event.



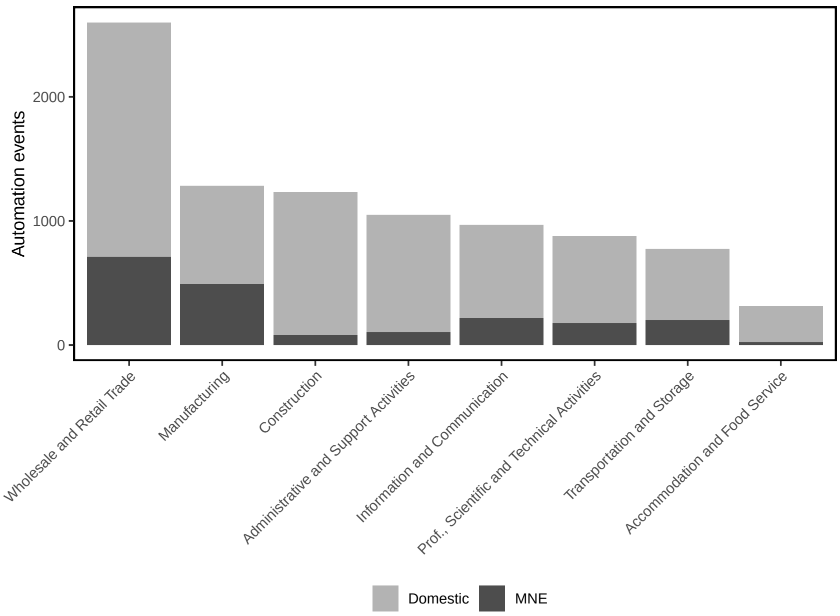
(a) Automation cost share.



(b) Automation costs per worker.

Notes: This plot depicts the distribution of automation cost shares and real automation costs per worker at the automation event, differentiated by firms' MNE and domestic status. Automation events constitute firms' first automation cost share spike. Automation cost shares are calculates as firms' real automation in a given year relative to its total operations costs (excluding automation costs) averaged across all years. Automation cost share spikes identify years that exceed three times the average cost share across all years; see Section 3.1 for details. Real values are in 2021 EURs.

Figure B3: Automation events in 2010 - 2021 by NACE sector.



Notes: This plot depicts the distribution of automation events - defined as the first spike in a firms' automation cost share - by NACE industry and firms' MNE and domestic status. Automation cost shares are calculates as firms' real automation in a given year relative to its total operations costs (excluding automation costs) averaged across all years. Automation cost share spikes identify years that exceed three times the average cost share across all years; see Section 3.1 for details.

C Matched sample

Table C1: Summary statistics, before and after matching.

	Before matching		Matched Control		Matched Treated	
	Mean	SD	Mean	SD	Mean	SD
N (workers)	667,391		184,548		53,259	
Unique workers	345,116		119,064		53,257	
N (firms)	131,36		7,439		1,605	
Unique firms	6,149		3,540		1,605	
N (matching groups)	667,391		13,526		13,526	
Female	0.31	0.46	0.27	0.44	0.27	0.45
Foreign born or foreign-born parents	0.14	0.35	0.12	0.32	0.14	0.34
Age	43.74	10.85	43.14	10.75	43.70	10.48
Temporary contract	0.12	0.32	0.12	0.32	0.11	0.31
Manager	0.02	0.14	0.03	0.17	0.02	0.15
Hourly wage real	25.81	18.01	28.52	18.58	28.55	19.08
Hourly wage growth	0.02	0.11	0.02	0.08	0.02	0.08
MNE	0.49	0.50	0.55	0.50	0.59	0.49
Exporter	0.70	0.46	0.72	0.45	0.72	0.45
Importer	0.81	0.39	0.84	0.36	0.83	0.38
Wholesale and Retail Trade (%)	24.57		27.06		27.06	
Manufacturing (%)	26.43		21.53		21.53	
Information and Communication (%)	4.87		7.09		7.09	
Transportation and Storage (%)	7.99		9.46		9.46	
Prof., Scientific and Technical Activities (%)	6.08		6.62		6.62	
Administrative and Support Activities (%)	16.69		11.67		11.67	
Construction (%)	11.67		13.15		13.15	
Accommodation and Food Service (%)	1.70		3.42		3.42	

Notes: This table shows summary statistics of the matched data in the pre-automation year; see Section 3.2 for details. Exporter and Importer are identifiers that take the value one if a firm's average real exports and imports exceed 10K EUR. Real values refer to 2021 EURs.

Table C2: Summary statistics, matched sample, treated MNE vs. domestic firm workers.

	MNE		Domestic	
	Mean	SD	Mean	SD
N (workers)	31,378		21,881	
Unique workers	31,378		21,880	
N (firms)	384		1,221	
Unique firms	384		1,221	
N (matching groups)	6037		8514	
Female	0.24	0.43	0.32	0.47
Foreign born or foreign-born parents	0.15	0.36	0.11	0.31
Age	44.17	9.99	43.02	11.12
Temporary contract	0.04	0.21	0.20	0.40
Manager	0.02	0.13	0.03	0.18
Hourly wage real	32.47	22.24	22.93	11.09
Hourly wage growth	0.02	0.09	0.02	0.07
MNE	1.00	0.00	0.00	0.00
Exporter	0.94	0.24	0.41	0.49
Importer	0.98	0.14	0.61	0.49
Wholesale and Retail Trade (%)	33.64		26.91	
Manufacturing (%)	29.72		13.94	
Information and Communication (%)	8.05		7.04	
Transportation and Storage (%)	10.97		7.83	
Prof., Scientific and Technical Activities (%)	6.71		6.31	
Administrative and Support Activities (%)	3.01		16.74	
Construction (%)	7.77		15.82	
Accommodation and Food Service (%)	0.13		5.41	

Notes: This table shows summary statistics of matched treated workers in the pre-automation year, differentiated by their MNE or domestic firm status; see Section 3.2 for details. Exporter and Importer are identifiers that take the value one if a firm's average real exports and imports exceed 10K EUR. Real values refer to 2021 EURs.

Table C3: Cumulative distribution of OLS weights among control workers.

	Weight
0%	0.004
10%	0.032
20%	0.055
30%	0.077
40%	0.102
50%	0.136
60%	0.179
70%	0.250
80%	0.333
90%	0.597
95%	1.000
99%	2.782
99.99%	17.000
100%	37.000

Notes: This table shows the cumulative distribution of weights assigned to control workers in the matched data. Weights are assigned according to the ratio of treated to control workers within a group of matched workers. Matching is based on 2-digit NACE industry, employment size, and log hourly wages (including two lags) in the pre-atuomation year; see Section 3 for details.

D Comparing automating to non-automating firms

We compare the firm employment, sales and wage growth trajectories of MNEs and domestic firms with and without an automation event. Following the approach in Bessen et al. (2023), we consider variations of the specification

$$\begin{aligned}\Delta lnY_{jts} = &\gamma_t + \gamma_s \\ &+ \beta^{MNE} \times \text{automator}_j^{MNE} + \beta^{Domestic} \times \text{automator}_j^{Domestic} + \beta^l \times MNE_j \\ &+ \mathbf{k_{jt}}\zeta + e_{jts},\end{aligned} \tag{4}$$

where j, t and s index firms, calendar year and two-digit sector; Y_{jt} is the outcome of interest; γ_t is a year fixed effect; and γ_s is a two-digit industry fixed effect. The dummies automator_j^{MNE} and $\text{automator}_j^{Domestic}$ identify MNEs and domestic firms with an automation cost spike, respectively. The dummy MNE_j dentifies MNEs. We include firms' initial (log) values of Y in the vector of control variables $\mathbf{k_{jt}}$. Finally, e_{jt} is an error term.

The estimation results are in Table D1. Our estimates confirm the results in Bessen et al. (2023) for automation events over the years 2010 - 2021: Automating compared to non-automating firms grow faster in employment. In addition, our data allows us to consider firm sales and firm-average hourly wages. We find that sales of automating firms grow faster than those of non-automating firms, while hourly wages do not grow faster at the firm level.

Taken together, the results in Table D1 imply that automating and non-automating firms are on different growth paths. This is why we use firms that automate later to proxy the counterfactual in specification (1), see Section 3 for details.

Table D1: Automating vs. non-automating firms.

	Employment		Sales		Hourly Wage	
	(1)	(2)	(3)	(4)	(5)	(6)
Automating & MNE	0.0134***	0.0134***	0.0137***	0.0095***	-0.0001	-0.0007
	(0.0024)	(0.0023)	(0.0038)	(0.0036)	(0.0007)	(0.0006)
Automating & Domestic	0.0114***	0.0123***	0.0152***	0.0114***	0.0000	-0.0009***
	(0.0014)	(0.0013)	(0.0018)	(0.0017)	(0.0003)	(0.0003)
MNE	-0.0140***	-0.0685***	-0.0100***	-0.0763***	0.0043***	-0.0306***
	(0.0018)	(0.0057)	(0.0028)	(0.0239)	(0.0005)	(0.0073)
Controls		✓		✓		✓
Fixed-effects						
Year	✓	✓	✓	✓	✓	✓
Industry (2 digit)	✓	✓	✓	✓	✓	✓
Observations	232,415	232,415	232,415	232,415	232,415	232,415
R^2	0.0190	0.0434	0.0079	0.0136	0.0083	0.0244

Notes: ***Significant at the 0.1% level; **significant at the 1% level; *significant at the 5% level; .significant at the 10% level. The table shows estimations of eq. (4). The regressions compare automating MNEs and domestic firms to non-automating firms. MNEs include foreign firms and domestic firms with foreign subsidiaries. 'Automating' identifies firms with an automation event; see Section 3.1. Dependent variables are log employment growth (Columns one, two), log sales growth (Coumns three, four), Log hourly wage growth (Columns five, six). Controls are initial log values of the dependent variables (year 2010). Standard errors are clustered at the firm level.

E Supporting tables and figures

Table E1: The effect of automation on workers in MNEs vs. domestic firms.

	Separation prob.	Stayer log wage
	(1)	(2)
event time = -3 × MNE × treated	0.0003	-0.0037
	(0.0007)	(0.0028)
event time = -2 × MNE × treated	0.0001	0.0001
	(0.0003)	(0.0016)
event time = 0 × MNE × treated	0.0651***	0.0115***
	(0.0170)	(0.0038)
event time = 1 × MNE × treated	0.1417***	0.0076
	(0.0393)	(0.0058)
event time = 2 × MNE × treated	0.1396***	0.0142**
	(0.0343)	(0.0067)
event time = 3 × MNE × treated	0.1416***	0.0269***
	(0.0320)	(0.0065)
event time = 4 × MNE × treated	0.1318***	0.0301***
	(0.0297)	(0.0069)
event time = -3 × treated	0.0002	0.0008
	(0.0005)	(0.0010)
event time = -2 × treated	0.0001	0.0010
	(0.0002)	(0.0008)
event time = 0 × treated	0.0348***	-0.0053***
	(0.0050)	(0.0015)
event time = 1 × treated	0.0761***	-0.0042**
	(0.0084)	(0.0018)
event time = 2 × treated	0.0923***	-0.0044*
	(0.0084)	(0.0022)
event time = 3 × treated	0.1037***	-0.0102***
	(0.0092)	(0.0024)
event time = 4 × treated	0.1058***	-0.0144***
	(0.0100)	(0.0026)
Controls	✓	✓
Fixed-effects		
Matched-group-year	✓	✓
Worker-cohort	✓	✓
event time-additional spikes-(MNE | Domestic)	✓	✓
Observations	1,902,456	1,252,686
R^2	0.6408	0.9768

Notes: ***Significant at the 0.1% level; **significant at the 1% level; *significant at the 5% level; .significant at the 10% level.

This table presents difference-in-differences coefficients for MNE and domestic firm workers, see eq. (1). MNEs include foreign firms and domestic firms with foreign subsidiaries. Dependent variables are an indicator whether a worker has left the automating firm (Column one) and the log hourly wage of stayers (Column two). Controls include age and its square, delineated by the workers' contract type in the pre-automation year. The regressions compare incumbent workers at automating firms with matched controls at firms that automate later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Automation events are based on firms' costs on third-party services; see Section 2. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

Table E2: Separation probability in MNEs, conditional on other automation effects.

Reference group	Main	Trade		Automation cost		Industry
	Domestic firms	Export	Import	per worker	share	
	(1)	(2)	(3)	(4)	(5)	(6)
event time = -3 × MNE × treated	0.0003	-0.0006	-0.0015*	-0.0003	0.0003	0.0000
	(0.0007)	(0.0008)	(0.0009)	(0.0008)	(0.0007)	(0.0008)
event time = -2 × MNE × treated	0.0001	-0.0003	-0.0007*	-0.0001	0.0001	0.0000
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
event time = 0 × MNE × treated	0.0651***	0.0818***	0.0602***	0.0607***	0.0682***	0.0812***
	(0.0170)	(0.0169)	(0.0159)	(0.0181)	(0.0151)	(0.0184)
event time = 1 × MNE × treated	0.1417***	0.1530***	0.1047***	0.1200***	0.1405***	0.1685***
	(0.0393)	(0.0302)	(0.0278)	(0.0332)	(0.0309)	(0.0384)
event time = 2 × MNE × treated	0.1396***	0.1535***	0.1103***	0.1128***	0.1453***	0.1596***
	(0.0343)	(0.0289)	(0.0299)	(0.0302)	(0.0293)	(0.0342)
event time = 3 × MNE × treated	0.1416***	0.1493***	0.1017***	0.1109***	0.1452***	0.1429***
	(0.0320)	(0.0276)	(0.0301)	(0.0278)	(0.0279)	(0.0316)
event time = 4 × MNE × treated	0.1318***	0.1413***	0.0956***	0.0989***	0.1329***	0.1325***
	(0.0297)	(0.0252)	(0.0281)	(0.0250)	(0.0257)	(0.0290)
event time × group × treated	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Fixed-effects						
Matched-group-year	✓	✓	✓	✓	✓	✓
Worker-cohort	✓	✓	✓	✓	✓	✓
event time-MNE	✓	✓	✓	✓	✓	✓
event time-additional spikes-group		✓	✓	✓	✓	✓
Observations	1,902,456	1,902,456	1,902,456	1,902,456	1,902,456	1,902,456
R^2	0.6408	0.6442	0.6432	0.6455	0.6451	0.6475
Adjusted R^2	0.5609	0.5649	0.5637	0.5666	0.5661	0.5687

Notes: ***Significant at the 0.1% level; **significant at the 1% level; *significant at the 5% level; .significant at the 10% level. This table presents difference-in-differences coefficients for MNE workers, see eq. (3). Column one shows the main difference estimate; Columns two to five adjusts the reference group by export, import, automation cost per worker, automation cost share percentile groups; Column six adjusts the reference group at the 2-digit NACE industry level. MNEs include foreign firms and domestic firms with foreign subsidiaries. The dependent variable is an indicator whether a worker has left the automating firm. Controls include age and its square, delineated by the workers' contract type in the pre-automation year. The regressions compare incumbent workers at automating firms with matched controls at firms that automate later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Automation events are based on firms' costs on third-party services; see Section 2. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

Table E3: Log wage of stayers in MNEs, conditional on other automation effects.

Reference group	Main	Trade		Automation cost		Industry
	Domestic firms	Export	Import	per worker	share	
	(1)	(2)	(3)	(4)	(5)	(6)
event time = -3 × MNE × treated	-0.0037	-0.0063**	-0.0070**	-0.0048**	-0.0041*	-0.0044
	(0.0028)	(0.0031)	(0.0028)	(0.0023)	(0.0025)	(0.0030)
event time = -2 × MNE × treated	0.0001	0.0006	0.0007	-0.0008	0.0000	0.0017
	(0.0016)	(0.0019)	(0.0020)	(0.0017)	(0.0019)	(0.0017)
event time = 0 × MNE × treated	0.0115***	0.0052	0.0135***	0.0118***	0.0136***	0.0073*
	(0.0038)	(0.0044)	(0.0043)	(0.0037)	(0.0039)	(0.0039)
event time = 1 × MNE × treated	0.0076	0.0032	0.0123*	0.0110*	0.0091	0.0045
	(0.0058)	(0.0067)	(0.0071)	(0.0059)	(0.0059)	(0.0053)
event time = 2 × MNE × treated	0.0142**	0.0112	0.0148*	0.0171***	0.0164**	0.0161**
	(0.0067)	(0.0076)	(0.0078)	(0.0066)	(0.0069)	(0.0064)
event time = 3 × MNE × treated	0.0269***	0.0246***	0.0272***	0.0310***	0.0307***	0.0308***
	(0.0065)	(0.0073)	(0.0073)	(0.0062)	(0.0067)	(0.0068)
event time = 4 × MNE × treated	0.0301***	0.0298***	0.0279***	0.0333***	0.0350***	0.0326***
	(0.0069)	(0.0067)	(0.0081)	(0.0068)	(0.0073)	(0.0071)
event time × group × treated	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Fixed-effects						
Matched-group-year	✓	✓	✓	✓	✓	✓
Worker-cohort	✓	✓	✓	✓	✓	✓
event time-MNE	✓	✓	✓	✓	✓	✓
event time-additional spikes-group		✓	✓	✓	✓	✓
Observations	1,252,686	1,252,686	1,252,686	1,252,686	1,252,686	1,252,686
R^2	0.9768	0.9769	0.9769	0.9770	0.9769	0.9772
Adjusted R^2	0.9715	0.9717	0.9717	0.9717	0.9717	0.9720

Notes: ***Significant at the 0.1% level; **significant at the 1% level; *significant at the 5% level; .significant at the 10% level. This table presents difference-in-differences coefficients for MNE workers, see eq. (3). Column one shows the main difference estimate; Columns two to five adjusts the reference group by export, import, automation cost per worker, automation cost share percentile groups; Column six adjusts the reference group at the 2-digit NACE industry level. MNEs include foreign firms and domestic firms with foreign subsidiaries. The dependent variable is the log hourly wage of stayers. Controls include age and its square, delineated by the workers' contract type in the pre-automation year. The regressions compare incumbent workers at automating firms with matched controls at firms that automate later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Automation events are based on firms' costs on third-party services; see Section 2. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

Table E4: Controlling for other treatments, aggregated control coefficients (exporter and importer groups).

	Export groups		Import groups	
	Separation prob.	Stayer log wage	Separation prob.	Stayer log wage
	(1)	(2)	(3)	(4)
event time = -3 × above median × treated	0.0019**	0.0031	0.0021**	0.0062**
	(0.0007)	(0.0028)	(0.0008)	(0.0026)
event time = -3 × below median × treated	-0.0007	-0.0018	0.0008	-0.0005
	(0.0008)	(0.0022)	(0.0007)	(0.0015)
event time = -3 × none × treated	0.0002	0.0008	-0.0014	-0.0020
	(0.0007)	(0.0013)	(0.0010)	(0.0018)
event time = -2 × above median × treated	0.0009**	-0.0011	0.0010**	0.0006
	(0.0004)	(0.0019)	(0.0004)	(0.0019)
event time = -2 × below median × treated	-0.0003	0.0025	0.0004	0.0014
	(0.0004)	(0.0016)	(0.0003)	(0.0012)
event time = -2 × none × treated	0.0001	0.0010	-0.0007	0.0006
	(0.0003)	(0.0010)	(0.0005)	(0.0015)
event time = 0 × above median × treated	0.0134	0.0053	0.0430***	-0.0027
	(0.0158)	(0.0039)	(0.0147)	(0.0033)
event time = 0 × below median × treated	0.0595***	-0.0124***	0.0443***	-0.0116***
	(0.0160)	(0.0041)	(0.0085)	(0.0025)
event time = 0 × none × treated	0.0334***	-0.0056***	0.0164**	-0.0067**
	(0.0070)	(0.0019)	(0.0081)	(0.0027)
event time = 1 × above median × treated	0.0647*	0.0038	0.1155***	-0.0038
	(0.0336)	(0.0060)	(0.0315)	(0.0046)
event time = 1 × below median × treated	0.1068***	-0.0131***	0.0903***	-0.0142***
	(0.0276)	(0.0049)	(0.0140)	(0.0031)
event time = 1 × none × treated	0.0761***	-0.0030	0.0552***	-0.0020
	(0.0119)	(0.0023)	(0.0127)	(0.0032)
event time = 2 × above median × treated	0.0752***	-0.0017	0.1221***	-0.0021
	(0.0271)	(0.0070)	(0.0293)	(0.0056)
event time = 2 × below median × treated	0.1337***	-0.0117*	0.1145***	-0.0118***
	(0.0272)	(0.0062)	(0.0136)	(0.0039)
event time = 2 × none × treated	0.0852***	-0.0047	0.0651***	-0.0027
	(0.0111)	(0.0030)	(0.0130)	(0.0039)
event time = 3 × above median × treated	0.0976***	-0.0084	0.1439***	-0.0105*
	(0.0252)	(0.0064)	(0.0292)	(0.0055)
event time = 3 × below median × treated	0.1432***	-0.0188***	0.1239***	-0.0134***
	(0.0266)	(0.0057)	(0.0143)	(0.0038)
event time = 3 × none × treated	0.0922***	-0.0095***	0.0740***	-0.0088**
	(0.0117)	(0.0032)	(0.0136)	(0.0045)
event time = 4 × above median × treated	0.1004***	-0.0129**	0.1427***	-0.0103*

	(0.0237)	(0.0065)	(0.0279)	(0.0061)
event time = 4 × below median × treated	0.1372***	-0.0202***	0.1206***	-0.0187***
	(0.0252)	(0.0056)	(0.0140)	(0.0042)
event time = 4 × none × treated	0.0965***	-0.0151***	0.0839***	-0.0148***
	(0.0123)	(0.0036)	(0.0155)	(0.0048)
event time = -3 × MNE × treated	-0.0006	-0.0063**	-0.0015*	-0.0070**
	(0.0008)	(0.0031)	(0.0009)	(0.0028)
event time = -2 × MNE × treated	-0.0003	0.0006	-0.0007*	0.0007
	(0.0004)	(0.0019)	(0.0004)	(0.0020)
event time = 0 × MNE × treated	0.0818***	0.0052	0.0602***	0.0135***
	(0.0169)	(0.0044)	(0.0159)	(0.0043)
event time = 1 × MNE × treated	0.1530***	0.0032	0.1047***	0.0123*
	(0.0302)	(0.0067)	(0.0278)	(0.0071)
event time = 2 × MNE × treated	0.1535***	0.0112	0.1103***	0.0148*
	(0.0289)	(0.0076)	(0.0299)	(0.0078)
event time = 3 × MNE × treated	0.1493***	0.0246***	0.1017***	0.0272***
	(0.0276)	(0.0073)	(0.0301)	(0.0073)
event time = 4 × MNE × treated	0.1413***	0.0298***	0.0956***	0.0279***
	(0.0252)	(0.0067)	(0.0281)	(0.0081)
Controls	✓	✓	✓	✓
Fixed-effects				
Matched-group-year	✓	✓	✓	✓
Worker-cohort	✓	✓	✓	✓
event time-MNE	✓	✓	✓	✓
event time-additional spikes-group	✓	✓	✓	✓
Observations	1,902,456	1,252,686	1,902,456	1,252,686
R^2	0.6442	0.9769	0.6432	0.9769
Adjusted R^2	0.5649	0.9717	0.5637	0.9717

Notes: ***Significant at the 0.1% level; **significant at the 1% level; *significant at the 5% level; .significant at the 10% level. This table presents difference-in-differences coefficients for MNE workers and aggregated coefficients for the reference groups, see eq. (3). Columns one and two adjust the reference group by percentile group of the log real export distribution in the pre-automation year; Columns three and four by the log real import distribution. The coefficients presented here are aggregated according to whether the reference group features no exports/imports ("none"), lies below the median (groups 1-5; "below median") or above the median (groups 6-10; "above median"). MNEs include foreign firms and domestic firms with foreign subsidiaries. Dependent variables are an indicator whether a worker has left the automating firm (Columns one, three) and the log hourly wage of stayers (Columns two, four). Controls include age and its square, delineated by the workers' contract type in the pre-automation year. The regressions compare incumbent workers at automating firms with matched controls at firms that automate later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Automation events are based on firms' costs on third-party services; see Section 2. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

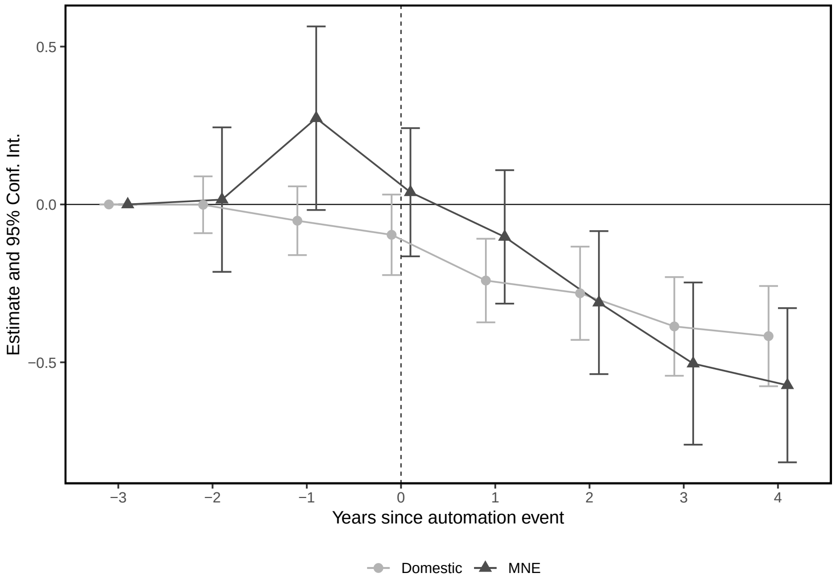
Table E5: Controlling for other treatments, aggregated control coefficients (automation intensity groups).

	Automation cost per worker		Automation cost share	
	Separation prob.	Stayer log wage	Separation prob.	Stayer log wage
	(1)	(2)	(3)	(4)
event time = -3 × above median × treated	0.0004	0.0007	0.0008	0.0006
	(0.0007)	(0.0022)	(0.0007)	(0.0016)
event time = -3 × below median × treated	0.0002	-0.0007	-0.0005	0.0017
	(0.0006)	(0.0014)	(0.0005)	(0.0015)
event time = -2 × above median × treated	0.0002	0.0014	0.0004	0.0009
	(0.0003)	(0.0016)	(0.0003)	(0.0012)
event time = -2 × below median × treated	0.0001	0.0007	-0.0002	0.0016
	(0.0003)	(0.0010)	(0.0003)	(0.0012)
event time = 0 × above median × treated	0.0488***	-0.0061*	0.0255***	-0.0086***
	(0.0127)	(0.0032)	(0.0092)	(0.0025)
event time = 0 × below median × treated	0.0282***	-0.0061***	0.0421***	-0.0030
	(0.0075)	(0.0020)	(0.0083)	(0.0022)
event time = 1 × above median × treated	0.1265***	-0.0074*	0.0663***	-0.0123***
	(0.0244)	(0.0043)	(0.0175)	(0.0034)
event time = 1 × below median × treated	0.0593***	0.0000	0.0899***	0.0040
	(0.0132)	(0.0027)	(0.0163)	(0.0028)
event time = 2 × above median × treated	0.1532***	-0.0023	0.0909***	-0.0084**
	(0.0233)	(0.0049)	(0.0172)	(0.0042)
event time = 2 × below median × treated	0.0747***	-0.0009	0.0962***	-0.0003
	(0.0127)	(0.0033)	(0.0157)	(0.0039)
event time = 3 × above median × treated	0.1649***	-0.0073	0.1141***	-0.0124***
	(0.0228)	(0.0050)	(0.0168)	(0.0042)
event time = 3 × below median × treated	0.0894***	-0.0043	0.0983***	-0.0051
	(0.0128)	(0.0033)	(0.0154)	(0.0040)
event time = 4 × above median × treated	0.1655***	-0.0104*	0.1164***	-0.0180***
	(0.0214)	(0.0055)	(0.0161)	(0.0045)
event time = 4 × below median × treated	0.0924***	-0.0091**	0.1022***	-0.0081*
	(0.0126)	(0.0036)	(0.0154)	(0.0042)
event time = -3 × MNE × treated	-0.0003	-0.0048**	0.0003	-0.0041*
	(0.0008)	(0.0023)	(0.0007)	(0.0025)
event time = -2 × MNE × treated	-0.0001	-0.0008	0.0001	0.0000
	(0.0004)	(0.0017)	(0.0004)	(0.0019)
event time = 0 × MNE × treated	0.0607***	0.0118***	0.0682***	0.0136***
	(0.0181)	(0.0037)	(0.0151)	(0.0039)
event time = 1 × MNE × treated	0.1200***	0.0110*	0.1405***	0.0091
	(0.0332)	(0.0059)	(0.0309)	(0.0059)
event time = 2 × MNE × treated	0.1128***	0.0171***	0.1453***	0.0164**
	(0.0302)	(0.0066)	(0.0293)	(0.0069)

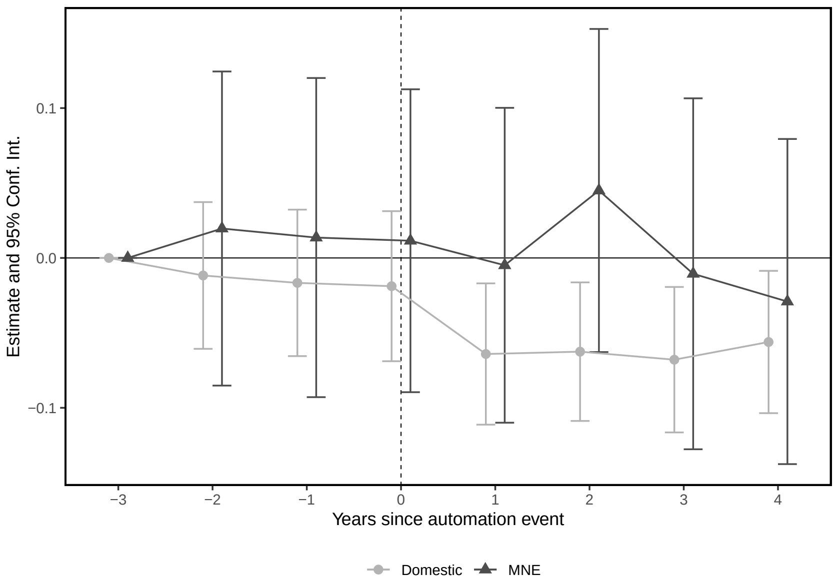
event time = 3 × MNE × treated	0.1109***	0.0310***	0.1452***	0.0307***
	(0.0278)	(0.0062)	(0.0279)	(0.0067)
event time = 4 × MNE × treated	0.0989***	0.0333***	0.1329***	0.0350***
	(0.0250)	(0.0068)	(0.0257)	(0.0073)
Controls	✓	✓	✓	✓
Fixed-effects				
Matched-group-year	✓	✓	✓	✓
Worker-cohort	✓	✓	✓	✓
event time-MNE	✓	✓	✓	✓
event time-additional spikes-group	✓	✓	✓	✓
Observations	1,902,456	1,252,686	1,902,456	1,252,686
R^2	0.6455	0.9770	0.6451	0.9769
Adjusted R^2	0.5666	0.9717	0.5661	0.9717

Notes: ***Significant at the 0.1% level; **significant at the 1% level; *significant at the 5% level; .significant at the 10% level. This table presents difference-in-differences coefficients for MNE workers and aggregated coefficients for the reference groups, see eq. (3). Columns one and two adjust the reference group by percentile groups of the log real automation cost per worker distribution in the automation year; Columns three and four by the automation cost share distribution. The coefficients presented here are aggregated according to whether the reference group features no lies below the median (groups 1-5; "below median") or above the median (groups 6-10; "above median"). MNEs include foreign firms and domestic firms with foreign subsidiaries. Dependent variables are an indicator whether a worker has left the automating firm (Columns one, three) and the log hourly wage of stayers (Columns two, four). Controls include age and its square, delineated by the workers' contract type in the pre-automation year. The regressions compare incumbent workers at automating firms with matched controls at firms that automate later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Automation events are based on firms' costs on third-party services; see Section 2. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

Figure E1: Firm-level hires.



(a) Number of hires.



(b) Average wage of hires.

Notes: This plot presents difference-in-differences coefficients for MNE and domestic firms, using a firm-level equivalent of eq. (1). The coefficients are estimated using Poisson regression. Dependent variables are the firm-level number of new hires (Panel (a)) and the mean hourly wage of new hires (Panel (b)). MNEs include foreign firms and domestic firms with foreign subsidiaries. The regressions compare automating firms with matched control firms that automate later, matched on 2-digit NACE industry, and employment size; see Sections 3 and 4.5. Automation events are based on firms' costs on third-party services; see Section 2.

Table E6: The effect of ICT investments on workers in MNEs vs. domestic firms.

	Separation prob.	Stayer log wage
	(1)	(2)
event time = -3 × MNE × treated	-0.0025*	0.0005
	(0.0013)	(0.0020)
event time = -2 × MNE × treated	-0.0013*	-0.0002
	(0.0007)	(0.0019)
event time = 0 × MNE × treated	-0.0130*	-0.0025
	(0.0078)	(0.0047)
event time = 1 × MNE × treated	-0.0175	-0.0004
	(0.0157)	(0.0051)
event time = 2 × MNE × treated	-0.0108	0.0124***
	(0.0174)	(0.0045)
event time = 3 × MNE × treated	0.0063	0.0147***
	(0.0207)	(0.0054)
event time = 4 × MNE × treated	0.0159	0.0224***
	(0.0221)	(0.0058)
event time = -3 × treated	0.0007	0.0009
	(0.0005)	(0.0011)
event time = -2 × treated	0.0003	-0.0004
	(0.0002)	(0.0007)
event time = 0 × treated	0.0120**	-0.0017
	(0.0054)	(0.0019)
event time = 1 × treated	0.0387***	-0.0032*
	(0.0116)	(0.0018)
event time = 2 × treated	0.0460***	-0.0043*
	(0.0116)	(0.0025)
event time = 3 × treated	0.0527***	-0.0074**
	(0.0114)	(0.0030)
event time = 4 × treated	0.0552***	-0.0113***
	(0.0106)	(0.0031)
Controls	✓	✓
Fixed-effects		
Matched-group-year	✓	✓
Worker-cohort	✓	✓
event time-additional spikes-(MNE|Domestic)	✓	✓
Observations	2,178,888	1,469,132
R^2	0.6276	0.9769

Notes: ***Significant at the 0.1% level; **significant at the 1% level; *significant at the 5% level; .significant at the 10% level. This table presents difference-in-differences coefficients for MNE and domestic firm workers, see eq. (1). MNEs include foreign firms and domestic firms with foreign subsidiaries. Dependent variables are an indicator whether a worker has left the automating firm (Column one) and the log hourly wage of stayers (Column two). Controls include age and its square, delineated by the workers' contract type in the pre-automation year. The regressions compare incumbent workers at firms with an ICT investment spike with matched controls at firms that spike later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. ICT investment spikes are based on firms' investments in ICT-related technologies: Computers, Communication equipment, and Software; see Section 5.3. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.

Table E7: The effect of Machinery investments on workers in MNEs vs. domestic firms.

	Separation prob.	Stayer log wage
	(1)	(2)
event time = -3 × MNE × treated	-0.0029***	-0.0060***
	(0.0009)	(0.0020)
event time = -2 × MNE × treated	-0.0014***	-0.0010
	(0.0004)	(0.0017)
event time = -1 × MNE × treated	-0.0066	0.0221**
	(0.0060)	(0.0101)
event time = 0 × MNE × treated	-0.0071	-0.0019
	(0.0127)	(0.0062)
event time = 1 × MNE × treated	0.0013	0.0056
	(0.0156)	(0.0060)
event time = 2 × MNE × treated	0.0024	0.0051
	(0.0176)	(0.0055)
event time = 3 × MNE × treated	0.0037	0.0095*
	(0.0182)	(0.0057)
event time = -3 × treated	0.0023***	0.0018*
	(0.0007)	(0.0011)
event time = -2 × treated	0.0011***	-0.0004
	(0.0003)	(0.0010)
event time = 0 × treated	0.0091**	0.0002
	(0.0043)	(0.0041)
event time = 1 × treated	0.0206**	0.0056
	(0.0091)	(0.0036)
event time = 2 × treated	0.0312***	0.0027
	(0.0102)	(0.0023)
event time = 3 × treated	0.0435***	0.0005
	(0.0101)	(0.0028)
event time = 4 × treated	0.0461***	-0.0020
	(0.0099)	(0.0031)
Controls	✓	✓
Fixed-effects		
Matched-group-year	✓	✓
Worker-cohort	✓	✓
event time-additional spikes-(MNE|Domestic)	✓	✓
Observations	1,894,184	1,346,698
R^2	0.6000	0.9773

Notes: ***Significant at the 0.1% level; **significant at the 1% level; *significant at the 5% level; .significant at the 10% level. This table presents difference-in-differences coefficients for MNE and domestic firm workers, see eq. (1). MNEs include foreign firms and domestic firms with foreign subsidiaries. Dependent variables are an indicator whether a worker has left the automating firm (Column one) and the log hourly wage of stayers (Column two). Controls include age and its square, delineated by the workers' contract type in the pre-automation year. The regressions compare incumbent workers at firms with a Machinery investment spike with matched controls at firms that spike later, matched on 2-digit NACE industry, employment size, and log hourly wages (including two lags); see Section 3. Machinery investment spikes are based on firms' investments in Machinery; see Section 5.3. Standard errors at clustered at the level of the firm where the worker is employed in the pre-automation year.