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FDI, technological progress and inequality

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ABSTRACT
How does foreign direct investment impact wages and the task content of jobs? Using linked employer-employee data from Hungary and an event study approach we show that FDI increases the returns to abstract tasks, while it does not affect the returns to routine and face-to-face tasks. This finding appears to be driven by skill-biased changes in technology, as acquired firms innovate more with their foreign partners, import more machines and improve product quality. These suggest that FDI-induced technological change is an important driver of growing inequality in developing countries.

JEL codes: J31, M52, F23
Keywords: wage inequality, foreign-owned firms

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Külföldi közvetlen tőkeberuházás, technológiai fejlődés és egyenlőtlenség

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ÖSSZEFOGLALÓ

Hogyan hat a külföldi közvetlen tőkeberuházás (foreign direct investment, FDI) a bérekre és a munkák feladat-tartalmára? Magyarországi kapcsolt munkáltató-munkavállaló panel adatok és eseményelemzés (event study) segítségével megmutatjuk, hogy a külföldi tőkeberuházás növeli a munkahelyen elvégzett absztrakt feladatok hozamát, miközben nincs hatása a rutin és a személyes kapcsolattartát igénylő feladatok hozamára. Elemzésünk alapján úgy tűnik, hogy ezen folyamat mögött az áll, hogy a külföldi tőkeberuházás hatására a cég képesség-igényes technológiára vált (skill-biased technological change). A külföldi felvásárlást követően a vállalatok többet innoválnak külföldi partnereikkel, több gépet importálnak, és javítják termékeik minőségét. Mindez azt sugallja, hogy a külföldi tőkeberuházás által kiváltott technológiai változás fontos mozgatórugója a növekvő egyenlőtlenségnek a fejlődő országokban.

JEL kódok: J31, M52, F23
Kulcsszavak: béregyenlőtlenségek, külföldi tulajdonú vállalat

FDI, technological progress and inequality

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Abstract

How does foreign direct investment impact wages and the task content of jobs? Using linked employer-employee data from Hungary and an event study approach we show that FDI increases the returns to abstract tasks, while it does not affect the returns to routine and face-to-face tasks. This finding appears to be driven by skill-biased changes in technology, as acquired firms innovate more with their foreign partners, import more machines and improve product quality. These suggest that FDI-induced technological change is an important driver of growing inequality in developing countries.

Keywords: wage inequality, foreign-owned firms
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1 Introduction

Global yearly FDI flows exceed more than 1000 billion dollars annually and a two percent share of the world GDP (OECD, 2023). In line with this, most nations established investment promotion agencies (Crescenzi et al., 2021) to foster economic growth by attracting more FDI (Haskel et al., 2007; Javorcik, 2004; Poole, 2013). As a negative side effect, FDI increases wage inequality in developing countries (Basu & Guariglia, 2007; Bhandari, 2007; Figini & Görg, 2011; Goldberg & Pavcnik, 2007; Herzer et al., 2014). Recent studies explain this fact by the increasing sorting of workers. The sorting of workers increases because the acquiring firms cherry-pick the best domestic firms and workers. In other words, FDI increases wages and employment at firms that offered a relatively high wage even before the acquisition (Heyman et al., 2007; Arnold et al. 2009; Brown et al. 2006, 2010; Wang and Wang, 2015; Helpman et al., 2016). On top of that, acquired firms upgrade their workforce after acquisition by hiring high-skilled workers who would earn relatively high wages at every firm (Hijzen et al., 2013; Koch & Smolka, 2019). These two mechanisms foster positive assortative matching between workers and firms, thereby increasing wage inequality even if foreign acquisition has no direct wage effect.

In this paper, we show that workers benefit unequally from the wage impact of FDI even if we filter out selectivity in FDI and workforce composition. In particular, wage growth is the highest in occupations in which people earn a relatively high salary and perform more abstract tasks. We argue that this result is driven by the technological progress taking place at the acquired firm. In line with this, we show a battery of suggestive evidence that acquired firms change their technology in a skill-biased way.

We use Hungarian linked employer-employee data and a novel empirical strategy for the estimation. The main focus of our empirical methodology is to estimate the causal effect of FDI on wages by filtering out the selectivity in FDI. We rely on the fact that firms most likely cannot control whether they are acquired one year earlier or later. Therefore, we restrict our attention in the main analysis to firms established as domestic companies and acquired later. Then, we use an event study approach to estimate the causal effect of FDI on wages.

Besides, we go beyond estimating the wage gap between blue- and white-collar workers. Instead, we follow Firpo et al. (2011) and measure the return to three specific tasks: (i) routine tasks with low skill requirements, (ii) abstract cognitive tasks with high skill requirements, and (iii) tasks that need face-to-face interaction across workers. The importance of this empirical strategy is that it enables us to infer the heterogeneity in the wage effects of FDI beyond a blue- and white-collar comparison, and makes the results comparable with previous results on skill-biased technological change (Acemoglu & Autor, 2011; Autor et al., 2003).

Our main results suggest that FDI increases the return to abstract tasks only. We find that FDI increases the return to one standard deviation larger abstract tasks by 3 percentage points, while the return to face-to-face tasks or routine tasks does not change. This implies that wages increase by more than 6 percent in occupations requiring a college degree. In contrast to this, wages in service-related occupations or in elementary jobs do not increase at all.

We conduct several robustness checks to show that these estimates are not driven by the change in workforce composition or selectivity in acquisition. We show that the results remain the same if we restrict the sample to incumbent workers who worked at the firm both before and after the acquisition. Furthermore, as an alternative estimation strategy, we use all Hungarian firms and extend our model with firm and worker fixed effects as in Abowd et al. (1999) and Frias et al. (2022). We show that the results are robust to the inclusion of firm-task fixed effects. The results are therefore not driven by the possibility that acquired firms had paid higher returns on abstract tasks even before the acquisition.

Finally, we show that the results are not driven by the growing export activities of acquired firms, as the results remain the same if we control for the task returns of exports. We also show that the effect is similar in the service and manufacturing sectors.

As the second step of the analysis, we investigate the employment effects of FDI. First, we show that employment increases by 8-10 percent after the acquisition. Then, we investigate how FDI affects workforce composition. If abstract, routine, and face-to-face tasks are imperfect substitutes, a decrease in abstract tasks would increase the relative productivity of, and the returns to, these tasks (Card et al., 2018; Jäger & Heining, 2022; Lindner et al., 2022). Furthermore, acquired firms may decrease the share of abstract tasks in production by selective firing or hiring. In this case, the return to abstract tasks would increase even if the technology of the acquired firms remained the same. In contrast to this hypothesis, we found that the average share of abstract, routine, and face-to-face tasks is unchanged after FDI. This result is robust to using an event study approach.

In the final part of the paper, we examine the possible underlying mechanisms. Our preferred explanation for the empirical findings is that firms upgrade their technology in a skilled-biased way after the acquisition. This means that the relative productivity of abstract tasks increases. As a consequence, the return to abstract tasks increases without the decrease of abstract tasks in the production function (Acemoglu & Autor, 2011). We provide a range of suggestive evidence for this mechanism. First, we use an event study approach to show that firms are more likely to report innovation activities right after FDI. They are also more likely to innovate in cooperation with foreign members of their company group, while the intensity of R&D activities does not change. This means in our interpretation that the acquired firms get access to and implement the (skill-biased) technology of the parent firm. Furthermore, there is more organizational innovation and an increase in the prevalence of occupational changes among incumbents at the acquired firms. These suggest that firms are reorganized after the acquisition. Regarding physical capital, we show that acquired firms import more machinery after FDI that may complement abstract tasks and substitute for routine tasks. In line with this, the return to routine tasks decreases significantly after a foreign investment from a high-income country, while it does not change at other firms. This further supports the hypothesis that firms get access to skill-biased technology from more advanced countries. Finally, we show that acquired firms switch to producing more expensive product varieties and increase product quality. We interpret this change in product composition as a sign of technology improvement as well.

Next, we investigate alternative explanations for the change in task returns. We test whether firm growth after FDI can explain these changes. Becker et al. (2019) argue that workers in larger firms have more specialized tasks. As a consequence, the number of different occupations and wage differences across occupations are also larger in firms with more employees. In contrast, we do not find evidence that the number or wage dispersion of occupations is increasing after FDI.

Another possible mechanism is related to the change in monitoring costs. According to Lazear (2018), firms use incentive contracts to increase effort if they cannot monitor it. Firms may introduce incentive contracting and bonus payments to incentivize workers to perform more abstract tasks. We show that FDI does not alter the share of workers receiving bonuses or overtime. Furthermore, it is intuitive to assume that monitoring costs are higher if the distance between the home country of the investor and Hungary is larger. Still, we do not find evidence that distance to the country of the investor affects the returns to tasks.

In addition to the research cited on the wage effects of FDI, we also contribute to the broader literature on firm-specific wage premia. In a perfectly competitive labor market, wages should not change on average if a worker moves from one firm to another. As opposed to this, empirical research showed that some firms offer a systematically larger premium (Abowd et al., 1999; Barth et al., 2016; Card et al., 2013; Song et al., 2019). One part of the premium comes from exports (Frıas et al., 2022) and FDI (Breau & Brown, 2011). We add to the literature by showing that FDI increases the wage premium more in the case of workers performing abstract tasks. We also provide evidence that this change may be driven by technological change taking place in the acquired firms.

We also contribute to the literature on rising residual wage inequality. Several papers documented that wage inequality increases not only across firms or occupations, but also across workers of the same occupation (Lemieux, 2006) or establishment (Mueller et al., 2017). A number of different mechanisms lead to within-firm inequality, such as performance payments (Barth et al., 2012; Lemieux, 2006), decreasing unionization (Bruns, 2019; Freeman, 1982; Svarstad & Nymoen, 2022), increasing firm size (Mueller et al., 2017) or technological change (Barth et al., 2020; Lindner et al., 2022). We enhance this literature by showing that FDI increases within-firm wage differences even after controlling for selectivity in FDI and worker composition.

We add to the literature on the effect of FDI on wage differences as well. Firms operating in developed countries pay a higher wage premium for abstract tasks (Baumgarten et al., 2013; Hakkala et al., 2014) and use less blue-collar workers (Koerner et al., 2023) after investing abroad. There is also evidence that FDI increases the relative wages of high-skilled workers in developing countries (Chen et al., 2011; Earle et al., 2018; Feenstra & Hanson, 1997). These results are in line with the Vanek theorem (Vanek, 1968), namely that FDI moves tasks between countries which are unskilled-biased in developed countries and skilled-biased in developing countries (Acemoglu & Autor, 2011; Lai & Zhu, 2007; Trefler & Zhu, 2010). We contribute to this literature by showing that firms in developing countries are more likely to innovate after FDI and may change their technology in a skilled-biased way.

Finally, our results relate to previous work on the effect of foreign ownership on firm outcomes in Hungary. Several papers showed that foreign ownership increases productivity (Brown et al., 2006; Schoors & Van Der Tol, 2002; Sgard, 2001; Szekeres, 2018). Furthermore, foreign ownership increases firm-level average wages as well (Csengödi et al., 2008; Earle et al., 2018; Kertesi & Köll, 2002; Köllő et al., 2021). We add to this literature by using administrative wage whereby we can filter out the selectivity in workforce, and by investigating within-firm wage inequality and the underlying mechanisms.

2 Institutional background

In addition to the abundance of available data, Hungary is an excellent laboratory for estimating the wage impact of FDI. First, Hungary entered the European Union in 2004. The relatively low wage level of Hungary compared with old member states and the legal certainty of the EU common market induced large-scale FDI in the last two decades. Second, Hungarian employment protection institutions are similar to those in Anglo-Saxon countries and are relatively weak compared with most Western European countries. It is relatively easy to dismiss workers and wage bargaining takes place primarily at worker level (Riboud et al., 2002; Tonin, 2009). The share of union members is less than 20 percent, which is lower than in other OECD countries (C. OECD, 2004), while industry-level agreements are rare (Neumann, 2006). These institutional circumstances enable foreign firms to adjust both employment and wages after investing in Hungary.

3 Data

We use the Panel of Linked Administrative Data (Admin3) database, provided by the Databank of the Centre for Economic and Regional Studies (KRTK).[1]

The Admin3 database contains administrative wage data for a 50 percent random sample of the population between 2003 and 2017. The dataset contains unique identifiers for employers and firms, the start and end date of employment contracts, and the monthly wage. This data structure enables us to follow workers between firms. In addition, the database contains information on the age, gender and 4-digit occupation code of the worker, and whether she works full- or part-time. The firm-level data contains the corporate income tax returns, submitted to the National Tax and Customs Administration, for the universe of incorporated firms. We observe the balance sheet and income statements of firms on a yearly level and the industry of the firm. We match the home country of the owner if the firm is foreign-owned. The ownership data is provided by Central European University MicroData.[2] The two datasets were merged using a probabilistic matching method based on the work of (Card et al., 2016). Appendix Section A.1 provides more detail on the dataset and the matching process.

We split foreign firms into two groups. The first group includes firms that entered our dataset as domestic firms and were acquired during the observed period. The second group contains all other foreign firms which entered our dataset as foreign firms because they were acquired before 2003 or were established by greenfield investment.

We use three additional data sources to investigate the mechanisms behind the main results.

Community Innovation Survey (CIS): We use the Community Innovation Survey (CIS) to investigate the innovation activities of firms. This database is a biannual survey available in every EU country. Recent literature uses it to estimate the effect of innovation activities on firm productivity (Crépon et al., 1998; Griffith et al., 2006). The CIS innovation dataset contains information on specific types of innovation (e.g. introduction of a new product, a new process, or an organization type) and R&D activities conducted in firms in the year of the survey and the previous two years. Every firm with more than 50 employees and a random sample of firms with less than 50 employees have to participate in the survey. We can merge the CIS database with the balance sheet data using unique firm identifiers, but we are not allowed to merge them with the administrative employment and wage data due to data security restrictions.

Hungarian Structure of Earnings survey: The Structure of Earnings Survey (SES) is requested by Eurostat and is available in every country of the European Union. Most importantly, the database includes information on wage elements (the base wage, bonuses, premia, and overtime payments) earned in May. Unlike in most other countries, the Hungarian version is repeated yearly and has a unique firm identifier that allows merging the SES with the administrative balance sheet data. Every firm with more than 50 employees and a random sample of firms between 5 and 50 employees has to participate in the survey. The SES has a repeated cross-section structure at worker level. Firms with less than 50 workers have to report wages for all workers, while larger firms have to report wages for a 10 percent sample of workers. Workers are in the sample if they were born on the 5^{th}, 15^{th}, or 25^{th} day of the month.

Customs Statistics: The Customs Statistics contain the universe of trading firms, recording their exports and imports in a 6-digit Harmonized System (HS) product breakdown for all years from 2004 to 2016. The database consists of the amount and unit value of imports and exports by country, year,

[1]The linked administrative data collection (Admin3) is the property of the data owners and their legal successors: NEAK, MÁK, NAV, ITM, and OH. The data used was processed by the KRTK Data Bank.

[2]HUN-REN KRTK (distributor). 2024. "Mérleg LTS [data set]" Published by Opten Zrt, Budapest. Contributions by CEU MicroData. Data usage is subject to a licensing agreement with Opten Kft. To process the data, MicroData received funding from the National Research, Development and Innovation Office (Forefront Research Excellence Program contract number 144193).

and product. We match the data to the balance sheet records of the firms based on a unique firm identifier. We cannot merge it with the administrative employment and wage data due to administrative restrictions.

We use this database to estimate product-level prices and quality measures, and to identify machine import. For the quality measures, we simply use export magnitudes and product prices by 6-digit HS code, export country and year. For defining machine imports, we use the official crosswalk for translating HS6 codes into Broad Economic Categories (BEC), a three-digit classification that groups transportable goods according to their main end-use. We define a firm as importing machines if it imported any goods from the category of "Capital goods (except transport equipment), and parts and accessories thereof" (BEC 4).[3] As a robustness test, we consider only the narrower group of "Capital goods (except transport equipment)" (BEC 41) as machine imports. The dataset is matched to the firms' balance sheet records based on a unique firm identifier.

3.1 Sample selection

In the main analysis, we use the Panel of Linked Administrative Data (Admin3) database and restrict our sample to one month (October) every year, as the firm-level data is available only on a yearly level. To construct our "Full Sample", we further restrict it to workers who were employed under a labor contract at least once during the observed period at a firm having at least 10 employees. We drop workers with missing occupation codes since we cannot merge our tasks measure indices in their case. Furthermore, we only keep workers in our sample who work full-time (i.e. work at least 36 hours per week) and have non-missing wage information. If a worker has more jobs at the same time, we use the job with the highest salary. Our main right-hand-side variable is the daily wage (monthly wage divided by the number of days worked). This sample contains 11,957,372 worker-year observations, corresponding to 1,845,958 workers working at 103,201 firms. 4,478,541 worker-year observations concern foreign-owned firms.

For the main part of the analysis, we construct a sample, called "Acquired Sample", in which we focus on the 2663 acquired firms only, where we observe years before and also after the acquisition. The number of acquisitions per year varies between 93 and 367 (see Appendix Table A.6). In this subsample, we have 628,331 worker-year observations, 311,361 of which correspond to foreign-owned years.

In our "Full Sample", we keep all firms even if they were foreign-owned in every observed year or have always been domestic. This is because we use individual fixed effects in our robustness checks, where fixed effects are identified from workers' movement between companies. If we restricted the sample to specific firms, we would not observe all worker movements and the variance of worker fixed effects (Bonhomme et al., 2023) would be underestimated.

3.2 Measurement of tasks

We use O*NET data to compute our task measures.[4] The O*NET survey asks questions about the abilities, skills, knowledge, and work activities required in an occupation. We only focus on "generalized work activities" and "work context".

To construct our summary indices, we rely on the work of Firpo et al. (2011). Later, we show that our results are robust to creating alternative summary indices.

Our first measure, "abstract", identifies tasks that require abstract cognitive skills, and are likely to be complemented by computers, while they do not need face-to-face interaction. As such, these tasks can be offshored, however, they cannot be automated. Our second measure, "automation", stands for routine and repetitive tasks that have the potential to be offshored or replaced by automation. Our last measure, "face-to-face interaction", refers to tasks that require personal interaction between workers or between workers and customers. These tasks are difficult to offshore or to replace with computers. See Appendix A.2 for more details about the construction of our task measurements.

The task measures indices are standardized to have zero mean and a standard deviation of 1 in the sample. According to the estimated correlations, jobs that require frequent face-to-face contact with other workers or customers also require more than the average level of abstract tasks from the worker and less routine tasks (see Appendix Table A.4).

[3] $https://unstats.un.org/unsd/classifications/Family/Detail/10$

[4] We use O*NET 20.1, released in October 2015, $https://www.onetcenter.org/db_releases.html$

Appendix Figure A.1 shows the distribution of the three tasks in our sample. The left panel corresponds to the full sample and shows task distribution separately for foreign- and domestic-owned firms. The figures on the right show the same, but within the subsample of acquired firms. On these figures, we compare the pre-acquisition (domestic-owned) and post-acquisition (foreign-owned) years of the acquired firms. The main message of the figures is that while tasks vary across workers to a large extent, the distribution of task indices is similar for domestic- and foreign-owned firms.

We follow the strategy of Ebenstein et al. (2014) and Hakkala et al. (2014) to calculate firm-level task use. We re-scale task measures to the 0-1 interval by dividing them by their maximum instead of standardization. Then, we aggregate up individual-level task use on the firm level to compute firm-level task use:

$$Taskuse_{njt} = \frac{\sum_i TaskMeasure_{nijt}}{\sum_{o=1}^{3} \sum_i TaskMeasure_{nijt}}, \tag{1}$$

where $TaskMeasure_{nijt}$ means the amount of task n performed by worker i at year t at firm j. Accordingly, the numerator means the total amount of task n used by firm j at year t. So $Taskuse_{njt}$ measures the share of task n in firm production on the [0,1] scale.

3.3 Measurement of product quality

We decompose firm-level product prices using the Customs Statistics database (see more in Section 3) to product variety and a residual price part, running the following regression:

$$P_{jvct} = \tau_t + P_v + P_c + \varepsilon_{jvt} \tag{2}$$

where the dependent variable is the log-price of product variety v produced by firm j at year t and exported to country c. The explanatory variables are year fixed effect, product fixed effects P_v showing the economy-level average price of variety v, and country fixed effects P_c showing whether the firms export the products more expensively to country c compared with other countries. In this setup, residual price (ϵ_{jvt}) has a direct interpretation as well (Faber, 2014; Fieler et al., 2018). If ϵ_{jvt} is positive, product variety v produced by firm j has a higher quality than the average quality of its competitors.

We define the firm-level average product variety price as

$$P_{jt} = \frac{\sum_v P_v Revenue_{jvt}}{\sum_v Revenue_{jvt}} \tag{3}$$

where $Revenue_{jvt}$ denotes the revenue of firm j from selling variety v at year t. If the -P_{jt} variable increases within the firm between years, it means that the firm sells relatively more expensive varieties compared with previous years. We define firm-level country price (P_{ct}) similarly as in Equation 3, but use country fixed effects (P_c) in the denominator.

Finally, we define firm-level residual prices at firm j at year t as

$$\varepsilon_{jt} = \frac{\sum_v \varepsilon_{jvt} Revenue_{jvt}}{\sum_v Revenue_{jvt}} \tag{4}$$

This firm-level residual price is increasing if firm j improves product quality between years.

3.4 Descriptive statistics

Table 1 Panel A shows workforce characteristics by firm ownership on our "Full Sample". Domestic firms employ somewhat more males and older workers than foreign firms. The average level of abstract tasks is lower at domestic than at foreign firms. It is also lower at acquired firms before than after the acquisition. The average level of face-to-face tasks is higher at domestic than at foreign firms. It does not change much around the event of a foreign acquisition. The difference by ownership type between the average level of routine tasks is small.

Panel B in the same table shows the descriptive statistics of the firms by ownership status. Foreign firms are more than three times larger on average than domestic firms and have higher sales. Acquired firms are also larger in terms of the number of employees and sales revenue than domestic firms even before the acquisition, and they became even larger after the acquisition.

Table 1: Worker and firm characteristics by ownership

	Always Domestic	Acquired Pre-Acquisition	Acquired Post-Acquisition	Always Foreign
Panel A: Worker characteristics				
Male (%)	63.4	63.7	63.1	56.5
Age	40.6	39.0	40.3	38.1
	(10.8)	(10.7)	(10.7)	(10.4)
Abstract	-0.12	-0.05	0.06	0.18
	(1.00)	(1.02)	(1.00)	(0.98)
Face-to-face	0.09	-0.04	0.00	-0.14
	(0.98)	(0.96)	(0.97)	(1.01)
Routine	-0.01	-0.02	-0.03	0.01
	(0.94)	(0.98)	(1.03)	(1.09)
Observation	6,949,920	239,083	389,248	4,379,121
Panel B: Firm characteristics				
Employment	24	39	57	106
	(200)	(114)	(241)	(459)
Log Sales	11.92	12.67	13.06	13.50
	(1.47)	(1.77)	(1.74)	(2.04)
Manufacturing (%)	38.8	30.4	28.9	37.8
Observation	678,140	13,775	15,412	92,304

Note: This Table shows descriptive statistics of our "Full Sample". Firms are classified as foreign-owned if the share of directly or indirectly owned foreign capital is at least 50%. We split foreign firms into two groups. The first group includes firms that entered our dataset as domestic firms and were acquired during the observed period. These firms have "pre-acquisition" and "post-acquisition" periods. The second group ("always foreign") contains all other foreign firms that entered our dataset as foreign firms because they were acquired before 2003 or were established by greenfield investment. Column (2) shows the pre-acquisition years and Column (3) the post-acquisition years of acquired firms. The last column shows firms that were foreign firms already at the beginning of the sampling period. Task measures are standardized to have zero mean and a standard deviation of one. Standard deviations are in the parentheses.

4 The effect of foreign acquisition on task returns

4.1 Estimation strategy

We run our main specification on the "Acquired Sample" that includes only firms acquired after 2003 (see more details in Section 3.1). We estimate the effect of FDI on task returns at worker level by using OLS and fixed effect regressions in a difference-in-differences setting:

$$\begin{aligned} lnw_{ijot} &= \delta_1 * Foreign_{jt} + \delta_2 * Foreign_{jt} * TaskMeasure_o + \\ &+ \tau_t * TaskMeasure_o + \gamma_1 * X_{ijt} + s_{jt} + f_j + \tau_t + [\nu_{ij}] + \epsilon_{ijt}, , \end{aligned} \tag{5}$$

where lnw_{ijot} denotes the logarithm of the daily wage of worker i working at firm j at occupation o in year t. $TaskMeasure_o$ denotes the occupation-level task indices defined in Section 3.2 (standardized to have a mean of zero and a standard deviation of one). The variable $Foreign_{jt}$ is a dummy denoting foreign ownership. The main coefficient of interest is δ_2 showing the effect of foreign acquisition on the returns to tasks. We control for worker characteristics (X_{ijt}) in the model, such as age, its square, and gender. We further add industry (s_{jt}) and year dummies (τ_t), and task-year interactions ($\tau_t * TaskMeasure_o$) to account for economic-level trends in task returns.

We add firm-specific fixed effects (f_j) to the model to control for selectivity in foreign ownership. Using this strategy, we can quantify how much the selectivity across firms affects returns to tasks after acquisition. The reason for using this strategy is that previous literature on FDI (Earle et al., 2018) showed that foreign firms tend to cherry-pick the best firms. See Appendix Table A.7 for the number of observations used for identification. The standard errors are clustered at the firm level.

Based on the findings of recent literature, interpreting the difference-in-differences parameters is challenging if the treatment is staggered. The main problem is that the estimated treatment effects may be biased if the treatment effects are heterogeneous. We use a two-stage difference-in-differences method suggested by Gardner et al. (2024) as a robustness check for this problem. This method estimates firm and time fixed effects using the untreated subsample in the first stage. Then, we subtract the estimated fixed effects from the observed outcomes and regress the resulting residualized outcomes on treatment status in the second stage. Gardner et al. (2024) show that this method identifies the treatment effects in a robust and unbiased way even if the treatment effects are heterogeneous.[5]

Next, we perform an event study analysis to examine how the effect of foreign acquisition evolves over time. We include leads and lags of the foreign acquisition interacted with the task measures:

$$\begin{aligned} lnw_{ijot} = \alpha_s * Foreign_j + \alpha_s * Foreign_j * TaskMeasure_o + \\ \gamma_1 * X_{ijt} + s_{jt} + \tau_t + \tau_t * TaskMeasure_o + [f_j] + \epsilon_{ijt}, \end{aligned} \tag{6}$$

where lnw_{ijot} denotes the logarithm of the daily wage of worker i working at firm j at occupation o in year t. $TaskMeasure_o$ is the task index and the control variables are the same as in Equation (5), except for one important change. Now, the coefficient of $Foreign_j * TaskMeasure_o$ has a time dimension. s is zero in the year of acquisition. We normalize δ_{-1} to zero. Therefore, δ_s shows the return to $TaskMeasure_o$ s year before or after the acquisition relative to the last year under domestic ownership. , and negative (positive) s denotes the years before (after) our reference period. All else remains the same as in the previous equation. We also show that the results are robust to using the estimation approach suggested by Gardner et al. (2024).

4.2 Results

Table 2 shows the effect of foreign acquisition on task returns (Equation (5)) by including all three task measures in a single regression. The first column shows that firms pay 15.7 percent higher wages to their workers after a foreign takeover, but this wage difference drops to 3 percent once we control for firm fixed effects, and fully disappears once we use the two-stage difference-in-differences method suggested by Gardner et al. (2024).

Turning to the main variable of interest, we find that workers receive a higher return to abstract tasks after a foreign acquisition. The first column shows that after a foreign takeover, a one standard deviation higher abstract task index corresponds to a 4.9 percent higher wage. This premium drops to 2.9 percent once we control for firm-specific fixed effects in Column (2) or use the two-stage difference-in-differences method in Column (3).

In contrast to abstract tasks, foreign firms pay lower returns on face-to-face and routine tasks. The difference is 2.4 percent for face-to-face and 1.7 percent for routine tasks. However, the difference fully disappears if we control for firm-specific fixed effects.

Finally, Column (3) shows that the results are robust to using the two-stage difference-in-differences method proposed by Gardner et al. (2024). Based on these results, we conclude that foreign takeover increases only the return to abstract tasks.

[5] As we use the subsample of firms acquired between 2004-2017, in the last year of the sample, 2017, there is no untreated firm. Therefore, we are unable to estimate the time fixed effect for this year in the first stage and have to leave out this year from the second stage as well. This results in a lower number of observations under this method.

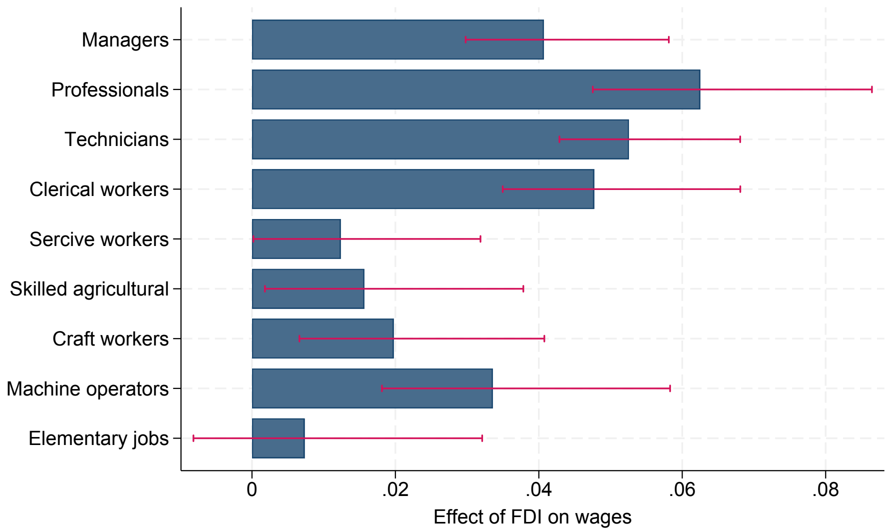
Table 2: The effect of foreign acquisition on task returns

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign	0.157***	(0.034)	0.031***	(0.011)	0.004	(0.017)
Foreign * Abstract	0.049***	(0.013)	0.029***	(0.007)	0.028***	(0.009)
Foreign * Face-to-face	-0.024*	(0.014)	-0.010	(0.007)	-0.021	(0.015)
Foreign * Routine	-0.017	(0.017)	0.006	(0.009)	0.005	(0.011)
Constant	7.915***	(0.063)	8.061***	(0.030)	7.898***	(0.011)
Observations	628,331		628,331		592,161	
R-squared	0.452		0.708			
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: This Table shows the effect of foreign acquisition on task returns. In particular, it shows the parameter estimates of Equation (5), in which the dependent variable is the logarithm of the daily wage of worker i working at firm j in year t. We estimated the model on our "Acquired Sample" (more details in Section 3.1). The main independent variables are the task indices (see more in Section 3.2 interacted with a dummy denoting foreign ownership. Year fixed effects and their interaction with task use indices are included in every regression. We further control for the gender and age of the worker, and whether the firm is a public firm, and 1-digit industry fixed effects. In the second column, we further control for firm-specific fixed effects. Column (3) uses the two-stage difference-in-differences method suggested by (Gardner et al., 2024). Standard errors are clustered at firm level. *** $p < 0.01, **p < 0.05, *p < 0.1$.

Next, we compute how changes in task returns affect wages by occupation. For this purpose, we predict the changes of average wages by one-digit ISCO codes based on Table 2 Column (2). The result on Figure 2 shows that wage growth is the highest among professionals (white-collar occupations requiring a college degree) where wages grew by more than 6 percent. Similarly, we find above than average wage growth among technicians and other clerical workers. As opposed to this, the wage growth after FDI is smaller than average in blue-collar occupations. We do not even find any significant wage growth among service workers and elementary occupations. To sum up, the results suggest that FDI-induced changes in task returns lead to the widening of the blue-collar/white-collar wage gap.

Figure 2: The predicted effect of task returns on wages



Note: The figure shows the wage gain from changes in task returns by 1-digit ISCO codes using Table 2 Column (2). The red lines show standard errors calculated by the delta method.

4.3 Robustness checks and heterogeneity analysis

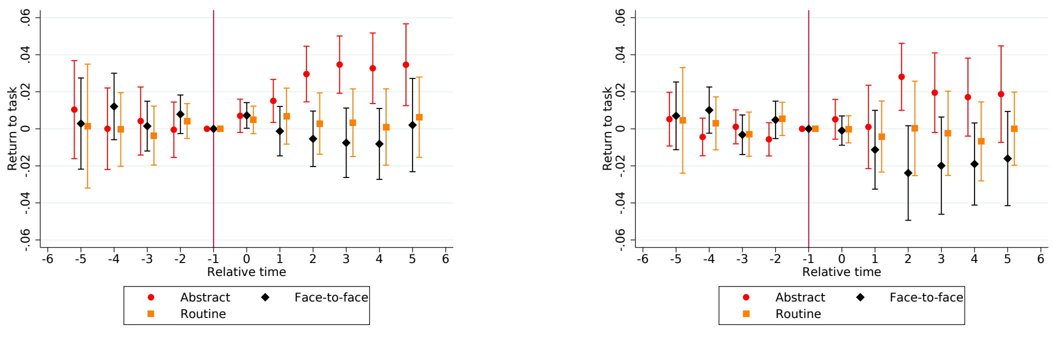
4.3.1 Event study approach

Figure 3 shows the results of estimating Equation (6) by including all three task measures in a single regression. We estimate the model on the "Acquired Sample" by event study method including firm-specific fixed effects (Figure 3a) and by using the two-stage estimation procedure suggested by Gardner et al. (2024) (Figure 3b). The red circles show the results for abstract tasks, the black rhombuses for face-to-face contacts, and the orange squares for routine tasks.

The results confirm our earlier findings and we do not find any evidence for a pre-trend. A foreign takeover increases the return to abstract tasks that do not need face-to-face interaction. By contrast, the return to tasks requiring face-to-face interaction remain the same around the foreign acquisition. Finally, the return to routine tasks does not change significantly either.

Figure 3: The effect of foreign acquisition on task returns – Event study approach

(a) OLS estimation (b) Two-stage diff-in-diffs



Note: The Figure shows the parameter estimates of event study Equation (6), in which the dependent variable is the logarithm of the daily wage of worker i working at firm j in year t. The model is estimated on the "Acquired Sample" (more details in Section 3.1). The main independent variables are the task indices (see more in Section 3.2) interacted with event years, to capture the time relative to the event of the foreign acquisition. Year fixed effects and their interaction with task use indices are included. We further control for the gender and age of the worker, whether the firm is a public firm, and 1-digit industry fixed effects. We further control for firm-specific fixed effects. The bars show 95% confidence intervals and standard errors are clustered at firm level.

To sum up, the results show that after a foreign takeover, the return to abstract tasks that are potentially complementary to automation and are relatively easy to offshore increases. By contrast, the return to face-to-face tasks that are difficult to offshore or the return to tasks that are potentially substituted by new technologies and are relatively easy to offshore do not change. These results are in line with the hypothesis that the skill premium increases after FDI.

4.3.2 Selectivity in acquisition

Previous literature emphasized the importance of firm-level selectivity in the case of foreign acquisition, i.e. foreign firms tend to cherry-pick the best domestic firms (Almeida, 2007; Earle et al., 2018). We overcome this issue by (i) considering only acquired firms and comparing their behavior under domestic and foreign ownership, and (ii) including firm fixed effects in the model.

Nevertheless, there are situations in which firm fixed effects alone are not enough to control for all potential differences across firms. First, acquisition firms grow larger in terms of both the number of employees and sales revenue, and they engage in export activities more often than domestic firms. These changes in firm characteristics may affect task returns independently from firm ownership. To rule out this scenario, we re-estimate Equation (5) in Appendix Table C.9 Panel A by controlling for the logarithm of sales revenue, the logarithm of the number of employees, and a dummy indicating that the firm participates in export activities.

The second issue is that foreign firms may not cherry-pick those firms that are better in cross-sectional comparison but rather have a larger growth potential. Furthermore, if high-growing firms have a different wage dynamics than other firms, the firm fixed effect regression may show biased results on the effect of task return even without foreign acquisition. To investigate this issue, we add firm-specific trends to the model in Panel B.

Third, firms may pick those firms that pay high returns to abstract tasks even before acquisition. We investigate this possibility in Panel C where we also add firm-task fixed effects to the model. Reassuringly, the results do not change quantitatively in either case.

4.3.3 General equilibrium effects

Foreign acquisitions may have spillover effects by altering the labor demand at specific labor markets. Namely, foreign investors may increase the local labor demand which may increase the wages of workers doing abstract tasks. We include county-year fixed effects in Appendix Table C.9 in Column (3), industry-year fixed effects in Column (4), and industry-county-year fixed effects in Column (5) to filter out spillover effects. The results are robust to these changes in the main specification, and the size of the parameters remains almost the same.

4.3.4 Selectivity in workforce

The composition of the workforce may change after acquisition. If foreign firms screen workers' abilities better than domestic firms, foreign acquisition will improve worker composition by selective hiring. If foreign firms hire workers who are better in doing abstract tasks, we would overestimate the causal effect of FDI on task return.

We conduct two robustness checks to investigate this problem. First, we restrict our sample to incumbent employees who had been with the firm for three years, from the year before the acquisition to the first year after the acquisition. The results hold on this subsample as well. Panel A in Appendix Table C.17 confirms that our results are not driven by changes in workforce composition only.

Second, we add worker fixed effects to Equation (5). We use all the firms in this specification, even if they were foreign in every observed year or were always domestic. The reason for this is that worker fixed effects are identified from the movement of workers between companies. If we restricted the sample to specific firms, we would not observe all worker movements and would underestimate the variance of worker fixed effects (Bonhomme et al., 2023). Furthermore, we control for the possibility that firms that were foreign already at the beginning of the sampling period paid different returns to tasks compared to firms that started domestic and were acquired during our years of observation. For more detail on the estimation strategy, see Appendix Section C.2.

Table 3 shows the results. We find that workers at firms acquired during the years of observation receive a higher return to abstract tasks. The gap between domestic and other foreign firms in the return to abstract tasks shrinks if we control for firm fixed effects in Column (2) or add worker fixed effects in our preferred estimates (Column (3)). Here, we find that foreign acquisition increases the return to abstract tasks by 1.5 percentage points, while the return to face-to-face tasks or routine tasks does not change significantly. These results are confirmed by the event study style analysis provided in Appendix Figure C.4, showing that they are not driven by different pre-trends.

Table 3: The effect of foreign acquisition on task returns

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign	0.150***	(0.033)	0.029***	(0.008)	0.026***	(0.006)
Foreign * Abstract	0.049***	(0.012)	0.034***	(0.006)	0.015***	(0.004)
Foreign * Face-to-face	-0.033***	(0.013)	-0.016**	(0.007)	-0.006	(0.004)
Foreign * Routine	-0.026*	(0.016)	0.007	(0.009)	0.002	(0.004)
Constant	7.799***	(0.016)	8.057***	(0.012)	9.251***	(0.010)
Observations	11,957,372		11,957,372		11,957,372	
R-squared	0.567		0.761		0.925	
Worker charact.	YES		YES		YES	
Industry-year FE	YES		YES		YES	
trend in skill usage	YES		YES		YES	
Firm FE	NO		YES		YES	
Worker FE	NO		NO		YES	

Note: This Table shows the effect of foreign acquisition on task returns. In particular, it shows the parameter estimates of Equation (5), in which the dependent variable is the logarithm of the daily wage of worker i working at firm j in year t. The model is estimated on our "Full Sample" by including all the firms, even if they were foreign at the beginning of our sampling period or were always domestic (more details in Section 3.1). The main independent variables are the task indices (see more in Section 3.2) interacted with a dummy denoting foreign ownership. Year fixed effects and their interaction with task use indices are included. We include a dummy indicating that the firm was acquired during our sampling period and a dummy showing that the firm was foreign-owned at the beginning of the sampling period. We interact these dummies with the task measures. We further control for the gender and age of the worker, whether the firm is a public firm, and 1-digit industry fixed effects. Additionally, we control for firm fixed effects (second column), and worker fixed effects (third column). Standard errors are clustered at firm level. *** $p < 0.01, **p < 0.05, *p < 0.1$.

4.3.5 Divestment

Some foreign-acquired firms become domestically owned again a few years after the first acquisition. In this robustness check, we exclude all post-divestment years from our sample, and re-estimate Equation (5) to check the robustness of the wage effect. Table C.12 shows that the results are robust to excluding post-divestment years from the sample and the point estimates do not change.

4.3.6 The effect of export activity on task returns

We examine whether our results could be explained by the fact that acquired firms start to export with a higher probability after a foreign takeover. This is important as entering the export markets increases the firm wage premium (Frıas et al., 2022) and may change labor demand at the firm along several dimensions. To examine this channel, we include a dummy variable in our main regression that is 1 if the firm is exporting and otherwise zero (Equation (5)). We also include the interaction term of this dummy with our task measure indices to control for the possibility that export changes task returns.

The results presented in Appendix Table C.15 show that exporting firms pay 22 percent more compared to non-exporting firms (Column (1)). However, this difference is solely due to the composition effect as it fully disappears once we control for firm-specific fixed effect. Furthermore, we found evidence that exporting firms pay different task returns compared with other firms. More specifically, we found that exporting firms pay a lower return to routine and face-to-face tasks.

The most important message of Appendix Table C.15 is that acquired firms pay a 2.1-2.8 percent higher wage premium for abstract tasks, even if we control for export activities (Column (2)-(3)). Furthermore, we do not find evidence that acquired firms pay different returns on routine and face-to-face tasks compared with domestic firms if we control for the change in export activities after acquisition.

4.3.7 Specific subsamples

In this section, we investigate whether the effect of foreign acquisition differs by worker type or firm group.

First, we investigate only large firms and drop firms that did not exceed the 50 employee threshold during our sampling period. The results are robust to this change (Appendix Table C.17, Panel B).

Second, foreign owners may increase only the wages of managers and leave the wages of other workers untouched. In this case, we would get similar results, as managers perform more abstract tasks and less routine tasks. To rule out this explanation, Panel C of Appendix Table C.17 shows that the main results hold if managers are dropped from our sample.

Finally, we show that the results are robust to matching the acquired firms to similar non-acquired firms. See Table C.14. We also use this sample to conduct a placebo test. See Appendix Section C.4 for the details.

4.3.8 Sectoral comparison

Many acquired firms in the service sector provide business services to their parent company. The effect of FDI on task returns might differ at these firms compared with the manufacturing sector. To examine this possibility, we re-estimate Equation (5) with a slight modification to be able to compare the return to tasks in the service and the manufacturing sectors. We include a dummy indicating that the firm operates in the service industry, which we interact with the foreign dummy and the task measures. We further include the triple interaction term of the three variables.

Appendix Table C.20 summarizes our results. The return to abstract tasks increases after a foreign takeover in the manufacturing sector, while there is no significant difference between the manufacturing and the service sector. The return to other tasks does not change after the takeover in any of the two sectors.

4.3.9 Alternative task measures

In the main part of the analysis, we follow the work of Firpo et al. (2011) in constructing the task measure indices. In this part, we re-scale each task measure so that it equals the percentile rank in 2003 by following the work of Autor et al. (2003), Deming and Kahn (2018), and Ottaviano et al. (2013). The re-scaled indices are between 0 and 1, and represent the relative importance of that task among all workers in 2003. To construct our summary indices, we simply take the average of the corresponding re-scaled indices. We use the same questions as in the main part of the text (see Table A.2).

We re-estimate Equation (5) and Equation (6) using these new indices in Appendix Table C.22 and in Appendix Figure C.5. The results are robust to using these alternative task measures, and the figure further confirms that we do not see a pre-trend with these measures either.

5 The effect of foreign acquisition on employment and task composition

This section estimates the effect of acquisition on employment and task composition in production. This exercise is important because if tasks are imperfect substitutes in production, a decrease of abstract tasks in the task mix increases the relative productivity and return to these tasks. In addition to this, acquired firms may change their technology after the acquisition, which directly affects the share of tasks in production.

5.1 Estimation strategy

As for the estimation of wage effects, we start the analysis with the firms which were domestic at the first observed year and are acquired later, i.e. firms in our "Acquired Sample" (see Section 3.1 for more details). We estimate the following equation at the firm-year level to investigate the employment effect of FDI:

$$y_{jt} = \alpha * Foreign_{jt} + \beta * X_{jt} + [f_j] + s_j + \tau + \epsilon_{ijt}, \tag{7}$$

where y_{jt} denotes employment and the firm-level task use indices introduced in Section 3.2 at firm j in year t. Our main independent variable is the $Foreign_{jt}$ dummy which is equal to one if the firm is majority foreign-owned. We control for industry fixed effects (s_j) and year dummies (τ) in the baseline specification, and add firm fixed effects (f_j) as a robustness check. Lastly, we also test the robustness to the same two-stage difference-in-differences method proposed by Gardner et al. (2024) as in our wage estimates. The standard errors are clustered at the firm level.

In our preferred specification where firm fixed effects are included, the parameter of $Foreign_{jt}$ is identified from ownership change.

Similarly to the wage-regression, to examine the dynamic effects, we estimate an event-study regression which takes the following form:

$$y_{jt} = \alpha_s * Foreign_j + \beta * X_{jt} + f_j + s_j + \tau + \epsilon_{ijt}, \tag{8}$$

where y_{jt} denotes employment and the firm-level task use indices introduced in Section 3.2 at firm j in year t. Now the coefficient of our main independent variable, the $Foreign_j$ dummy, has a time dimension (s). s is zero in the year of acquisition so that δ_s shows the return to $TaskMeasure_o$ s year before or after this year. We normalize δ_{-1} to zero, and negative (positive) s denotes the years before (after) our reference period. We control for industry fixed effects (s_j), year dummies (τ), and add firm fixed effects (f_j) as a robustness check. All else remains the same as in Equation (7). We also estimate the model using the two-stage difference-in-differences method suggested by Gardner et al. (2024).

As a next step, we follow the work of Koerner et al. (2023) to examine whether foreign acquisition induces within-firm task restructuring across incumbent workers. Specifically, we estimate the probability of job changing. We match acquired firms with similar always domestic firms. In particular, we use the matching procedure suggested by Koerner et al. (2023) to achieve a unique one-to-one matching of acquired and always domestic firms over the entire period. This procedure allows us to assign the year of acquisition of the acquired firm to its always domestic pair as a pseudo-acquisition year (see Appendix A.3 for more detail on the matching procedure).

Then, we estimate proportional hazard models to recover the dynamic effects of acquisition on job changes on this matched sample. More specifically, we estimate the following proportional hazard model:

$$lnh_e(t|x_{ity}) = lnh_{0e}(t) + \sum_{j=1}^{4}(\alpha_j * Acquired_f * d_jt) + \beta_1' * X_{ift} + \beta_2' * X_{ift} * t + \tau_y + q_t + \epsilon_{ijt}, \quad (9)$$

where $h_e(t|x_{ity})$ is the hazard rate for the event of job change in quarter t. $Acquired_f$ is a dummy that indicates whether a firm is an acquired firm. We include the interaction between the acquisition dummy and the time interval relative to the investment (d_{jt}) in the regression. We split our time window into four intervals: (i) from 2 years before the acquisition to the year of the acquisition, (ii) the year of the acquisition, (iii) one year after the acquisition, and (iv) two years after the acquisition. We control for gender, age, and its square in the regression. We also include an interaction term between these characteristics and the number of quarters from the (pseudo-) investment in the regression. We further add industry, year and quarter fixed effects to the model. The results are robust to controlling for 1-digit occupation codes. We examine the cumulative hazard of job changes from 2 years (8 quarters) before to 2 years after the year of the (pseudo-) acquisition. We only keep workers in our sample who were working at the firm 2 years before the (pseudo-) acquisition took place and remained at the firm until the year of the acquisition.

5.2 Results

5.2.1 Total employment and task composition

Table 4 presents how total employment and firm-level task usage changes after acquisition. Panel A shows the results for total employment, Panel B for abstract tasks, Panel C for face-to-face contacts, and Panel D for routine tasks. We find that acquired firms employ almost 25 percent more workers than domestic firms (Column (1)). This gap halves as we control for firm fixed effects in Column (2) or use the two-stage difference-in-differences method in Column (3), but remains large and significant even at one percent level.

The table shows that acquired firms use 0.3 percentage points more abstract tasks than domestic firms (see Panel B), a 0.1 percentage points lower share of face-to-face tasks (see Panel C) and a 0.2 percentage points lower share of routine tasks (see Panel D) in production. Even though these differences are small in magnitude, they are significantly different from zero. Furthermore, these differences disappear once we control for the selectivity in FDI by including firm fixed effects in Column (2) or when using the two-stage difference-in-differences strategy of Gardner et al. (2024) in Column (3). The results are robust to using the size of the firm (measured by the number of employees) as weights in the regression (see Appendix Table B.8).

To sum up, we do not find evidence that firms change the composition of tasks used in production in an economically significant magnitude after acquisition. Our event study style analysis confirms this result (see Appendix Figure B.3 and B.2).

Table 4: The effect of foreign ownership on task composition

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
			Panel A: Total employment			
Foreign	0.246***	(0.029)	0.080***	(0.014)	0.106***	(0.021)
Constant	2.827***	(0.021)	2.893***	(0.005)	2.792***	(0.007)
Observations	29,187		29,187		27,778	
R-squared	0.072		0.771			
			Panel B: Abstract tasks			
Foreign	0.003***	(0.001)	0.000	(0.000)	0.001	(0.000)
Constant	0.337***	(0.001)	0.338***	(0.000)	0.336***	(0.000)
Observations	29,187		29,187		27,778	
R-squared	0.319		0.796			
			Panel C: Face-to-face			
Foreign	-0.001**	(0.000)	-0.000	(0.000)	0.000	(0.000)
Constant	0.324***	(0.000)	0.324***	(0.000)	0.324***	(0.000)
Observations	29,187		29,187		27,778	
R-squared	0.264		0.742			
			Panel D: Routine			
Foreign	-0.002***	(0.001)	-0.000	(0.000)	-0.000	(0.001)
Constant	0.339***	(0.001)	0.338***	(0.000)	0.339***	(0.000)
Observations	29,187		29,187		27,778	
R-squared	0.231		0.740			
Year	YES		YES		YES	
Industry	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: This Table shows the effect of foreign ownership on task composition. In particular, it shows the parameter estimates of Equation (7), in which the dependent variables are the employment and firm-level task use indices (see Section 3.2) and the main independent variable is the foreign-ownership dummy. The model is estimated on our "Acquired Sample" (for more details, see Section 3.1). We control for a set of year dummies and 1-digit industry dummies in column (1), while in column (2) we further add firm-specific fixed effects to the model. Column (3) uses the two-stage difference-in-differences method following Gardner et al. (2024). Standard errors are clustered at firm level. $***p < 0.01, **p < 0.05, *p < 0.1$

5.2.2 Robustness checks and heterogeneity analysis

As with our wage equations, we conduct a large variety of robustness checks to investigate the sensitivity of the results. First, we show that the results are robust to adding always domestic firms and firms that were foreign-owned already at the beginning of the observed period to the sample (i.e. "Full Sample", see Section 3.1 for more details). Appendix Table C.11 shows the results.

Second, as some foreign-acquired firms become domestically owned again a few years after the first acquisition, we show that our results are robust to the exclusion of all post-divestment years from our sample (see Appendix Table C.13).

Third, just as in our wage estimates, we take into account that foreign firms are larger in terms of both the number of employees and sales revenue, and also the appearance of foreign investors may alter the local demand for skilled workers. Our results are robust to the inclusion of firm-specific trends, time-varying firm-level characteristics, and county-year, industry-year, or county-industry-year-specific fixed effects (see Appendix Table C.10).

Fourth, as in our wage estimates, we take into account that acquired firms start to export with a higher probability after the foreign takeover, and this pattern can affect the size and composition of the firm. In Appendix Table C.16, we show that our results are robust to controlling for the firms' export activity status.

Fifth, the results are robust to the exclusion of firms having 50 employees at the maximum (see Appendix Table C.18 and Table C.19).

Sixth, we compare the manufacturing and service sectors in Appendix Table C.21. According to Panel A, the observed size growth after acquisition is driven by service-sector firms. Firm composition patterns are the same in the service and the manufacturing sectors (see Panel B-Panel D).

Last, but not least, the results are robust to using an alternative method for defining the summary indices (see Appendix Table C.23, Appendix Figure C.6, and in more detail in Section 4.3.9).

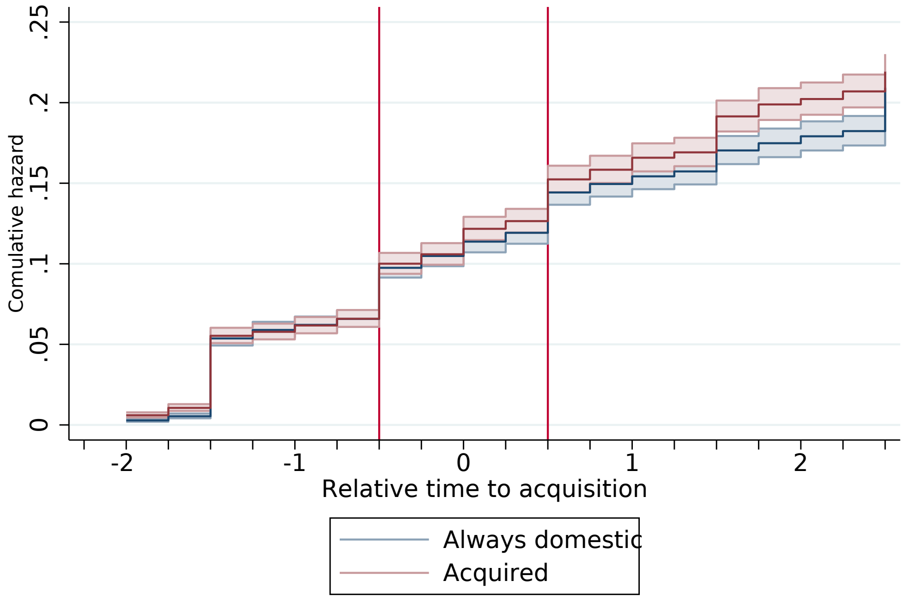
5.2.3 Reallocation of tasks across incumbents

Even though acquired firms do not change worker composition on average, they can still change the allocation of tasks across incumbent workers. Figure 4 shows descriptive evidence for internal workforce restructuring after a foreign takeover. This figure presents the cumulative hazards for job changes. Cumulative hazard indicates the probability of a job change occurring since the foreign takeover. The figure shows that the hazard of experiencing a job change for workers is the same at acquired and always domestic firms before the event of the acquisition. After the year of the acquisition, the likelihood of a job change at acquired firms exceeds the likelihood of a job change at always domestic firms. This suggests that workforce adjustment after an acquisition occurs at acquired firms, mainly within the firms. This finding is in line with the results of the original paper (Koerner et al., 2023) that found a similar pattern in the case of German firms investing in the Czech Republic. The paper shows evidence for within-firm restructuring at the domestic company after a foreign investment.

Our regression analysis confirms this finding (see Table 5). The pre-acquisition likelihood of job changes for workers is the same at domestic and future acquired firms. There is a small but insignificant instant effect of FDI on the likelihood of job switches within firm. Instead, the effect becomes large and significant one year after the acquisition takes place. The likelihood of any occupation changes is about ($e^{0.435} = 1.54 \approx$) 50 percent higher at foreign than at domestic firms.

To sum up, we do not find evidence that firms after acquisition change the composition of tasks used in production, but we show evidence for internal workforce restructuring after a takeover.

Figure 4: Cumulative hazards for job changes in domestic and acquired firms



Note: The figure shows the cumulative hazards for job changes by quarters. The observed time window starts 8 quarters before and ends 24 quarters after the (pseudo-) acquisition. Results are presented separately for acquired and always domestic firms. Cumulative hazard indicates the probability of an event occurring within a given time frame. The model is estimated on our matched sample, in which we only keep workers in our sample who were working at the firm 2 years before the (pseudo-) acquisition took place and remained at the firm until the year of the acquisition (for more details see Appendix Section A.3). The light blue and light red colors indicate 95% confidence bands. The vertical red lines show the beginning and end of the year of the (pseudo-) acquisition.

Table 5: The effect of FDI on hazard ratios for occupation changes

	(1)	(2)	(3)
VARIABLES	Occupation change		
Before acquisition	0.031	0.059	0.071
	(0.120)	(0.109)	(0.109)
Year of acquisition	0.133	0.145	0.149
	(0.259)	(0.258)	(0.256)
One year after the acquisition	0.450**	0.434**	0.435**
	(0.221)	(0.218)	(0.217)
Two years after the acquisition	-0.269	-0.281	-0.280
	(0.370)	(0.354)	(0.345)
Observations	290,475	290,475	290,475
Worker Characteristics	YES	YES	YES
Interaction with quarter	YES	YES	YES
Year FE	YES	YES	YES
Quarter FE	YES	YES	YES
Industry	NO	YES	YES
Occupation	NO	NO	YES

Note: The Table shows the effect of foreign-acquisition of the hazard ratios for occupation changes. In particular, it shows the parameter estimates of Equation (9), where $h_e(t|x_{ity})$ is the hazard rate for the event of job change in quarter t. The main independent variables are the interaction terms between the acquisition dummy and the time interval relative to the investment (d_{jt}). We split our time window into four intervals: (i) from 2 years before the acquisition to the year of the acquisition, (ii) the year of the acquisition, (iii) one year after the acquisition, and (iv) two years after the acquisition. In column (1), we control for gender, age, and its square in the regression. We also include an interaction term between these characteristics and the number of quarters from the (pseudo-) investment in the regression. We also include year and quarter fixed effects onto the mode. In column(2), we add a set of industry dummies to the model. The results are robust to controlling for 1-digit occupation codes (column (3). We examine the cumulative hazard of job changes from 2 years (8 quarters) before to 2 years after the year of the (pseudo-) acquisition. The model is estimated on our matched sample, in which we only keep workers in our sample who were working at the firm 2 years before the (pseudo-) acquisition took place and remained at the firm until the year of the acquisition (for more details see Appendix Section A.3). Standard errors are clustered at firm level. *** $p < 0.01, **p < 0.05, *p < 0.1$

6 Underlying mechanisms

The previous sections showed that the return to abstract tasks increased while the task composition in production remained the same after foreign acquisition. This section investigates the possible mechanisms that drive these results. Our most likely explanation is that acquired firms change their technology in a skill-biased way. We show suggestive evidence in line with this hypothesis in the first part of the section, then investigate other potential mechanisms.

6.1 Skill-biased technological change after FDI

More innovation after FDI. Hungarian firms may get access to the parent firms' more developed and skill-biased technology after acquisition. Consequently, Hungarian firms may increase their innovation activities by adapting the skill-biased technology of their parent company. The relevance of this channel is supported by Lindner et al. (2022) who showed that firm-level innovation increases the within-firm college premium.

To test this hypothesis, we investigate the effect of FDI on innovation with an event study approach. For this analysis, we use the Community Innovation Survey (CIS) dataset that is linked to the balance sheet information of the firm (for more details about the data, see Section 3). We run the following regression at firm-year level for this purpose:

$$innov_{jt} = delta_s * Foreign_j + s_j + f_j + \nu_t + \epsilon_{jt}, \tag{10}$$

where the dependent variable shows whether firm j conducted any innovation activity in year t. $delta_s$ shows the effect of FDI on innovation s year before (after) the acquisition. Since the CIS survey is conducted every second year only, we make a biannual panel from the balance sheet data. s takes the value of -1 one and 2 years before the acquisition, 1 in the year of acquisition and one year later, etc. We normalize δ_{-1} to zero, and negative (positive) s denotes the years before (after) the event of the acquisition. As in Equation (7), we control for industry fixed effect s_j, firm fixed effects f_j and year fixed effects ν_t.[6]

The results are presented in Figure 5. The most important result on Figure 5a shows that the probability of innovating with other foreign firms in the business group increases by 5 percentage points two years after the acquisition. In contrast to this, we do not find evidence that firms conduct more R&D activities after FDI than non-acquired firms (Figure 5b). In our interpretation, the increase in cooperation without additional R&D means that the acquired firms get access to and implement the technology of the parent company.[7]

The other panels investigate the type of innovation after FDI. Figure 5c shows that the probability of process innovation increases by 7 percentage points two years after FDI, while it does not differ significantly from non-acquired firms either before or more than 2 years after the acquisition. This finding suggests that acquired firms are re-organized in line with previous findings showing more occupational changes among incumbents after FDI.

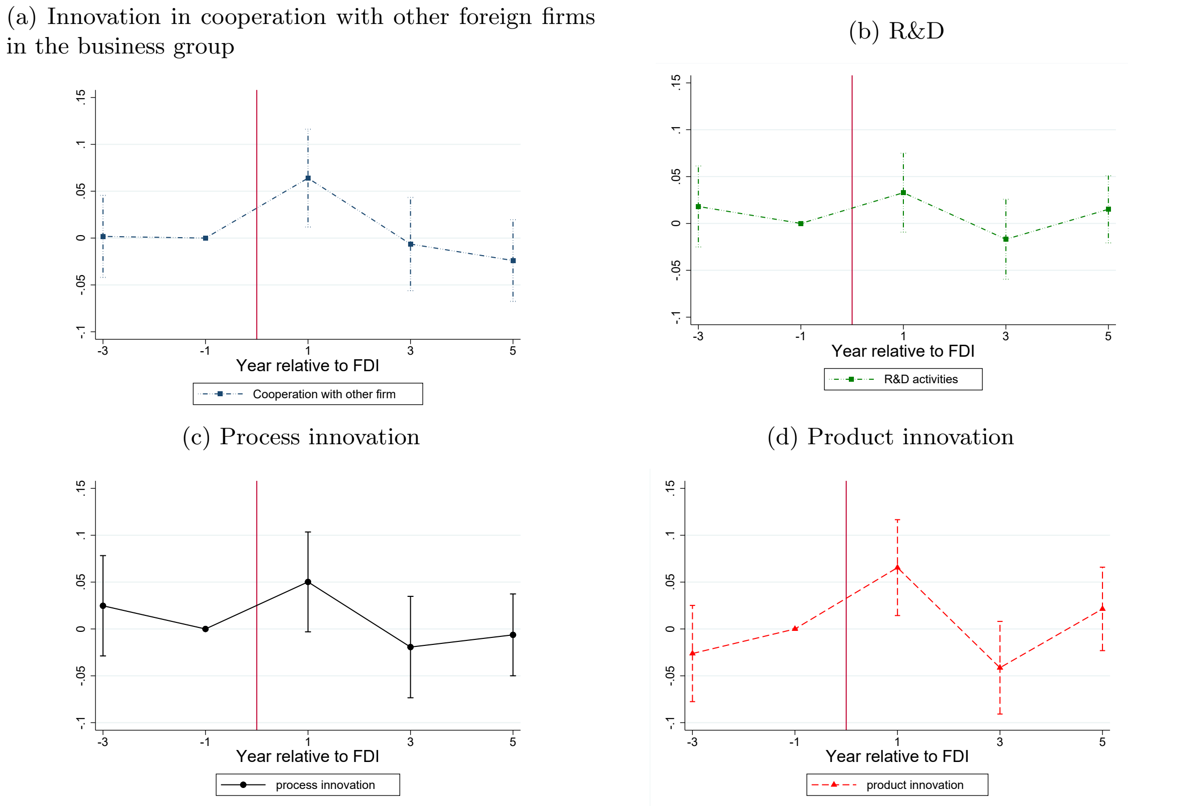
Finally, Figure 5d shows that the probability of introducing a new product is higher in two years after FDI than in other years.

Based on these results we investigate the channels of innovation in more detail. First, we show that acquired firms start to import more machinery (which may lead to process innovation), and then we show that acquired firms upgrade their products.

[6]The results remain the same even if we control for size, productivity, and the share of workers with college and high-school diplomas.

[7]Note: This result can be considered only suggestive evidence because the CIS survey does not have detailed information on the firms with which the acquired firms cooperate.

Figure 5: Innovation activities of acquired firms



(a) Innovation in cooperation with other foreign firms in the business group

(b) R&D

(c) Process innovation

(d) Product innovation

Note: This Figure investigates the effect of FDI on innovation with an event study approach. In particular, the figure shows the parameter estimates of Equation 10, where the dependent variable shows whether firm j conducted any innovation activity in year t. The event years capture the time relative to the onset of foreign acquisition. For the purpose of this analysis, we use Community Innovation Survey (CIS) dataset that is linked to the balance sheet information of the firm (for more details about the data, see Section 3). We control for firm fixed effects and year fixed effects in the model. The bars show 95% confidence intervals and standard errors are clustered at firm level.

Technology upgrading through import. In this section, we explore the effect of foreign acquisition on a firm's import behavior. Following Koren et al. (2020), we assume that imported machines represent a newer technology than the existing machine stock of the country.

We investigate the effect of FDI on capital import and we run the following regression on firm-year level data by using Customs Statistics dataset that is linked to the balance sheet information of the firm (for more details on the data see Section 3):

$$CapitalImport_{jt} = \delta_1 * Foreign_{jt} + s_j + f_j + \tau_t + \epsilon_{jt}, \tag{11}$$

where the dependent variable shows whether firm j imported capital goods in year t or the share of capital import in the total import in year t. δ_1 shows the effect of FDI on capital import. We control for industry fixed effects s_j, firm fixed effects f_j, and year fixed effects τ_t. We also carry out an event study analysis, including the leads and lags around the acquisition instead of including a foreign dummy. Here, we estimate the following regression:

$$CapitalImport_{jt} = \delta_s * Foreign_{jt} + s_j + f_j + \tau_t + \epsilon_{jt}, \tag{12}$$

where the dependent variable shows whether firm j imported capital goods in year t. But this time, instead of a single δ parameter, we have δ_s parameters. s is zero in the year of acquisition so that δ_s shows the change in capital import year before or after this year. We normalize δ_{-1} to zero, so that the parameter estimates shows the effect of foreign ownership relative to this reference point. We control for industry fixed effects s_j, firm fixed effects f_j, and year fixed effects τ_t. We further control for the fact that firms that are already under foreign ownership at the beginning of our sampling period may have a different capital import behavior compared with domestic firms.

The results are presented in Table 6. Columns (1)-(4) show the probability of machine import, while Columns (5)-(8) show the share of machines imported in the total import. For the first two columns, we use our broad definition, while in the third and fourth columns, we use our narrow definition to detect machine imports (see Section 3 for more detail on the definitions). Also, the probability of importing capital goods and its share within the total import is higher at foreign firms than at domestic firms, and this is true even if we include within-firm variation (Columns (2), (4), (6) and (8)) in the identification. The parameter estimates are qualitatively the same and remain significant even at a one percent level if we add time-varying firm-level characteristics to the model (the results are available upon request).

The event study analysis in Figure 6 is in line with the regression analysis. The probability of importing capital goods increases in the first three years after a foreign takeover and stays at a higher level thereafter. The share of capital import in the total import jumps to a higher level after the takeover and stays there for about 2-3 years.

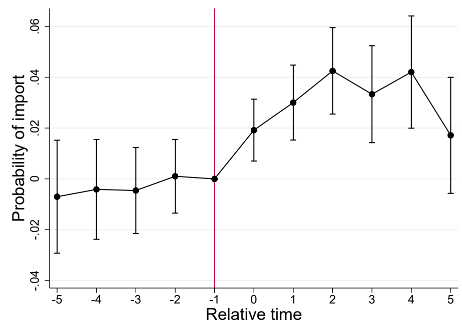
Table 6: The effect of foreign acquisition on machine import

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probability				Share in total import value			
	broad definition		narrow definition		broad definition		narrow definition	
Foreign	0.257***	0.042***	0.242***	0.040***	0.072***	0.011***	0.046***	0.010***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Constant	0.089***	0.113***	0.074***	0.096***	0.027***	0.034***	0.028***	0.032***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	719,642	719,642	719,642	719,642	719,642	719,642	719,642	719,642
R-squared	0.201	0.698	0.184	0.677	0.109	0.676	0.057	0.523
Year	YES	YES	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	Yes	YES	YES	YES	YES
Firm FE	NO	YES	NO	YES	NO	YES	NO	YES

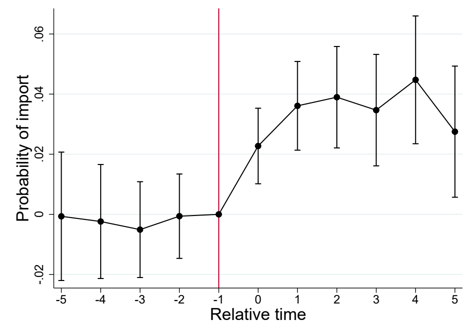
Note: This Table shows the effect of foreign acquisition on machine import. For the purpose of this analysis, we use the Customs Statistics that contains the universe of trading firms. In particular, it shows the parameter estimates of Equation (11). In Columns (1)-(4), the dependent variable equals one if the firm imported machines in the given years and is zero otherwise, while in Columns (5)-(8), it is the share of the value of imported machines in the total imported value. In columns (1), (3), (5), and (7) we control for a set of year and industry dummies, while in columns (2), (4), (6), and (8), we add firm fixed effects to the model. We define a firm as importing machines if it imports any goods from the category of "Capital goods (except transport equipment), and parts and accessories thereof" (BEC 4). As a robustness test, we consider only the narrower group of "Capital goods (except transport equipment)" (BEC 41) as machine imports. The dataset is matched to the firms' balance sheet records based on a unique firm identifier. See Section 3 for more details. Standard errors are clustered at firm level.*** $p < 0.01, **p < 0.05, *p < 0.1$.

Figure 6: The effect of foreign acquisition on machine import - event study approach

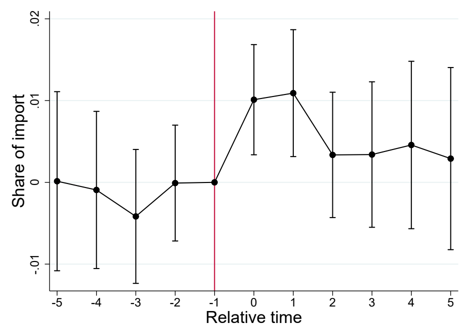
(a) Probability of importing machines
(broad definition)



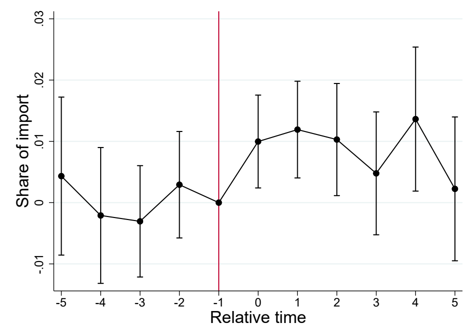
(b) Probability of importing machines
(narrow definition)



(c) Share of machine import
(broad definition)



(d) Share of machine import
(narrow definition)



Note: This Figure shows the effect of foreign acquisition on technology import. In particular, it shows the parameter estimates of Equation (12). For the purpose of this analysis, we use the Customs Statistics that contains the universe of trading firms. In Figures (a) and (b), the dependent variable equals one if the firm imported machines in the given years and zero otherwise, while in Figures (c) and (d), it is the share of the value of imported machines in the total imported value. We control for a set of year and industry dummies and firm fixed effects in the regression. We define a firm as importing machines if it imports any goods from the category of "Capital goods (except transport equipment), and parts and accessories thereof" (BEC 4).[8] As a robustness test, we consider only the narrower group of "Capital goods (except transport equipment)" (BEC 41) as machine imports. The dataset is matched to the firms' balance sheet records based on a unique firm identifier. See Section 3 for more details. The bars show 95% confidence intervals and standard errors are clustered at firm level.

Product upgrading. Based on Figure 5d, this section shows that firms start to produce more expensive and higher quality product varieties after they are acquired by foreign firms. For this purpose, we estimate the following regression by using Customs Statistics dataset (for more details on the data see Section 3):

$$Y_{jvt} = \beta_1 * Foreign_{jt} + f_j + f_t + \chi_{jt}, \tag{13}$$

where the dependent variable is the price of product v produced by firm j at year t. The main variable of interest is β_1 which shows whether firm-level prices change after acquisition. We control for firm (f_j) and year fixed effects (f_t), while χ_{jt} denotes the error term. Then, we decompose the effect of foreign acquisition into quality and composition effects. In particular, we use the average quality and variety of the price measures introduced in Section 3.3 as the dependent variables.

The effect of the foreign acquisition on product prices is summarized in Table 7. The first column shows that firms after acquisition have 10.6 percent higher average prices than firms that were not acquired. Columns (2)-(4) show that 5.4 percent of this increase can be attributed to the fact that firms start to export more expensive product varieties after acquisition and 5.1 percent to the increase in product quality. We do not see evidence that firms start to export to countries that buy the same product for a higher price after acquisition.

[8] $https://unstats.un.org/unsd/classifications/Family/Detail/10$

Table 7: The effect of foreign acquisition on product quality

	(1)	(2)	(3)	(4)
	Total price	Contribution of		
VARIABLES		country	variety	quality
Foreign	0.106**	0.001	0.054*	0.051**
	(0.045)	(0.002)	(0.030)	(0.025)
Constant	4.609***	-0.001	-0.054***	-0.032**
	(0.029)	(0.001)	(0.019)	(0.016)
Year	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	114,643	114,628	114,628	114,628
R-squared	0.980	0.874	0.988	0.631

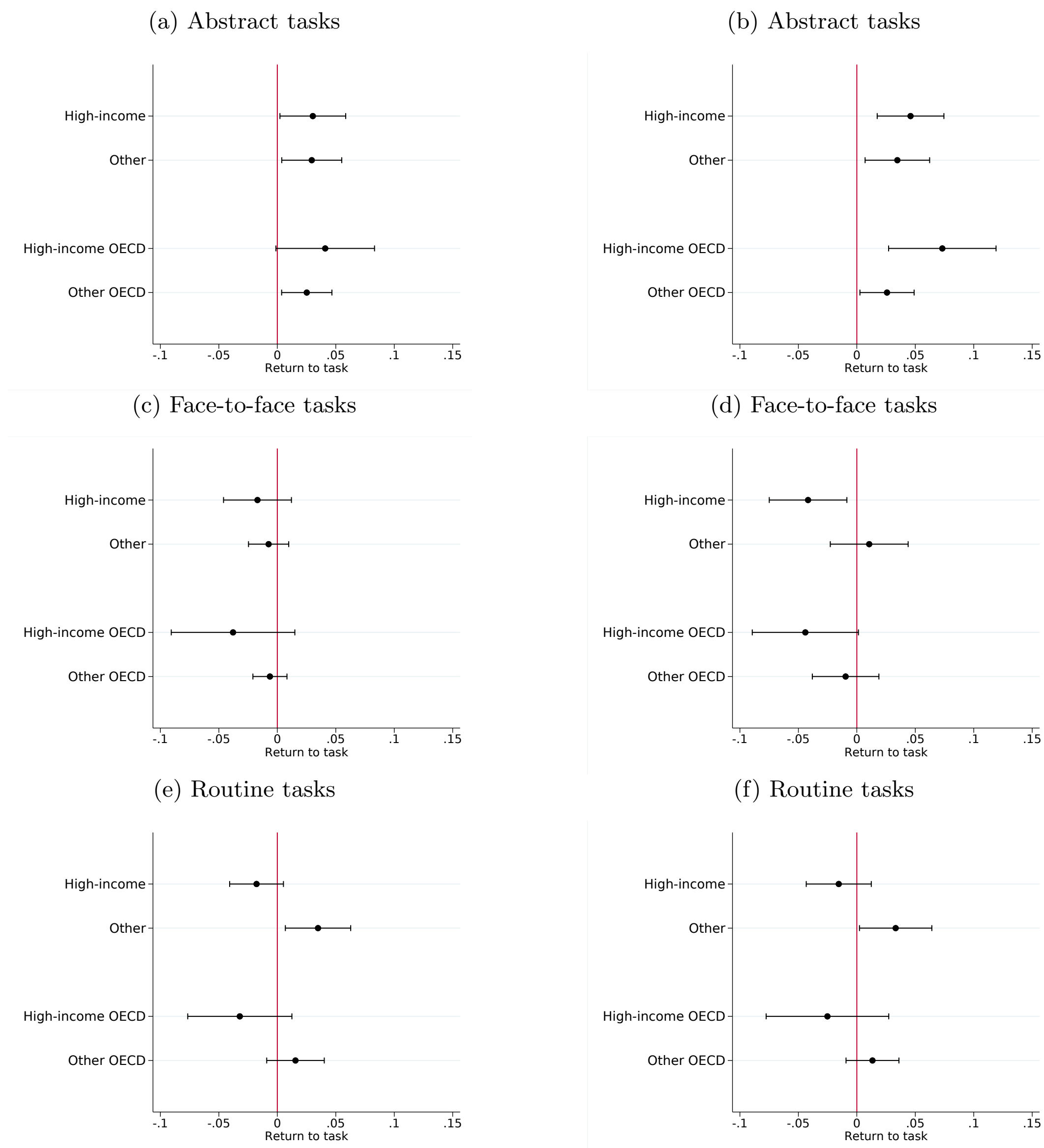
Note: This Table shows the effect of foreign acquisition on product quality. In particular, it shows the parameter estimates of Equation (13), where the dependent variable is the price of product v produced by firm j at year t. The main variable of interest is β_1 which shows whether firm-level prices change after acquisition. In particular, we use the Customs Statistics (for more details on the data see Section 3) and calculate the average quality and variety of the price measures introduced in Section 3.3 as the dependent variables. Then, we decompose the effect of foreign acquisition into quality and composition effects. Our main independent variables is the foreign dummy. We control for firm and year fixed effects in the model. Standard errors are clustered at firm level. *** $p < 0.01, ** p < 0.05, *p < 0.1$

FDI from high-income countries. Foreign investors come from heterogeneous countries. Since more developed countries use more skill-biased technology (Burstein et al., 2013), it is possible that investors from these countries use more skill-biased technology as well. As a consequence, investors from a more developed country may change the technology of the acquired firm in a more skill-biased way. To test this hypothesis, we re-estimate Equation 5 on the "Acquired Sample" (see more details in Section (3.1)) with a slight modification. We now allow foreign ownership to have a different effect on the returns to tasks based on the characteristics of the source country. We define a country to be a high-income country if it was in the top 25 by GDP per capita in 2011 (we use Gravitational Data developed by CEPII; see Appendix Section A.1 for more detail on the measurements used to compare the countries of origin of the FDI). The results are robust to categorizing a country as high-income if it is among the top 10 OECD countries based on GDP per capita.

The results are presented in Figure 7. The horizontal axis shows the return to the given task, while the vertical axis shows the dimension of comparison. Figures on the left correspond to the regular difference-in-differences specification with firm-specific fixed effects. The figures on the right correspond to the two-stage difference-in-differences estimates proposed by Gardner et al. (2024).

The results show that the return to abstract tasks increases after a foreign acquisition regardless of whether the investor is coming from a high-income country or not (see Figure 7a-7b). We do not find significant heterogeneity in the effect of foreign acquisition on the return to face-to-face tasks (see Figure 7c-7d) either. By contrast, there is a large heterogeneity in the effect of FDI on the return to routine tasks between high-income and other countries. The return to routine tasks decreases in firms originating in high-income countries (see Figure 7e-7f). This result is in line with the hypothesis that firms get access to the parent company's technology after a takeover. In the case of more advanced countries, this would mean getting access to technologies that automate the production process, thereby substituting routine tasks.

Figure 7: The effect of foreign acquisition on task returns by source country



Note: This Figure shows the effect of a foreign acquisition on task returns by the source country of the FDI. In particular, we re-estimate Equation (5) on the "Acquired Sample" (see more details in Section 3.1) with a slight modification. We now allow foreign ownership to have a different effect on the return to tasks based on the characteristics of the source country. We define a country to be a high-income country if it was in the top 25 by GDP per capita in 2011 (we use Gravitational Data developed by CEPII; see Appendix Section A.1 for more detail on the measurements used to compare the countries of origin of the FDI). We include year fixed effects and their interaction with task use indices in the model. We further control for the gender and age of the worker, whether the firm is a public firm, 1-digit industry fixed effects and firm fixed effects. In panels (a), (c), and (e), we use the regular two-way fixed effect model, while in panels (b), (d), and (f), we use the two-stage difference-in-differences method of Gardner et al. (2024). Standard errors are clustered at firm level.

6.2 Alternative mechanisms

6.2.1 Imperfect competition on the labor market

The returns to tasks within-firm can change after FDI even if the technology of the firm does not change after acquisition. Assume, for the sake of argument, that the labor market is oligopsonistic[9]

[9] If the labor market is perfectly competitive, we expect that only the amount of abstract tasks changes, but their return remains the same.

and the firm-level labor supply curve is steeper for workers conducting abstract tasks as in Card et al. (2018). In this setup, the rise of firm size or a Hicks-neutral technology changes the share of abstract tasks in production and the return to abstract tasks in the opposite direction. Since the return to abstract tasks increased, the share of cognitive task in production should decrease (Lindner et al., 2022). As opposed to this, in Section 5 we found no evidence for a change in the composition of tasks used in production of an economically significant magnitude.

6.2.2 Change in firm size and task specialization

Becker et al. (2019) showed that larger firms are characterized by higher within-firm inequality. They argue that workers of large firms specialize in specific activities, which results in a higher number of different occupations. Furthermore, the higher number of occupations increases wage inequality across occupations compared with smaller firms. This mechanism implies in our case that the number of occupations increases after FDI, and the higher return to abstract tasks reflects only task specialization in high-paid occupations.

We formally test this hypothesis even though we control for firm size in some regressions to filter out the effect of firm growth. In particular, we re-estimate Equation (7) on the sample of firms that were acquired after 2003 (for more details on the sample, see Section 3.1), but now the dependent variable is the Herfindahl index or the number of different occupations at firm j at year t. We use 4-digit ISCO codes to differentiate occupations, while the control variables are the same as in Equation (7). We also include logarithmic employment in the regression.

The results are shown in Table 8. According to Column (1), the number of occupations is larger by 1.36 at foreign firms than at domestic firms, but this difference drops to 0.2 if we control for firm fixed effects in Column (2), and becomes insignificant if we use the two-stage difference-in-differences method. Panel B shows that this difference is driven by the size difference across domestic and acquired firms. In line with Becker et al. (2019), Panel B shows that larger firms use more occupations. According to Column (1), the number of occupations grows by 5 if the size of the firm grows by 100 percent. The parameter shrinks if we take into account firm-level selectivity (Column (2)), but remains large and significant. In contrast to this, the parameter estimates on the $Foreign$ dummy are much lower and insignificant in most of the specifications.

Panel C and D of Table 8 highlight that the Herfindahl index of occupations remains unchanged after acquisition.

Table 8: The effect of foreign acquisition on task specialization

VARIABLES	(1) coef	se	(2) coef	se	(3) coef	se
			Number of occupations			
		Panel A: without controlling for the size of the firm				
Foreign	1.359***	(0.242)	0.211***	(0.080)	0.126	(0.132)
Constant	5.408***	(0.139)	5.880***	(0.032)	5.593***	(0.036)
Observations	29,187		29,187		27,778	
R-squared	0.062		0.864			
		Panel B: with controlling for the size of the firm				
Foreign	0.165	(0.138)	0.007	(0.068)	0.027	(0.117)
Log Employment	4.858***	(0.263)	2.566***	(0.131)	0.424***	(0.114)
Constant	-8.323***	(0.704)	-1.541***	(0.384)	4.392***	(0.313)
Observations	29,187		29,187		27,778	
R-squared	0.520		0.895			
			Herfindahl index			
		Panel C: without controlling for the size of the firm				
Foreign	-0.045***	(0.006)	-0.015***	(0.005)	-0.009	(0.005)
Constant	0.490***	(0.005)	0.478***	(0.002)	0.484***	(0.002)
Observations	29,187		29,187		27,778	
R-squared	0.031		0.609			
		Panel D: without controlling for the size of the firm				
Foreign	-0.014**	(0.005)	-0.004	(0.004)	-0.003	(0.005)
Log Employment	-0.127***	(0.003)	-0.133***	(0.004)	-0.025***	(0.002)
Constant	0.850***	(0.010)	0.863***	(0.012)	0.556***	(0.007)
Observations	29,187		29,187		27,778	
R-squared	0.266		0.672			
Year	YES		YES		YES	
Industry	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: This Table shows the effect of foreign ownership on task specialization. In particular, it shows the estimated parameter of Equation (7) on the sample of firms that were acquired after 2003, but the dependent variables are the number of different occupations and the Herfindahl index at firm j in year t. We use 4-digit ISCO codes to differentiate occupations, while the control variables are the same as in Equation (7). In column (1), we control for a set of year and industry dummies, while in columns (2) and (3) we also add firm fixed effects to the model. Column (3) uses the two-stage difference-in-differences method following Gardner et al. (2024). Standard errors are clustered at firm level. $***p < 0.01, **p < 0.05, *p < 0.1$

To sum up, we do not find evidence that increasing task specialization after foreign acquisition increases the return to abstract tasks.

6.2.3 Efficiency wages and monitoring

The cost of monitoring a worker is different depending on the tasks the worker performs. Some tasks are well-suited to supervision. At the extreme, they can be paid for on an output basis, while the output of other tasks is difficult to measure (Lazear, 2018). It is possible that monitoring repetitive tasks, and measuring their output are easier than monitoring abstract tasks, especially from abroad. In that case, foreign-owned firms may struggle with monitoring abstract tasks, and may try to incentivize workers to perform more abstract tasks with a higher salary. We conduct two exercises to investigate this mechanism.

First, we investigate whether foreign firms use more performance payments to incentivize workers in general, or do so only in the case of workers performing more abstract tasks. Second, we test whether firms incentivize abstract tasks by a larger return when the distance between the owner and Hungary is larger as well.

Incentive contracts and foreign ownership

To test whether foreign-owned firms use more incentive contracts, we run the following firm-year level regression on the Hungarian Structure of Earnings survey (for more details on the data, see Section 3):

$$Y_{jt} = \beta_1 * Foreign_{jt} + f_j + f_t + \epsilon_{jt}, \tag{14}$$

where the dependent variable is various measures of incentive contracts, $Foreign_{jt}$ shows whether the firm was acquired, and we control for firm and year fixed effects. If β_1 is positive, the firms use more incentive contracts after acquisition. Table 9 shows that the share of workers receiving bonuses (Column (1)), the share of workers receiving overtime payments (Column (2)), the share of workers receiving any type of flexible wage elements (Column (3)), and the ratio of flexible wages in the total wage bill (Column (4)) all remain the same after acquisition. We do not find evidence that foreign firms offer more flexible wages if we add other firm-level controls or drop firm fixed effects either. The results are available upon request.

Table 9: The effect of foreign acquisition on the prevalence of flexible wages

	(1)	(2)	(3)	(4)
	Share of workers with			Ratio of flex. wage
VARIABLES	bonus	overtime	any flex wage	and total wage
Foreign	0.005	0.016	0.017	0.005
	(0.013)	(0.010)	(0.011)	(0.008)
Constant	0.482***	0.287***	0.577***	0.330***
	(0.003)	(0.002)	(0.002)	(0.002)
Observations	103,493	103,493	103,493	102,492
R-squared	0.721	0.745	0.760	0.809
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Note: This Table shows the effect of foreign acquisition on the prevalence of flexible wages. For this analysis, we use the Hungarian Structure of Earnings survey (for more details, see Section 3). In particular, it shows the parameter estimates of Equation (14). The dependent variables are the share of workers receiving bonuses (Column (1)), the share of workers receiving overtime payments (Column (2)), the share of workers receiving any type of flexible wage elements (Column (3)), or the ratio of flexible wages and the total wage bill (Column (4)). We control for a set of industry dummies, and firm fixed effects. *** $p < 0.01, **p < 0.05, *p < 0.1$.

Even if firms do not pay bonuses to more workers on average, it is possible that they pay a higher amount of bonuses to workers performing more abstract tasks. To test this hypothesis, we use the individual observations in the Hungarian Structure of Earnings Survey (for more details on the data, see Section 3), and run the following regression:

$$Y_{i(j)t} = \beta_1 * Acquired_{jt} + \beta_s * Foreign_{jt} * TaskMeasure_o + \beta * X_{ijt} + \tau_t * TaskMeasure_o + f_j + f_t + \epsilon_{i(j)t}, \tag{15}$$

where the dependent variable is whether worker i at firm j at year t receives flexible wages. The explanatory variables are the foreign dummy, the tasks measures and their interaction. We also control for the individual characteristics of the worker (X_{ijt}) and task-year interactions ($\tau_t * TaskMeasure_o$) to account for economic trends in task returns. The main variable of interest is the interaction of task measures and the foreign dummy, which is positive if workers performing more tasks of a specific category also have a higher change in receiving flexible wages if the firm is foreign-owned.

The results are summarized in Table 10. The first column uses the total wage as the dependent variable, and shows that the estimated effect of FDI on total wages is similar using HSES data and the Admin3. Here, we find that a one standard deviation higher abstract task index increases wages by 2.2 percent, while the return to routine and face-to-face tasks does not change after acquisition. Based on Column (2), the probability of receiving bonuses does not change after FDI, while Column (3) shows that the probability of receiving overtime payments decreases somewhat after acquisition among workers performing more abstract tasks compared with other workers. At the same time, Column (4) shows that the share of flexible wage components in the total wage bill remains unchanged after acquisition.

To sum up, we do not find evidence that foreign-owned firms are more likely to pay flexible wages to workers performing more abstract tasks.

Table 10: The effect of FDI on wage structure

VARIABLES	(1) Total wage	(2) Probability of receiving bonus	(3) Probability of receiving overtime	(4) Ratio of flex wage and total wage
Foreign	0.023	-0.015	0.033**	-0.007
	(0.016)	(0.039)	(0.014)	(0.015)
Foreign* Abstract	0.022**	0.013	-0.027**	0.016
	(0.011)	(0.009)	(0.012)	(0.017)
Foreign* Face-to-face	0.001	-0.007	-0.000	-0.004
	(0.009)	(0.008)	(0.008)	(0.010)
Foreign* Routine	-0.002	-0.006	0.011	0.019*
	(0.012)	(0.010)	(0.011)	(0.011)
Constant	11.891***	0.430***	0.154***	0.186***
	(0.037)	(0.040)	(0.027)	(0.033)
Observations	83,854	83,855	83,855	83,855
R-squared	0.692	0.616	0.348	0.557
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Note: The Table shows the effect of FDI on the wage structure of the firm. In particular, it shows the parameter estimates of Equation (15) on the Hungarian Structure of Earnings survey (for more details on the data, see Section 3), where the dependent variable is whether worker i at firm j at year t receives flexible wages. The explanatory variables are the foreign dummy, the tasks measures and their interaction. We also control for the individual characteristics of the worker and task-year interactions to account for economic trends in task returns. The main variable of interest is the interaction of task measures and the foreign dummy, which is positive if workers performing more tasks of a specific category also have a higher change in receiving flexible wages if the firm is foreign-owned.

Monitoring costs by distance

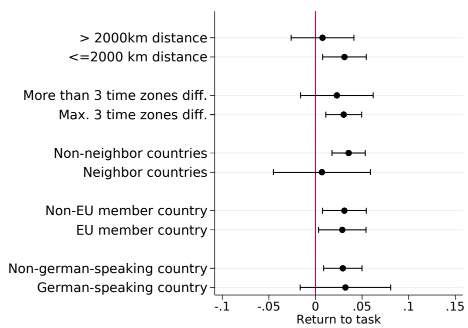
In this section, we test whether firms whose owner is farther from Hungary have more difficulty in monitoring abstract tasks, and therefore try to incentivize these tasks more. If our main results are driven by this mechanism, we would expect that firms pay a higher return to abstract tasks if the owner's headquarters are farther away. For this purpose, we re-estimate Equation (5) with a slight modification. In this modified model, we allow foreign ownership to have a different effect on returns to tasks by (cultural and geographical) distance between the source country of the FDI and Hungary. We use the firm's country of origin as a proxy for distance, as we do not observe the exact locations of the parent firms' headquarters.

We measure the distance between Hungary and the source country by using several distance measures: geographical location, time zone difference and cultural differences. In terms of cultural setting, we assume that legal systems are similar within the European Union, and compare firms from EU member countries and firms from the rest of the world. To analyze this pattern further, we also look at FDI from German-speaking countries that are historically and economically connected to Hungary in many ways (Germany and Austria were the target countries for 32.4 percent of total exports in 2017 ("WITS World Integrated Trade Solution", n.d.)). (For more details on the distance measure, see Appendix Section A.1.)

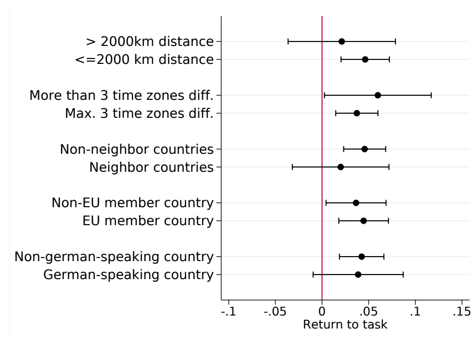
Figures 8a-8b show the comparisons of the return to abstract tasks by the source country of the FDI. In Figure 8a, we use the standard difference-in-differences method, while in Figure 8b, we rely on the two-stage difference-in-differences method used by Gardner et al. (2024). The parameter estimates are close to each other and comparable to the results in the main part of the analysis (see Table 2). Firms having their parent firms close to Hungary pay an almost 4 percentage points higher return to

Figure 8: The effect of foreign acquisition by the distance between the host and source country of the FDI

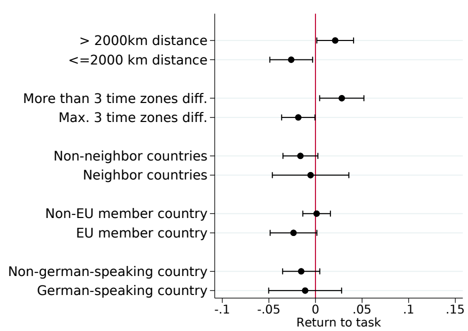
(a) Abstract tasks



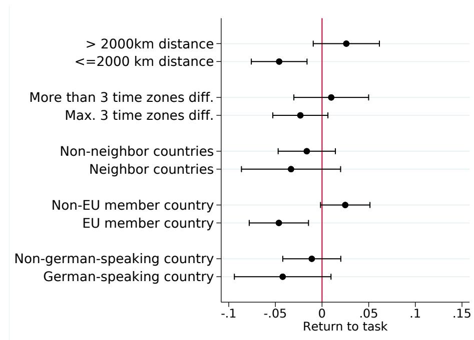
(b) Abstract tasks



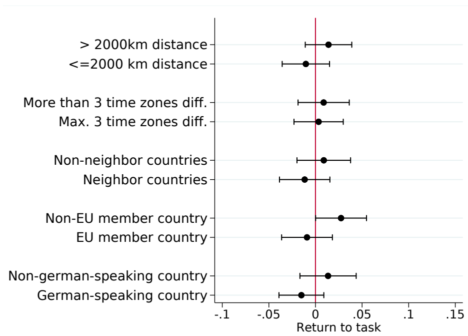
(c) Face-to-face



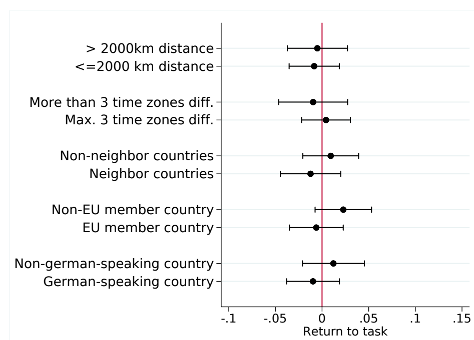
(d) Face-to-face



(e) Routine



(f) Routine



Note: The Figure shows the effect of foreign acquisition on the task returns by the distance between the source and host country of the FDI. In particular, it shows the estimated parameters of Equation (5) on our "Acquisred Sample" (see more details in Section 3.1) with a slight modification: in the modified model, we allow foreign ownership to have a different effect on returns to tasks by (cultural and geographical) distance between the source country of the FDI and Hungary. For more details on the distance measure, see Appendix Section A.1. Figures on the left present the results using the regular two-way fixed effect model, while the figures on the right show the results of using the two-stage difference-in-differences method of Gardner et al. (2024).

abstract tasks than domestic firms. This premium is significant regardless of the measurement used. The foreign premium of abstract tasks is comparable in magnitude at firms having their parent firms at a longer or a closer distance, irrespective of how distance is measured.

The estimations on the return to face-to-face tasks (Figures 8c-8d) and routine tasks (Figures 8e-8f) show similar results. The point estimates are not significant and are close to each other independent of the distance between the parent company's country and Hungary.

7 Conclusion

In this paper, we investigated the effect of foreign acquisitions on task returns in Hungary. We found that foreign acquisition increases the returns to abstract tasks, while it does not change the returns to face-to-face and routine tasks. We show that these results hold even if we control for selectivity in acquisition or changes in workforce composition. At the same time, we find that the composition of tasks in the production process remains the same.

We investigated the possible mechanisms behind these empirical facts. The most likely interpretation of these results is that firms change their production technology in a skilled-biased way by implementing new technology. We provide a battery of suggestive evidence for this interpretation. In particular, we show that (i) firms conduct more innovation in cooperation with other foreign firms in the business group without increasing their R&D activities after foreign acquisition; (ii) acquired firms start to import more machines (which are most likely complements to abstract tasks); (iii) they improve their product quality; and (iv) foreign acquisition decreases the return to routine tasks only if the investor comes from a highly developed country.

Our results imply that foreign direct investment is an important driver of skilled-biased technological change in developing countries such as Hungary.

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Appendix

A Dataset and variable construction

A.1 Linking of ownership information

We use the Panel of the Linked Administrative Data (Admin3) extended by the corporate income tax returns submitted to the National Tax and Customs Administration. This dataset shows only whether the firm is foreign, domestic or publicly-owned, but not the nationality of the foreign owner. The information on the nationality of the owner comes from the administrative firm register. The data was provided by Central European University MicroData.[10]. The firm register contains information on the balance sheet of the firm and on the nationality of the owner for the universe of firms.

We apply probabilistic matching to connect the firm register and the Admin3 based on the balance sheet information observed in both datasets. We use the following variables for matching, observed in both datasets: (1) sales; (2) sales revenue before tax; (3) total equity; (4) 2-digit industry code; (5) export revenue; (6) wage bill; and (7) number of workers.

We use a multi-step matching procedure following the strategy of Card et al. (2016). We apply exact matching at each step and sequentially decrease the number of variables that have to match exactly. Firms matched and validated at one step are removed from both datasets before moving to the next step.

STEP 1: We conduct exact matching on a yearly level based on the seven common variables described above. If we find a perfect match in a given year, we consider the entire history of the firm as a pair. In case the firm was matched to different firms in different years, we treat the matches invalid and the firm unmatched. Once a potential match is found, we check the plausibility of the match. In particular, we compare the annual observations on sales for all years from 2003 to 2017 in which non-missing data were available in both datasets. We consider a match as valid only if either the deviation in annual sales revenue between the two datasets is less than 10%, or if there is a larger deviation in any year, but the values are the same in both datasets in all other years.

STEP 2: We exclude firms matched and validated in STEP 1 from the sample, and relax the number of variables used in the matching process. We conduct the exact matching based on four variables: (i) year; (ii) 2-digit industry code; (iii) annual sales revenue; and (iv) any one of sales revenue before tax, total equity, number of employees, export revenue, wage bill. After finding the exact matches, we follow the same routine as in STEP 1. We exclude pairs in which a firm was matched to different firms in different years and only consider firms as matched pairs if we could validate the match using annual sales revenue information. After finding and validating the matched pairs, we exclude them from both datasets before STEP 3.

STEP 3: We exclude firms from the sample that were matched and validated in STEP 1 or STEP 2, and relax the criteria used in the procedure. We conduct the exact matching based on sales revenue before tax, total equity, number of employees, export revenue, and wage bill. We identify a match if any two variables of these are the same within a 2-digit industry and year cell. After finding the exact matches, we follow the same routine as in STEP 1.

Defining the origin country of foreign direct investment. A firm is considered foreign if the share of foreign-owned capital is above 50 percent. We only know the country of origin for firms directly owned by foreign investors. If the firm is owned by a firm that is considered a majority foreign-owned firm, the firm is also considered a foreign firm, but the country of origin is missing. If the investment comes from more than one country, we consider all countries with equal shares as source countries. We use the CEPII gravity database (Conte et al., 2022) to measure the distance between Budapest, the capital of Hungary, and the capital of the source country, the time zone difference between the two countries, and GDP per capita. We consider a country to be a high-income country if the GDP per capita in 2015 was in the top 25 in the world according to the CEPII dataset. We consider the top 10 OECD countries based on their GPD per capita as high-income countries to check the robustness of our results.

[10]HUN-REN KRTK (distributor). 2024. "Mérleg LTS [data set]" Published by Opten Zrt, Budapest. Contributions by CEU MicroData. Data usage is subject to a licensing agreement with Opten Kft. To process the data MicroData received funding from the National Research, Development and Innovation Office (Forefront Research Excellence Program contract number 144193).

We define investors' country of origin based on the year of acquisition. For example, if the firm became foreign-owned in 2007, we use the ownership structure of the year 2007 to define the investors' country of origin even if the ownership structure changes afterwards. If foreign capital originates from more than one countries, we define the distance based on the shortest distance. We use the same approach when measuring distances based on time zones. To categorize firms into "close" and "far" groups, we use 2000 km distance and 3 time zones difference as a threshold. The results are robust to using the average geographical and time zone difference instead of the shortest. If the investor originates at least partly from the European Union, the investor is considered to have EU origins. We apply the same rule when defining firms as originating from a neighboring country or from German-speaking countries. A firm is categorized to have originated in a high-income country if at least one of the source countries of the FDI originated from such a country.

Table A.1 shows high-income countries and the number of observations related to them. Investments from Germany, the Netherlands, and Austria are the most common in our sample.

Table A.1: High-income countries

Country	Number of worker-year observations	Top 10 among OECD
Germany	1,220,065	
Netherlands	657,153	YES
Austria	655,884	
France	277,121	
United States	254,723	YES
Great Britain	170,716	
Switzerland	170,366	YES
Luxembourg	127,903	YES
Japan	89,330	
Belgium	86,164	
Sweden	75,141	YES
Denmark	59,505	YES
Finland	48,457	
Canada	27,944	
Ireland	18,725	YES
Norway	9,803	YES
Israel	9,589	
Australia	7,133	YES
Hong Kong	6,247	
Singapore	1,854	
United Arab Emirates	1,083	
Iceland	897	YES
New Zealand	435	

Note: If the foreign capital comes from more than one countries and at least one of these countries is among the top 25 countries based on their GDP per capita, the investor is defined as coming from a high-income country. If the owners originate from more than one countries in the top 25 ranking, they are listed under the name of the first country in the ranking (i.e., the one with the higher GDP per capita). The third column shows whether the origin country is in the top 10 OECD countries based on its GDP per capita.

A.2 Construction of task measures

The information on the task contents of occupations is taken from the O*NET[11] which uses SOC codes. We follow the work of Hardy et al. (2018) to translate the SOC nomenclature to the ISCO nomenclature. Then we use the crosswalk[12] provided by the Hungarian Central Statistical Office to translate the ISCO codes to the Hungarian nomenclature (called FEOR).

[11]We use O*NET 20.1, released in October 2015, $https://www.onetcenter.org/db_releases.html$

[12]$https://www.ksh.hu/docs/osztalyozasok/feor/fordkulcs_isco_feor.pdf$, date of download: 06.02.2023

We rely on the work of Firpo et al. (2011) to construct task indices from the O*NET data. The O*Net provides information on the "importance" (IMP) and "level" (LEV) of each required work activity. To calculate the weighted sum of the two, we assign a Cobb-Douglas weight of two-thirds to "importance" (IMP) and one-third to "level" (LEV). For work context, the information is reported on five categorical levels. In this case, we multiply the frequency (F) by the value of the level (V). Equation A.1 summarizes our method. Each task measure for occupation "o" is computed as

$$TaskMeasure_o = \sum_{n=1}^{N} IMP_n^{2/3} * LEV_n^{1/3} + \sum_{m=1}^{M} F_k * V_k, \tag{A.1}$$

where N denotes the number of work activity elements and M denotes the number of work context elements used to define the given summary task index. IMP corresponds to the "importance" and LEV to the "level" of the given work activity. We standardize the indices to have 0 mean and a standard deviation of 1 in the wage regression or re-scale them to the (0 1] intervals by dividing them by their maximum in the employment regressions. We show in the robustness check section that our results hold when the task indices are constructed differently. The work activities and context used to create the summary indices are outlined in Table A.2.

These task indices show large differences across occupations. For example "Software developer" (FEOR 2142) requires a high level of abstract tasks, but a very low level of face-to-face contact. On the other hand, "Tour operator, consultant" (FEOR 4221) requires both a high level of abstract tasks and frequent face-to-face contact. "Finance administrator" (FEOR 3611) requires a high level of abstract tasks, but can be automated easily. Even though "Client (customer) information clerk" (FEOR 4224) requires frequent face-to-face contact, it also involves a large amount of routine tasks. Appendix Table A.3 shows further examples of occupations from each quartile of the distribution of the given index and the average index value within the quartile. For example "Early childhood educator", "Ornamental plants, flowers and tree nursery gardener", and "Roofer" are three examples of occupations that have the lowest value on the abstract task index.

Table A.4 shows the relationship between the three indices in a more structured way. The table shows that there is a positive correlation between the amount of abstract and face-to-face tasks across occupations. People in occupations involving more routine tasks also tend to have relatively less abstract and face-to-face tasks.

Appendix Figure A.1 shows the distribution of the three tasks in our sample. The left panel corresponds to the full sample and shows the task distribution separately for foreign- and domestic-owned firms. The figures on the right show the same, but within the subsample of acquired firms (for more details on the sample, see Section 3.1). On these figures, we compare the pre-acquisition (domestic-owned) and post-acquisition (foreign-owned) years of the acquired firms.

Table A.2: The task from O*net used to construct our summary task indices

Information	
	getting information
	processing information
	analyzing data or information
	working with computers
	documenting/recording information
Face-to-face	
	establishing and maintaining interpersonal relation
	assisting and caring for others
	performing for or working directly with the public
	coaching and developing others
	face-to-face discussion
Automation	
	degree of automation
	importance of repeating the same task
	structured versus unstructured work
	pace determined by speed of equipment
	spend time making repetitive motion

Note: This Table shows the tasks from O*Net used to create the summary indices. We rely on the method suggested by Firpo et. al 2011 to construct our summary indices.

Table A.3: Occupation examples from the distribution of the indices

Decile	FEOR	Occupation	Value
		Panel A: Abstract	
	2432	Early childhood educator	
1	6115	Ornamental plants, flowers and tree nursery gardener	-1.37
	7532	Roofer	
	3135	Quality assurance technician	
2	8190	Other manufacturing machine operator	-.27
	6121	Cattle, horse, pig, sheep producer	
	5111	Shopkeeper	
3	4121	Accountant (analytical)	.78
	1333	Sales and marketing manager	
	2123	Telecommunications engineer	
4	3613	Stock exchange and finance representative, broker	1.57
	2122	Electrical engineer (electronics engineer)	
		Panel B: Face-to-face	
	3153	Chemical processing plant controller	
1	5243	Building caretaker	-1.19
	2122	Electrical engineer (electronics engineer)	
	7538	Glazier	
2	8143	Cement, stone, minerals processing machine operator	-.16
	3163	Working and operating safety specialist	
	5241	Cleaning supervisor	
3	8423	Public hygiene, local sanitation machine operator	.74
	5132	Waiter	
	5211	Hairdresser	
4	1416	Advertising and PR manager	1.98
	5251	Police officer	
		Panel C: Routine	
	2139	Other engineer	
1	3514	Signing interpreter	-1.86
	1325	Childcare service manager	
	5255	Nature conservation warden	
2	5133	Bartender	-.88
	2717	Specialized coach, sports organizer, manager	
	3112	Metallurgical and materials technician	
3	7325	Welder and flamecutter	-.03
	7533	Building, construction plumber	
	4114	Data entry clerk, encoder	
4	3153	Chemical processing plant controller	1.14
	8131	Oil and natural gas processing machine operator	

Note: The table shows three examples from each quantile of the unweighted distribution of the corresponding index.

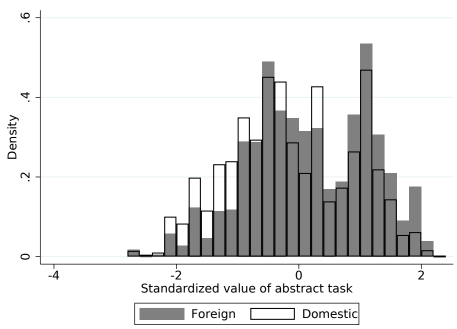
Table A.4: Correlation between indices

	Abstract	Face-to-face
Face-to-face	0.43***	
Routine	-0.46***	-0.49***

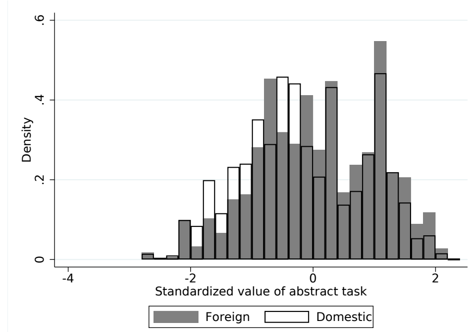
Note: This Table shows the correlation between our summary task indices on our full sample. The number of observations: 11,957,372.

Figure A.1: Distribution of tasks

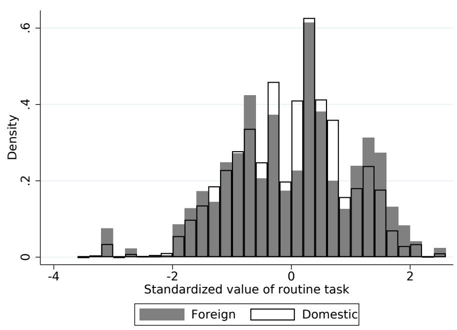
(a) Abstract tasks, full sample



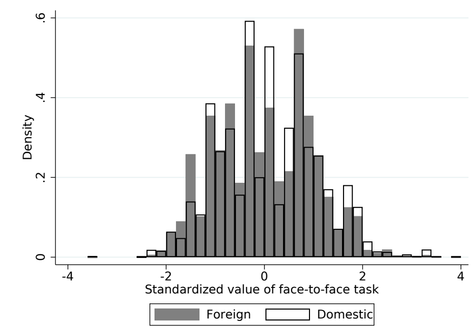
(b) Abstract tasks, sample of acquired firms



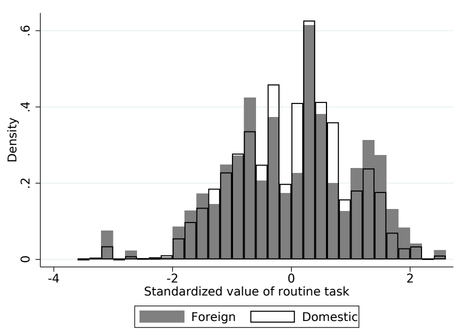
(c) Face-to-face tasks, full sample



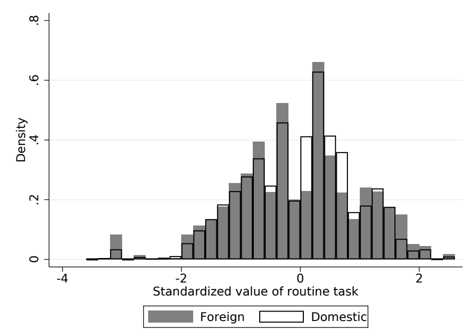
(d) Face-to-face tasks, sample of acquired firms



(e) Routine tasks, full sample



(f) Routine tasks, sample of acquired firms



Note: The figure shows the distribution of tasks. The left panel corresponds to the full sample and shows the task distribution separately for foreign- and domestic-owned firms. The panel on the right corresponds to the sample of acquired firms and shows the distribution for the domestic (pre-acquisition) and foreign (post-acquisition) years separately.

A.3 Matching foreign and domestic firms

We construct a control group to acquired firms by propensity score matching as a robustness check. In particular, we rely on the procedure proposed by Koerner et al. (2023). We match acquired firms to non-acquired firms based on firm characteristics, as acquisition is a firm-level event.

For acquired firms (treated firms), we only keep the year of the acquisition in the analysis. We include acquired firms that we observe for four consecutive years, from two years before the acquisition until one year after the acquisition. We also exclude acquired firms with missing observations on the variables used for matching one or two years before the acquisition. For the control group, like in the case of treated firms, we include firms that we observe for four consecutive years and do not have missing matching variables. We also exclude firms from the sample that were ever publicly owned.

We run a logit model on the sample to get the propensity score of being acquired. The left-hand side variable of the regression equals one if the firm is acquired. In the regression sample, we use the acquisition year for acquired firms. For always domestic firms, we use all years satisfying the above-mentioned criteria. We pool all years together to increase sample size, and control for year fixed effects.

The independent variables are as follows: the number of job changes at the firms one and two years before the acquisition and their square, the logarithm of the number of workers, the logarithm of value added per worker, the logarithm of the wage bill, the age of the firm, the share of female workers, the share of pink- and blue-collar workers, the growth of the value added per employee, the growth of the wage bill and the growth in the number of employees from two years to one year prior to the acquisition, industry, county and year. All independent variables are taken from the year before the acquisition.

To ensure common support, we drop acquired firms having larger propensity scores than the maximum among always domestic firms as well as always domestic firms having lower propensity scores than the lowest value among acquired firms. We force an exact match on industry and year. Within each industry-year cell, we match (without replacement) each acquired firm to its three nearest neighbor measured by the propensity score. Then, we apply the iterative matching procedure suggested by Koerner et al. (2023) to achieve a unique one-to-one matching of acquired and domestic firms over the entire period. By adopting his procedure, we can assign the year of acquisition of the acquired firm to its always domestic pair as a pseudo-acquisition year. To ensure that the nearest neighbor is not too far, we drop matched pairs where the gap in propensity score is larger than 0.1 in absolute terms.

Appendix Table A.5 compares domestic and foreign firms in the full sample and our matched sample in the last year before the (pseudo-) acquisition. Acquired firms are larger in terms of employment and wage bill, while they are also more productive and younger even before the acquisition than domestic firms. The number of occupation changes is also larger. The share of white-collar workers is larger at acquired firms even before the acquisition takes place. All the differences observed before the acquisition disappear in our matched sample.

Table A.5: Descriptive statistics for the unmatched and matched samples

	Always domestic	Pre-acquisition	Difference	St. error	t value	p value
		Panel A: Unmatched sample				
Log productivity	8.044	8.447	-0.404	0.025	-16.15	0
No occupation changes	0.538	1.049	-0.511	0.082	-6.30	0
Log employment	2.646	3.121	-0.475	0.031	-15.20	0
Log wage bill	10.099	10.852	-0.753	0.036	-21.05	0
Firm age	12.659	11.572	1.088	0.230	4.75	0
Share of white-collar	0.395	0.533	-0.138	0.012	-11.50	0
Share of pink-collar	0.151	0.103	0.049	0.010	4.95	0
Share of blue-collar	0.454	0.365	0.089	0.013	7.10	0
		Panel B: Matched sample				
Log productivity	8.383	8.415	-0.032	0.038	-0.85	0.406
No occupation changes	0.935	1.024	-0.089	0.157	-0.55	0.570
Log employment	3.067	3.093	-0.026	0.051	-0.50	0.607
Log wage bill	10.769	10.799	-0.03	0.058	-0.55	0.599
Firm age	11.306	11.63	-0.325	0.299	-1.10	0.279
Share of white-collar	0.534	0.525	0.009	0.018	0.50	0.604
Share of pink-collar	0.094	0.104	-0.01	0.011	-0.90	0.360
Share of blue-collar	0.372	0.371	0.001	0.017	0.05	0.951

Note: The table shows descriptive statistics for the unmatched (Panel A) and the matched sample (Panel B) in the last year before the (pseudo-) acquisition took place. In the unmatched sample, there are 223,779 firm-year observations corresponding to always domestic firms (a firm can be included in the sample as many years as it satisfies the criteria) and 922 firm-year observations corresponding to acquired firms (a firm is included in the sample only once, in the year before the acquisition event took place). In the matched sample, there are 899 firms corresponding to always domestic as well as foreign firms.

A.4 Number of observations used for identification

Table A.6 shows the number of acquired firms by year. We observe more than a hundred acquisitions every year. The number of acquisitions was the highest between 2007 and 2008 when the number of acquisitions was more than 300. We observe fewer acquisitions at the end of the observed period.

See Table A.7 for the number of individual observations relating to the identification of the wage effect. In the database, we have 11,957,372 worker-year observations from 1,845,958 separate workers. From these observations, 628,331 worker-year observations belong to acquired firms.

We need worker transitions between firms to identify individual fixed effects in the AKM-type model. We observe 1,002,500 worker transitions, of which such a change occurred together with an occupation change in 603,933 cases. There are 226,575 cases in total where either a worker left the domestic firm to start a new job at a foreign firm, or there was a change in the ownership status of the firm where the worker was employed. Workers changed occupation at the same time in about 66 percent of the cases. We observe 68 thousand cases where either a worker entered an acquired firm after the acquisition, or the worker of an acquired firm stayed with the firm around the acquisition event. 26 percent of these workers changed occupation around this event.

Table A.6: Number of acquisitions per year

Year	Observation
2004	174
2005	213
2006	228
2007	355
2008	367
2009	261
2010	163
2011	200
2012	169
2013	121
2014	108
2015	93
2016	115
2017	96
Total	2663

Note: This Table shows the number of acquisition by year.

Table A.7: Number of cases

	Number of worker-year observations	Number of observed workers
All firms	11,957,372	1,845,958
Never changed firm	4,832,963	955,017
Changed firm at least once	7,124,409	890,941
Never changed occupation	3,627,979	860,733
Changed occupation at least once	8,329,393	985,225
Changed occupation within worker-firm spell	4,376,003	550,080
Acquired firm	628,331	176,716
—— of which changed occupation within worker-firm spell (only acquired)	220,081	30,048

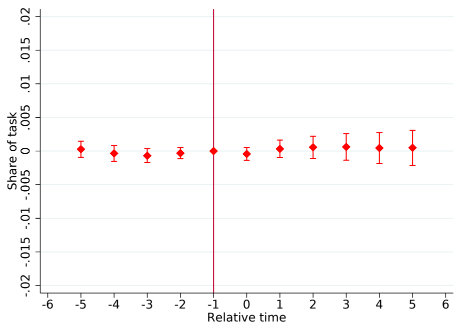
	No cases
Worker transition	1,002,500
—— of which changed occupation at the same time	603,933
from domestic to foreign*	226,575
—— of which also changed occupation	125,533
from foreign to domestic*	196,513
—— of which also changed occupation	109,389
workers who stayed with the firm after ownership change**	113,498
—— of which also changed occupation	10,305
workers entering after the acquisition or incumbent workers around the acquisition	68,700
—— of which also changed occupation	18,936
workers entering after the acquisition	27,325
—— of which also changed occupation	16,018
workers who stayed at the firm around the acquisition	41,375
—— of which also changed occupation	2,918

Note:
*ownership change can happen in two ways: either the firm has been acquired, or the worker changed firm.
** a firm can change its ownership status in two ways: either the firm was domestic and becomes foreign, or the otherway round.

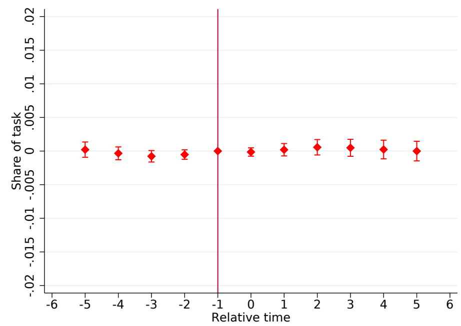
B Additional results

Figure B.2: The effect of foreign ownership on the task composition in production

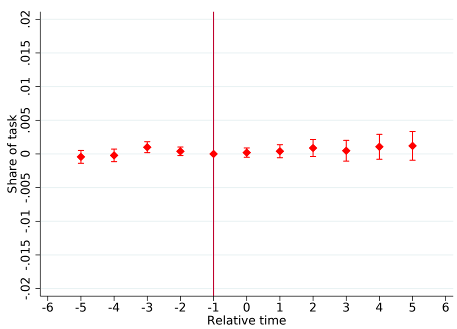
(a) Abstract task



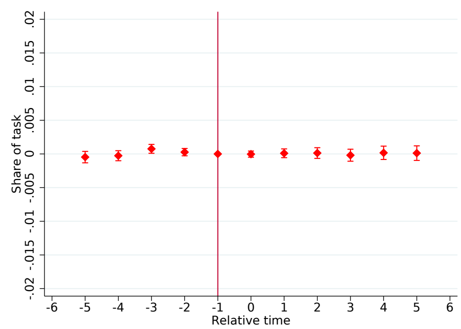
(b) Abstract task, two-stage DID



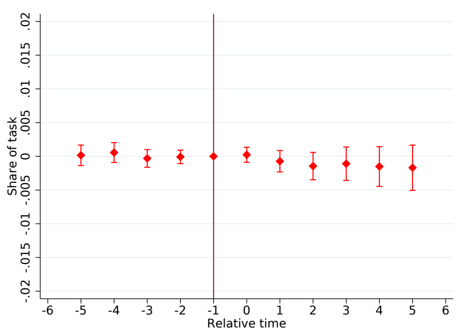
(c) Face-to-face task



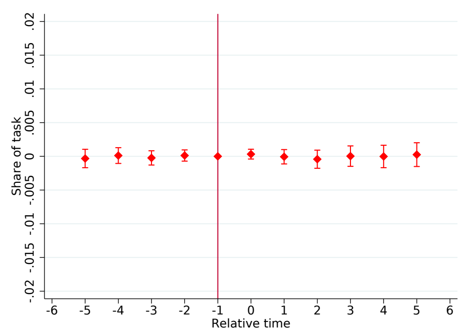
(d) Face-to-face task, two-stage DID



(e) Routine task



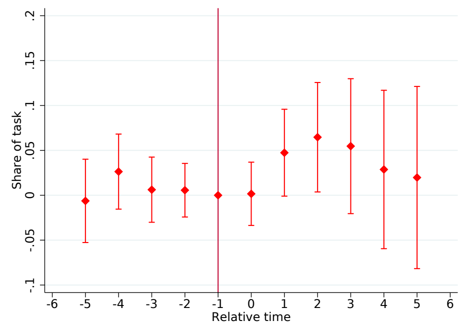
(f) Routine task, two-stage DID



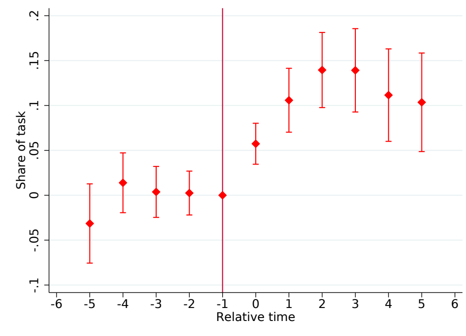
Note: The Figure shows the effect of foreign ownership on the task composition in firm's production around the event of the foreign acquisition. In particular, the Figure shows the parameter estimates of Equation (8), in which the dependent variables are the firm-level task use indices. Relative times capture the time relative to the event of the foreign acquisition. The figure shows the share of each task in the production relative to the share in the last year under domestic ownership. We control for industry fixed effects, year dummies, and firm fixed effects. Figures (b), (d), and (f) show the change of task composition in production using the two-stage difference-in-differences method proposed by Gardner et al. (2024). The bars show the 95% confidence intervals, and the standard errors are clustered at the firm level.

Figure B.3: The effect of foreign ownership on the size of the firm - Event-study approach

(a) Firm size



(b) Firm size, two-stage DID



Note: The Figure shows the effect of foreign ownership on firm size around the event of the foreign acquisition. In particular, the Figure shows the parameter estimates of Equation (8), in which the dependent variable is the logarithm of the number of employees at the firm. Relative times capture the time relative to the event of the acquisition. The figure shows the size of the firm relative to the last year under domestic ownership. We control for industry fixed effects, year dummies, and firm fixed effects. Figure (b) shows the change of task composition in production using the two-stage difference-in-differences method proposed by Gardner et al. (2024). The bars show 95% confidence intervals and standard errors are clustered at firm level.

Table B.8: The effect of foreign ownership on task composition – Replication of Table 4 weighted with firm size

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
			Panel A: Employment			
Foreign	0.730***	(0.255)	0.098*	(0.058)	0.314***	(0.080)
Constant	4.877***	(0.140)	5.209***	(0.029)	4.871***	(0.021)
Observations	29,187		29,187		27,216	
R-squared	0.275		0.961			
			Panel B: Abstract tasks			
Foreign	0.005***	(0.002)	-0.001	(0.001)	-0.001	(0.001)
Constant	0.328***	(0.002)	0.331***	(0.000)	0.327***	(0.000)
Observations	29,187		29,187		27,216	
R-squared	0.389		0.907			
			Panel C: Face-to-face			
Foreign	0.000	(0.001)	-0.000	(0.001)	0.001	(0.001)
Constant	0.318***	(0.001)	0.319***	(0.000)	0.319***	(0.000)
Observations	29,187		29,187		27,216	
R-squared	0.378		0.860			
			Panel D: Routine			
Foreign	-0.005***	(0.002)	0.001	(0.001)	0.000	(0.002)
Constant	0.354***	(0.001)	0.350***	(0.001)	0.353***	(0.000)
Observations	29,187		29,187		27,216	
R-squared	0.423		0.884			
Year	YES		YES		YES	
Industry	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: This Table shows the effect of foreign ownership on task composition. In particular, it shows the parameter estimates of Equation (7) using the size of the firm (measured by the number of employees) as weights in the regression. The dependent variables are the firm-level task use indices (see Section 3.2) and the main independent variable is the foreign-ownership dummy. The model is estimated on our "Acquired Sample" (for more details, see Section 3.1). We control for a set of year dummies and 1-digit industry dummies in column (1), while in column (2) we further add firm-specific fixed effects to the model. Column (3) uses the two-stage difference-in-differences method following Gardner et al. (2024). Standard errors are clustered at firm level. $***p < 0.01, **p < 0.05, *p < 0.1$

C Robustness Analysis

C.1 Additional control variables

We controlled for firm fixed effects in the main text to filter out selectivity in firm acquisition. In this section, we control for other characteristics as well to investigate the robustness of our results. Table C.9 Panel A controls for employment and export activities to check whether changes in firm characteristics can explain the main results. Panel B adds firm-specific fixed trends to investigate whether acquired firms have different wage growth trends, while Panel C adds firm-task fixed effects to control for the possibility that firms which are acquired earlier have different task returns even before the acquisition. Furthermore, we also filter out general equilibrium or spillover effects by adding country-year fixed effects in Column (2), industry-year fixed effects in Column (3), and county-industry-year fixed effects in Column (4). Reassuringly, the results are similar to the main results in every specification. The results are robust to the inclusion of additional control variables, as the point estimates are very similar to those in the main specification.

Then, we repeat this exercise for the change of task composition in Table C.10. Here, we replicate only Panel A and Panel B, as it is not possible to control for firm-task fixed effects by design. Again, the results are very close to the main findings.

Table C.9: The effect of foreign acquisition on task returns - Robustness to selectivity in acquisition

VARIABLES	(1) coef	(2) se	(3) coef	(4) se	(5) coef	(6) se	(7) coef	(8) se
Panel A: Additional controls								
Foreign	0.029***	(0.011)	0.027***	(0.008)	0.030***	(0.008)	0.028***	(0.007)
Foreign*Abstract	0.029***	(0.007)	0.029***	(0.006)	0.030***	(0.007)	0.031***	(0.007)
Foreign*Face-to-face	-0.011	(0.007)	-0.009	(0.007)	-0.010	(0.007)	-0.009	(0.007)
Foreign*Routine	0.006	(0.009)	0.005	(0.009)	0.006	(0.009)	0.005	(0.009)
Constant	7.904***	(0.046)	7.912***	(0.044)	7.915***	(0.046)	7.929***	(0.045)
Observations	628,331		625,725		625,725		625,725	
R-squared	0.708		0.712		0.713		0.721	
Industry	YES		YES		NO		NO	
Firm Charact.	YES		YES		YES		YES	
County-Year	NO		YES		YES		NO	
Industry-Year	NO		NO		YES		NO	
County-Ind-Year	NO		NO		NO		YES	
Panel B: Adding firm-specific trends to the model								
Foreign	0.007	(0.007)	0.006	(0.006)	0.006	(0.006)	0.005	(0.006)
Foreign * Abstract	0.029***	(0.007)	0.028***	(0.007)	0.029***	(0.007)	0.029***	(0.007)
Foreign * Face-to-face	-0.008	(0.007)	-0.006	(0.006)	-0.006	(0.006)	-0.005	(0.006)
Foreign * Routine	0.002	(0.009)	0.002	(0.009)	0.003	(0.009)	0.003	(0.009)
Constant	8.062***	(0.050)	8.078***	(0.048)	8.079***	(0.048)	8.084***	(0.048)
Observations	628,331		625,725		625,725		625,725	
R-squared	0.730		0.733		0.734		0.740	
Industry	YES		YES		NO		NO	
Firm Charact.	YES		YES		YES		YES	
County-Year	NO		YES		YES		NO	
Industry-Year	NO		NO		YES		NO	
County-Ind-Year	NO		NO		NO		YES	
Firm trend	YES		YES		YES		YES	
Panel C: Adding firm-task FE to the model								
Foreign	0.006	(0.007)	0.006	(0.006)	0.006	(0.006)	0.006	(0.006)
Foreign * Abstract	0.013**	(0.006)	0.012**	(0.006)	0.013*	(0.007)	0.013*	(0.007)
Foreign * Face-to-face	-0.001	(0.004)	0.000	(0.004)	0.001	(0.004)	0.002	(0.004)
Foreign * Routine	0.011	(0.007)	0.012*	(0.007)	0.013*	(0.008)	0.012*	(0.007)
Constant	8.076***	(0.030)	8.071***	(0.046)	8.070***	(0.047)	8.079***	(0.047)
Observations	628,331		625,725		625,725		625,725	
R-squared	0.767		0.769		0.770		0.775	
Industry	YES		YES		NO		NO	
Firm-task FE	YES		YES		YES		YES	
Firm-trend	YES		YES		YES		YES	
Firm Charact.	NO		YES		YES		YES	
County-Year	NO		YES		YES		NO	
Industry-Year	NO		NO		YES		NO	
County-Ind-Year	NO		NO		NO		YES	

Note: This Table shows the effect of foreign acquisition on task returns by controlling for selectivity. In particular, we re-estimate Column (2) of Table 2 by including additional control variables. The original model included year fixed effects and their interaction with task use indices, the gender and age of the worker, whether the firm is a public firm, 1-digit industry fixed effects, and firm-specific fixed effects. In Panel A, we extend the list of control variables by time-varying firm-specific controls (logarithm of sales and employment, a dummy indicating that the firm participates in export activities) in the first column. We further add county-year fixed effects in the second, industry-year fixed effects in the third, and industry-county-year fixed effects in the last column. In Panel B, we further control for firm-specific trends. In Panel C, we also tííííake firm-task-specific trends into consideration. Standard errors are clustered at firm level.*** $p < 0.01, **p < 0.05, *p < 0.1$

Table C.10: The effect of foreign ownership on task composition - Robustness to selectivity in acquisition

	(1)		(2)		(3)		(4)	
VARIABLES	coef	se	coef	se	coef	see	coef	se
Panel A: Firm size								
Foreign	0.029***	(0.011)	0.027**	(0.011)	0.028***	(0.011)	0.031***	(0.012)
Constant	0.887***	(0.117)	0.898***	(0.117)	0.851***	(0.103)	0.911***	(0.114)
Observations	29,187		29,185		29,185		29,185	
R-squared	0.912		0.913		0.915		0.930	
Panel B: Abstract tasks								
Foreign	0.001**	(0.000)	0.001**	(0.000)	0.001**	(0.000)	0.001**	(0.000)
Constant	0.349***	(0.002)	0.349***	(0.002)	0.349***	(0.002)	0.349***	(0.002)
Observations	29,187		29,185		29,185		29,185	
R-squared	0.886		0.888		0.889		0.909	
Panel C: Face-to-face								
Foreign	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Constant	0.326***	(0.001)	0.326***	(0.001)	0.326***	(0.001)	0.326***	(0.001)
Observations	29,187		29,185		29,185		29,185	
R-squared	0.857		0.858		0.860		0.881	
Panel D: Routine								
Foreign	-0.001**	(0.000)	-0.001**	(0.000)	-0.001**	(0.000)	-0.001**	(0.000)
Constant	0.324***	(0.002)	0.325***	(0.002)	0.325***	(0.002)	0.325***	(0.002)
Observations	29,187		29,185		29,185		29,185	
R-squared	0.858		0.860		0.861		0.886	
Year	YES		NO		NO		NO	
Industry	YES		YES		NO		NO	
Firm FE	YES		YES		YES		YES	
Firm contr	YES		YES		YES		YES	
Firm-trend	YES		YES		YES		YES	
County-Year	NO		YES		YES		NO	
Industry-Year	NO		NO		YES		NO	
County-Ind-Year	NO		NO		NO		YES	

Note: This Table shows the effect of foreign acquisition on task composition by controlling for selectivity. In particular, we re-estimate column (2) of Table 4 by including additional control variables. In the original model, we control for a set of year and industry dummies and firm fixed effects. In addition to these, we add firm-level controls and firm-specific trends to the model in column (1). Firm-level controls in Panel (A) include the logarithm of sales revenue and an indicator for export activity. Firm-level controls in Panels (B)-(D) include the logarithm of the number of employees, sales revenue, and an indicator for export activity. We extend the list of control variables with county-year fixed effects in column (2), industry-year fixed effects in column (3) and county-industry-year fixed effects in column (4). Standard errors are clustered at firm level. $***p < 0.01, **p < 0.05, *p < 0.1$

C.2 Worker selectivity

Workforce composition may change after an acquisition. If foreign firms assess workers' abilities more effectively than domestic firms, foreign acquisitions could improve worker composition through selective hiring. In other words, the causal effect of FDI on task returns is overestimated if foreign firms tend to hire employees whose abilities in conducting abstract tasks are better, unless we control for changing worker composition as well.

To address this issue, we conduct two robustness checks. First, we limit our "Acquired Sample" to incumbent employees who had been with the firm for three years, from the year preceding the acquisition to the first year after it occurred (see Panel A in Appendix Table C.17). Second, to account for workforce- and firm-level selectivity, we use our "Full Sample" (including always domestic, acquired, and other firms). On this large sample, we estimate the effect of FDI on task returns using worker and firm fixed effects in the following difference-in-differences setting:

$$\begin{aligned} lnw_{ijot} = {} & \alpha_1 * AlwaysForeign_j + \alpha_2 * AlwaysForeign_j * TaskMeasure_o + \\ & \beta_1 * Acquired_j + \beta_2 * Acquired_j * TaskMeasure_o + \\ & \delta_1 * Acquired_j * Foreign_{jt} + \delta_2 * Acquired_j * Foreign_{jt} * TaskMeasure_o + \\ & + \tau_t * TaskMeasure_o + \gamma_1 * X_{ijt} + s_j + \tau_t + [\nu_i + f_j + f_j * t] + \epsilon_{ijt},, \end{aligned} \tag{C.2}$$

where lnw_{ijot} denotes the logarithm of the daily wage of worker i working at firm j in occupation o in year t. $TaskMeasure_o$ stands for the occupation-level task indices described in Section 3.2 (standardized to have a mean of zero and a standard deviation of one).

$AllwaysForeign_j$ is a dummy denoting that the firm entered our dataset as a foreign firm. This variable indicates whether firms that were always foreign-owned pay a higher wage premium compared to domestic and acquired firms. We interact this dummy with task indices, the corresponding parameter, β_2, shows whether domestic firms that were acquired later had different task returns compared to the task return of always domestic firms.

$Acquired_j$ is a dummy denoting that the firm started as domestic in the database and was acquired by a foreign investor during our observed period. We allow tasks to have different returns at firms before acquisition by interacting this dummy with the task measure dummy. $Acquired_j * Foreign_{jt}$ corresponds to the post-acquisition period of acquired firm compared to the pre-acqusistion years. The main coefficient of interest is δ_2 showing the difference in task returns at acquired firms between the pre-acquisition and post-acquisition years. This way, we can identify the effect of FDI on task returns using only within firm variation in ownership.

The main purpose of this exercise that we can add individual fixed effects, ν_i, to control for selectivity in workforce. We further add firm-specific fixed effects (f_j) and firm-specific time trends in wages ($f_j * t$) to the model to control for selectivity in foreign ownership. Furthermore, we control for industry fixed effects (s_j), year dummies (τ_t), and task-year interactions ($\tau_t * TaskMeasure_o$) to account for economic level trends in task returns. Finally, we allow tasks to have different returns at firms before acquisition or at firms that were foreign-owned already at the beginning of the sampling period. This way, we can identify the effect of FDI on task returns using only within firm variation in ownership.

As we control for individual fixed effects, δ_2 is identified from the wage change of three different worker groups: (i) incumbent workers who stayed at the firm around the ownership change (with or without changing their occupation), (ii) workers who work at foreign-owned firms and change occupation, (iii) workers who entered the firm after the acquisition. See Appendix A.4 and Table A.7 for a more detailed discussion and for the number of relevant cases.

As shown in the main text, we estimate the model without firm and worker fixed effects, then we include firm fixed effects (f_j) only (ν_i is excluded), and finally include firm and worker fixed effects at the same time. With this strategy, we can quantify how much selectivity across firms affects the returns to tasks after acquisition.

As a next step, we perform an event-study-style analysis to examine how the effect of foreign acquisition evolves over time. We include leads and lags of the acquisition interacted with the task measures:

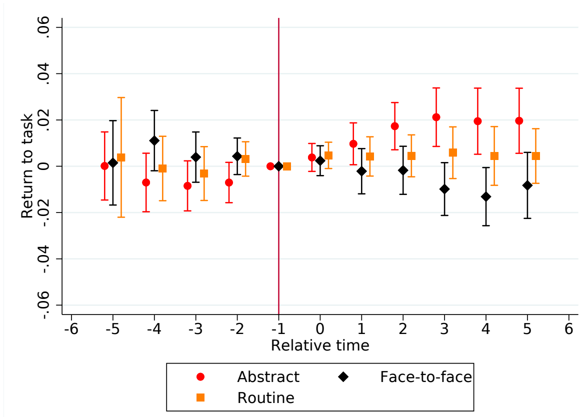
$$lnw_{ijot} = \delta_{1s} * Foreign_{jt} + \delta_{2s} * Foreign_{jt} * TaskMeasure_o + \\ + \alpha * TaskMeasure_o * AlwaysForeign_j + \alpha_t * TaskMeasure_o + \\ + \alpha_t * TaskMeasure_o + \gamma_1 * X_{ijt} + s_j + \tau_t + [\nu_i + f_j + f_j * t] + \epsilon_{ijt}, \tag{C.3}$$

where lnw_{ijot} denotes the logarithm of the daily wage of worker i working at firm j in occupation o in year t. $TaskMeasure_o$ is the task index and the control variables are the same as in Equation (5). There is one important change compared to Equation (5). Now, the coefficient of $Foreign_j * TaskMeasure_o$ has a time dimension. s is zero in the last year under domestic ownership so that δ_{2s} shows the return to $TaskMeasure_o$ s year before or after this year. We normalize δ_0 to zero, and negative (positive) s denotes the years before (after) our reference period. All else remains the same as in the previous equation.

According to Table 3, our results are robust to these changes. The return to abstract tasks increases after an acquisition, even after accounting for firm and worker-level selectivity. The return to our tasks is unaffected by the event of acquisition. Appendix Figure C.4 confirms that there is no-pretrend in task returns either.

To be consistent, we also re-estimate Equation 7 on the full sample, including always domestic and always foreign firms. We allow tasks to have different returns at firms before acquisition or firms that were foreign-owned already at the beginning of the sampling period. Appendix Table C.11 presents the results. The size of the firm increases after a foreign acquisition, while the task composition of tasks is unaffected by this event.

Figure C.4: The effect of foreign acquisition on task returns – controlling for worker-level selectivity



Note: This Figure shows the effect of foreign acquisition on task returns in an event-study approach by accounting for workforce- and firm-level selectivity. In this analysis, we use our "Full Sample" (including always domestic, acquired, and other firms) and estimate our Equation (C.3), in which our main dependent variable is the logarithm of daily wage and the main independent variables are the foreign dummy interacted with our task indices. Year fixed effects and their interaction with task use indices are included. We include a dummy indicating that the firm was acquired during our sampling period interacted with the task indices, and another dummy showing that the firm was foreign-owned at the beginning of the sampling period also interacted with the task indices. We further control for the age of the worker, whether the firm is a public firm, 1-digit industry fixed effects, and firm and worker-specific fixed-effects. Standard errors are clustered at firm level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table C.11: The effect of foreign ownership on task composition by including all firms

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Panel A: Firm size						
Always Foreign	0.782***	(0.015)				
Acquired	0.373***	(0.020)				
Acquired * Foreign	0.244***	(0.026)	0.096***	(0.014)	0.052***	(0.012)
Constant	2.451***	(0.003)	2.586***	(0.001)	2.587***	(0.001)
Observations	799,631		799,631		799,631	
R-squared	0.149		0.825		0.919	
Panel B: Abstract tasks						
Always Foreign	0.010***	(0.000)				
Acquired	0.006***	(0.001)				
Acquired * Foreign	0.002***	(0.001)	-0.000	(0.000)	0.000	(0.000)
Constant	0.327***	(0.000)	0.329***	(0.000)	0.329***	(0.000)
Observations	799,631		799,631		799,631	
R-squared	0.275		0.798		0.888	
Panel C: Face-to-face						
Always Foreign	-0.004***	(0.000)				
Acquired	-0.001***	(0.000)				
Acquired * Foreign	-0.001***	(0.000)	-0.001***	(0.000)	0.000	(0.000)
Constant	0.327***	(0.000)	0.326***	(0.000)	0.326***	(0.000)
Observations	799,631		799,631		799,631	
R-squared	0.265		0.768		0.872	
Panel D: Routine						
Always Foreign	-0.007***	(0.000)				
Acquired	-0.005***	(0.001)				
Acquired * Foreign	-0.000	(0.001)	0.001**	(0.000)	-0.000	(0.000)
Constant	0.346***	(0.000)	0.345***	(0.000)	0.345***	(0.000)
Observations	799,631		799,631		799,631	
R-squared	0.224		0.757		0.867	
Year	YES		YES		YES	
Industry	YES		YES		YES	
Firm FE	NO		YES		YES	
Firm-trend	NO		NO		YES	

Note: This Table shows the effect of foreign ownership on task composition by including all firms (always domestic, acquired, and firms that were foreign owned already at the beginning of the sampling period). In particular, We re-estimate Equation (7) on this larger sample. The dependent variables are the firm-level task use indices introduced in Section 3.2 at firm j in year t. We include a dummy variable showing that the firm was foreign-owned already at the beginning of the sampling period and a dummy that shows the firm was acquired during our sampling period ($Acquired_j$). Our main independent variable is the interaction term of the $Acquired_j$ dummy and $Foreign_{jt}$. The coefficient of this interaction term shows the effect of foreign acquisition on the task composition of the firm. In column (1), we control for year and industry dummies, in column(2), we additionally control for firm fixed effects, while in column (3), we add firm-specific trends to the model. $***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at firm level.

C.3 Divestment

This section investigates the robustness of the results to divestment. The issue here is that some parent companies may decide to disinvest, so the acquired firms become domestic again. These divestments may affect our main results in case of subsequent changes in task returns and composition. To check this hypothesis, we re-estimate Table 2 and Table 4 by omitting firm-year observations after disinvestment. The results of the re-estimation below are very close to the main estimates.

Table C.12: The effect of foreign acquisition on the task returns - Re-estimation of Table 2 by excluding post-divestment years

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign	0.172***	(0.037)	0.033***	(0.010)	-0.003	(0.014)
Foreign * Abstract	0.045***	(0.014)	0.028***	(0.007)	0.028***	(0.009)
Foreign * Face-to-face	-0.012	(0.016)	-0.008	(0.008)	-0.021	(0.015)
Foreign * Routine	-0.005	(0.017)	0.003	(0.009)	0.005	(0.011)
Constant	7.853***	(0.070)	8.042***	(0.033)	7.904***	(0.001)
Observations	550,444		550,444		526,374	
R-squared	0.463		0.718			
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: This Table shows the effect of foreign acquisition on task returns by excluding post divestment period. In particular, it shows the parameter estimates of Equation (5) by excluding the post-divestment years. The dependent variable is the logarithm of the daily wage of worker i working at firm j in year t. We estimated the model on our "Acquired Sample" (more details in Section 3.1). The main independent variables are the task indices (see more in Section 3.2) interacted with a dummy denoting foreign ownership. Year fixed effects and their interaction with task use indices are included in every regression. We further control for the gender and age of the worker, and whether the firm is a public firm, and 1-digit industry fixed effects. In the second column, we further control for firm-specific fixed effects. Column (3) uses the two-stage difference-in-differences method suggested by (Gardner et al., 2024). Standard errors are clustered at firm level. *** $p < 0.01, **p < 0.05, *p < 0.1$.

Table C.13: The effect of foreign ownership on the task composition of firms - Re-estimation of Table 4 by excluding post-divestment years

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
			Panel A: Firm size			
Foreign	0.298***	(0.035)	0.086***	(0.017)	0.106***	(0.021)
Constant	2.798***	(0.024)	2.893***	(0.008)	2.803***	(0.001)
Observations	24,192		24,192		23,543	
R-squared	0.080		0.790		0.005	
			Panel B: Abstract tasks			
Foreign	0.004***	(0.001)	0.001	(0.000)	0.001	(0.000)
Constant	0.336***	(0.001)	0.338***	(0.000)	0.336***	(0.000)
Observations	24,192		24,192		23,543	
R-squared	0.314		0.819		0.000	
			Panel C: Face-to-face			
Foreign	-0.001**	(0.001)	0.000	(0.000)	0.000	(0.000)
Constant	0.324***	(0.000)	0.324***	(0.000)	0.324***	(0.000)
Observations	24,192		24,192		23,543	
R-squared	0.266		0.763		0.000	
			Panel D: Routine			
Foreign	-0.002**	(0.001)	-0.001	(0.001)	-0.000	(0.001)
Constant	0.339***	(0.001)	0.339***	(0.000)	0.339***	(0.000)
Observations	24,192		24,192		23,543	
R-squared	0.228		0.770		0.000	
Year	YES		YES		YES	
Industry	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: This Table shows the effect of foreign ownership on task composition. In particular, it shows the parameter estimates of Equation (7) by excluding post-divestment years. The dependent variables are the firm-level task use indices (see Section 3.2) and the main independent variable is the foreign-ownership dummy. The model is estimated on our "Acquired Sample" (for more details, see Section 3.1) We control for a set of year dummies and 1-digit industry dummies in column (1), while in column (2) we further add firm-specific fixed effects to the model. Column (3) uses the two-stage difference-in-differences method following Gardner et al. (2024). Standard errors are clustered at firm level. $***p < 0.01, **p < 0.05, *p < 0.1$

C.4 Matching across firms and placebo test

A key identification challenge is that acquired and non-acquired firms are different in many dimensions. Accordingly, the wage dynamics of the two groups may be different even without an acquisition. For this reason, the main analysis restricted the sample to firms that were acquired by a foreign investor during the observed period and used within-firm variation to estimate the casual relationship between returns to tasks and foreign investment. In the robustness analysis we even showed that our results are robust to considering worker-level selection. In this section, we show that our results hold even when comparing similar foreign and domestic firms. To do so, we match each acquired firm to a domestic firm (for more details on the matching procedure, see Appendix Section A.3). We use the matched sample to conduct two additional robustness checks.

First, we show that foreign investment increases the return to abstract tasks only, even if we restrict the sample to the subset of matched firms. We mimic Equation (5) on our matched sample. We report the parameter of the interaction term of the foreign dummy and our task measures in Panel A Table C.14. We control for the same variables as in our main analysis. Firm-specific fixed effects are added to the model in the second column, and the two-stage difference-in-differences method of Gardner et al. (2024) is used in the last column. The results are qualitatively similar to the main analysis, but point estimates are even a bit larger.

For the second robustness check, we conduct a placebo test. Our one-to-one matching procedure ensures that the year of acquisition of the acquired firm can be assigned to its always domestic pair as a pseudo-acquisition year. Consequently, in the case of domestic firms, we treat post-pseudo-acquisition years as pseudo-foreign years, and control for these years in the regressions. We also interact this pseudo-foreign dummy with our task measures to estimate whether there is any change in returns to tasks at domestic firms after the pseudo-acquisition compared with their pre-pseudo-acquisition years. The results are outlined in Panel B Table C.14. We do not find any effect of the pseudo-investment in domestic firms, while true foreign acquisition still has a positive effect on the return to abstract tasks.

Table C.14: The effect of foreign acquisition on task returns – matched sample and placebo test

VARIABLES	(1) coef.	se	(2) coef.	se	(3) coef.	se
Panel A: Matched sample						
Foreign	0.106***	(0.020)	0.030**	(0.012)	0.042**	(0.021)
Foreign * Abstract	0.060***	(0.020)	0.036***	(0.008)	0.055***	(0.011)
Foreign * Face-to-face	-0.019	(0.017)	-0.019	(0.014)	-0.029*	(0.018)
Foreign * Routine	-0.002	(0.016)	-0.014	(0.012)	-0.014	(0.015)
Constant	8.049***	(0.037)	8.038***	(0.028)	7.999***	(0.002)
Observations	446,374		446,374		446,374	
R-squared	0.445		0.683			
Panel B: Placebo test						
Pseudo Foreign	-0.039	(0.025)	0.005	(0.011)	-0.006	(0.015)
Pseudo Fo * Abstract	0.005	(0.022)	-0.002	(0.009)	-0.008	(0.010)
Pseudo Fo * Face-to-face	-0.004	(0.020)	0.012	(0.011)	0.014	(0.012)
Pseudo Fo * Routine	0.008	(0.019)	0.010	(0.011)	-0.004	(0.015)
Foreign	0.119***	(0.023)	0.028**	(0.014)	0.039	(0.029)
Foreign * Abstract	0.058**	(0.024)	0.037***	(0.009)	0.043***	(0.015)
Foreign * Face-to-face	-0.018	(0.019)	-0.024	(0.015)	-0.039*	(0.023)
Foreign * Routine	-0.005	(0.018)	-0.018	(0.014)	0.009	(0.022)
Constant	8.066***	(0.037)	8.036***	(0.029)	7.897***	(0.001)
Observations	446,374		446,374		387,941	
R-squared	0.445		0.683			
Year FE	YES		YES		YES	
Trend in task return	YES		YES		YES	
Worker Characteristics	YES		YES		YES	
Industry FE	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: This Table shows the effect of foreign acquisition on task returns on our matched sample (see Section A.3 for more details on the matching procedure). Panel A of the table contains the parameter estimates of Equation 5 on the matched sample. The dependent variable is the logarithm of the daily wage of worker i working at firm j in year t. The main independent variables are the task indices (see more in Section 3.2 interacted with a dummy denoting foreign ownership. Year fixed effects and their interaction with task use indices are included in every regression. We further control for the gender and age of the worker, and 1-digit industry fixed effects. In the second column, we further control for firm-specific fixed effects. Column (3) uses the two-stage difference-in-differences method suggested by (Gardner et al., 2024). Panel B shows the estimation results of our placebo test. Our one-to-one matching procedure ensures that the year of acquisition of the acquired firm can be assigned to its always domestic pair as a pseudo-acquisition year. Post-pseudo-acquisition years are therefore treated in the case of domestic firms as pseudo-foreign years, and we control for these years in the regressions. We also interact this pseudo-foreign dummy with our task measures to estimate whether there is any change in returns to tasks at domestic firms after the pseudo-acquisition compared with their pre-pseudo-acquisition years. Year fixed effects and their interaction with task use indices are included in every regression. We further control for the gender and age of the worker, and 1-digit industry fixed effects. In the second column, we also control for firm-specific fixed effects. Column (3) uses the two-stage difference-in-differences method proposed by Gardner et al. (2024). *** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at firm level.

C.5 Export activity

Acquired firms often start to export after acquisition. Since export increases wages (Frıas et al., 2022), it is possible that export changes task returns and not foreign acquisition *per se*. We investigate this in Table C.15 by adding export-foreign-task interactions to Equation (5).

Table C.15 shows two important results. First, foreign-owned firms pay a higher return to abstract tasks even if we control for the possibility that exporting firms pay different returns on tasks. Second, we do not find evidence that exporting firms pay different returns on tasks conditional on firm fixed effects. Both of these results suggest that the exporting activities of foreign-owned firms cannot explain the change of task returns after acquisition.

In parallel to the task return analysis, we also investigate the effect of export activity on the task composition of the firm. We re-estimate Equation (7) by controlling for the export activity status of the firm. According to Appendix Table C.16, firms engaged in export activity are larger, but their task composition is not affected by the export status of the firm once we control for firm fixed effects. Moreover, our results related to foreign ownership do not change as we take into account that foreign firms engaged in export activity with a higher probability.

Table C.15: The effect of export on task returns

	(1)		(2)		(3)	
Foreign	0.133***	(0.032)	0.030***	(0.011)	0.004	(0.017)
Foreign * Abstract	0.044***	(0.012)	0.028***	(0.006)	0.021***	(0.008)
Foreign * Face-to-face	-0.022*	(0.013)	-0.009	(0.007)	-0.015	(0.014)
Foreign * Routine	-0.012	(0.015)	0.009	(0.009)	0.017	(0.012)
Export	0.223***	(0.022)	0.009	(0.008)	-0.009	(0.015)
Export * Abstract	0.009	(0.016)	0.009	(0.009)	0.011	(0.007)
Export * Face-to-face	-0.026**	(0.012)	-0.010	(0.007)	-0.009	(0.008)
Export * Routine	-0.029**	(0.013)	-0.018**	(0.008)	-0.015	(0.010)
Constant	7.784***	(0.064)	8.053***	(0.031)	7.904***	(0.007)
Observations	628,331		628,331		592,161	
R-squared	0.474		0.708			
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: We re-estimate Table 2 by controlling for export activity. Year fixed effects and their interaction with task use indices are included in every regression. We further control for the gender and age of the worker, whether the firm is a public firm, and 1-digit industry fixed effects. In the second column, we further control for firm-specific fixed effects. Column (3) uses the two-stage difference-in-differences method of Gardner et al. (2024). Standard errors are clustered at firm level. *** $p < 0.01, **p < 0.05, *p < 0.1$

Table C.16: The effect of export on firm size and task composition

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Panel A: Firm size						
Foreign	0.180***	(0.027)	0.072***	(0.013)	0.090***	(0.020)
Exporter	0.689***	(0.035)	0.286***	(0.019)	0.134***	(0.018)
Observations	29,187		29,187		27,778	
R-squared	0.140		0.776		0.011	
Panel B: Abstract tasks						
Foreign	0.002***	(0.001)	0.000	(0.000)	0.001*	(0.000)
Exporter	0.007***	(0.001)	-0.001	(0.001)	-0.001**	(0.000)
Constant	0.335***	(0.001)	0.338***	(0.000)	0.336***	(0.000)
Observations	29,187		29,187		27,778	
R-squared	0.327		0.796		0.001	
Panel C: Face-to-face tasks						
Foreign	-0.001	(0.000)	-0.000	(0.000)	0.000	(0.000)
Exporter	-0.004***	(0.001)	-0.001	(0.000)	-0.000	(0.000)
Constant	0.326***	(0.000)	0.324***	(0.000)	0.324***	(0.000)
Observations	29,187		29,187		27,778	
R-squared	0.270		0.742		0.000	
Panel D: Routine tasks						
Foreign	-0.002**	(0.001)	-0.000	(0.000)	-0.000	(0.001)
Exporter	-0.003***	(0.001)	0.001*	(0.001)	0.002***	(0.001)
Constant	0.340***	(0.001)	0.337***	(0.000)	0.338***	(0.000)
Observations	29,187		29,187		27,778	
R-squared	0.233		0.740		0.001	
Year	YES		YES		YES	
Industry	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: This Table shows the effect of foreign ownership on the task composition of the firm by taking into account that firms are more involved in the international market after a foreign acquisition. We re-estimate Table 4 by controlling for export activity. In the second column, we control for firm-specific fixed effects. Column (3) follows the two-stage difference-in-differences method proposed by Gardner et al. (2024). Standard errors are clustered at firm level. *** $p < 0.01, **p < 0.05, *p < 0.1$

C.6 Heterogeneity analysis – Specific subsamples

In this section, we perform three robustness checks to examine the robustness of our results for specific subsamples of firms and workers.

First, we restrict our sample to incumbent employees who had been with the firm for three years, from the year before the acquisition to the first year after the acquisition. Panel A in Table C.17 shows that the observed patterns are similar on this subsample to our main results, confirming that our results are not driven by changes in workforce composition around the event of foreign acquisition.

Second, we show that our results are not driven by small firms. For this purpose, we omit firms that did not exceed the 50 employees threshold during our period of observation (Panel B in Appendix Table C.17). Third, we exclude managers from our sample to show that our results are not driven by this specific group of workers. The results are qualitatively the same as in the main specifications (Panel C). See the main text for a more detailed discussion.

Next, we use these subsamples in Table C.19 to investigate whether task composition in production changes after the acquisition. As in the previous table, Panel (A) investigates incumbent workers[13], Panel (B) concerns large firms, and Panel (C) excludes managers. The main message of the table is that no evidence is found for firms changing their task composition after acquisition. Moreover, Table C.18 confirms that even large firms grow after a foreign acquisition.

[13] Note that the tasks of incumbent workers change if they change their occupation.

Table C.17: The effect of foreign acquisition on task returns - Re-estimation of Table 2 on specific subsamples

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Panel A: Incumbent workers						
Foreign	0.160***	(0.037)	0.035***	(0.011)	0.025**	(0.010)
Foreign * Abstract	0.049***	(0.012)	0.025***	(0.007)	0.015*	(0.008)
Foreign * Face-to-face	-0.006	(0.014)	0.000	(0.007)	0.001	(0.006)
Foreign * Routine	-0.008	(0.018)	0.008	(0.009)	0.001	(0.009)
Constant	8.011***	(0.090)	8.191***	(0.053)	7.879***	(0.007)
Observations	219,702		219,702		201,702	
R-squared	0.424		0.701			
Panel B: Large firms						
Foreign	0.145***	(0.038)	0.034**	(0.013)	0.004	(0.019)
Foreign * Abstract	0.047***	(0.016)	0.034***	(0.008)	0.033***	(0.010)
Foreign * Face-to-face	-0.017	(0.016)	-0.010	(0.008)	-0.028	(0.018)
Foreign * Routine	-0.005	(0.019)	0.012	(0.011)	0.011	(0.013)
Constant	7.930***	(0.071)	8.078***	(0.037)	7.917***	(0.014)
Observations	505,669		505,669		475,788	
R-squared	0.479		0.687			
Panel C: Excluding managers						
Foreign	0.154***	(0.033)	0.029***	(0.011)	0.001	(0.016)
Foreign * Abstract	0.047***	(0.013)	0.026***	(0.006)	0.022**	(0.009)
Foreign * Face-to-face	-0.032*	(0.017)	-0.018***	(0.006)	-0.025**	(0.013)
Foreign * Routine	-0.018	(0.017)	0.005	(0.008)	0.011	(0.009)
Constant	7.928***	(0.060)	8.081***	(0.026)	7.893***	(0.012)
Observations	581,272		581,272		545,256	
R-squared	0.455		0.730			
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: This Table shows the effect of foreign acquisition on task returns using specific subsample. We use our "Acquired Sample" (more details in Section 3.1) and further restrict it to incumbent workers in Panel (A), large firms (we exclude firms that did not exceed the 50 employee threshold during our period of observation) in Panel (B), non-manager employees in Panel (C). This Table shows the parameter estimates of Equation (5), in which the dependent variable is the logarithm of the daily wage of worker i working at firm j in year t. The main independent variables are the task indices (see more in Section 3.2) interacted with a dummy denoting foreign ownership. Year fixed effects and their interaction with task use indices are included in every regression. We further control for the gender and age of the worker, and whether the firm is a public firm, and 1-digit industry fixed effects. In the second column, we further control for firm-specific fixed effects. Column (3) uses the two-stage difference-in-differences method suggested by (Gardner et al., 2024). Standard errors are clustered at firm level. *** $p < 0.01, **p < 0.05, *p < 0.1$

Table C.18: The effect of foreign ownership on firm size on the subsample of large firms

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign	0.289***	(0.053)	0.121***	(0.035)	0.188***	(0.050)
Constant	3.995***	(0.038)	4.068***	(0.015)	3.965***	(0.017)
Observations	8,472		8,472		8,065	
R-squared	0.079		0.633			
Year	YES		YES		YES	
Industry	YES		YES		YES	
Industry	NO		YES		YES	

Note: This Table shows the effect of foreign ownership on firm size on the subsample of large firm. The table contains the parameter estimates of Equation (7) on the subsample of large firms (we exclude firms that did not exceed the 50 employee threshold during our period of observation). We control for a set of year dummies and 1-digit industry dummies in column (1), while in column (2) we further add firm-specific fixed effects to the model. Column (3) uses the two-stage difference-in-differences method following Gardner et al. (2024). Standard errors are clustered at firm level. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table C.19: The effect of foreign ownership on task composition

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Panel A: Incumbent workers						
Abstract tasks						
Foreign	0.003***	(0.001)	0.000	(0.000)	0.001*	(0.000)
Constant	0.344***	(0.001)	0.345***	(0.000)	0.343***	(0.000)
Observations	17,798		17,798		15,981	
R-squared	0.277		0.868			
Face-to-face						
Foreign	0.000	(0.001)	0.000	(0.000)	0.000	(0.000)
Constant	0.320***	(0.001)	0.320***	(0.000)	0.319***	(0.000)
Observations	17,798		17,798		15,981	
R-squared	0.204		0.813			
Routine						
Foreign	-0.003**	(0.001)	-0.000	(0.001)	-0.001*	(0.001)
Constant	0.336***	(0.001)	0.335***	(0.000)	0.337***	(0.000)
Observations	17,798		17,798		15,981	
R-squared	0.215		0.845			
Panel B: Large firms						
Abstract tasks						
Foreign	0.003**	(0.001)	0.000	(0.001)	-0.000	(0.001)
Constant	0.333***	(0.001)	0.334***	(0.000)	0.331***	(0.000)
Observations	8,472		8,472		8,065	
R-squared	0.326		0.820			
Face-to-face						
Foreign	-0.001	(0.001)	-0.001**	(0.000)	0.000	(0.001)
Constant	0.321***	(0.001)	0.321***	(0.000)	0.320***	(0.000)
Observations	8,472		8,472		8,065	
R-squared	0.366		0.782			
Routine						
Foreign	-0.002*	(0.001)	0.001	(0.001)	0.000	(0.001)
Constant	0.347***	(0.001)	0.345***	(0.000)	0.348***	(0.000)
Observations	8,472		8,472		8,065	
R-squared	0.334		0.793			
Panel C: Excluding managers						
Abstract tasks						
Foreign	0.004***	(0.001)	0.000	(0.000)	0.000	(0.000)
Constant	0.332***	(0.001)	0.333***	(0.000)	0.330***	(0.000)
Observations	28,213		28,213		26,570	
R-squared	0.338		0.817			
Face-to-face tasks						
Foreign	-0.001**	(0.000)	-0.000	(0.000)	0.000	(0.000)
Constant	0.323***	(0.000)	0.322***	(0.000)	0.322***	(0.000)
Observations	28,213		28,213		26,570	
R-squared	0.292		0.773			
Routine tasks						
Foreign	-0.003***	(0.001)	-0.000	(0.000)	0.000	(0.001)
Constant	0.346***	(0.001)	0.345***	(0.000)	0.346***	(0.000)
Observations	28,213		28,213		26,570	
R-squared	0.260		0.773			
Year	YES		YES		YES	
Industry	YES		YES		YES	
Industry	NO		YES		YES	

Note: This Table shows the effect of foreign ownership on task composition. In particular, it shows the parameter estimates of Equation (7), in which the dependent variables are the firm-level task use indices (see Section 3.2) and the main independent variable is the foreign-ownership dummy. We use our "Acquired Sample" (more details in Section 3.1) and further restrict it to incumbent workers in Panel (A), large firms (we exclude firms that did not exceed the 50 employee threshold during our period of observation) in Panel (B), non-manager employees in Panel (C). We control for a set of year dummies and 1-digit industry dummies in column (1), while in column (2) we further add firm-specific fixed effects to the model. Column (3) uses the two-stage difference-in-differences method following

C.7 Sectoral comparison

Many acquired firms in the service sector provide business services to their parent company, which may lead to different FDI effects on task returns compared with the manufacturing sector. To investigate this question, we modify Equation (5) slightly to compare task returns between the service and manufacturing sectors. Specifically, we introduce a dummy variable indicating whether a firm operates in the service industry, and interact it with the *Foreign* dummy and the task measures. Additionally, we include a triple interaction term involving all three variables. The results in Table C.20 show no difference in the effect of foreign acquisition on task returns.

Next, we repeat this exercise for the estimation of task composition. We incorporate the service dummy and interact it with the *Foreign* dummy in Equation (7). The results in Table C.21 show that task composition in production does not change either in the manufacturing or in the service sector.

Table C.20: The effect of foreign acquisition on task returns by industry - Re-estimation of Table 2 by comparing the service and manufacturing sectors

	(1)		(2)		(3)	
Foreign	0.174***	(0.059)	0.036**	(0.016)	0.012	(0.019)
Foreign * Service	-0.035	(0.057)	-0.008	(0.016)	-0.009	(0.030)
Foreign * Abstract	0.048***	(0.017)	0.033***	(0.009)	0.034***	(0.009)
Foreign * Service * Abstract	0.002	(0.023)	-0.006	(0.012)	-0.011	(0.016)
Foreign * Face-to-face	-0.003	(0.013)	-0.004	(0.008)	-0.009	(0.011)
Foreign * Service * Face-to-face	-0.024	(0.019)	-0.009	(0.014)	-0.018	(0.023)
Foreign * Routine	0.005	(0.020)	0.012	(0.014)	0.010	(0.013)
Foreign * Service * Routine	-0.046*	(0.025)	-0.010	(0.017)	-0.008	(0.022)
Constant	7.972***	(0.068)	8.060***	(0.031)	7.897***	(0.011)
Observations	628,331		628,331		592,161	
R-squared	0.454		0.708		0.003	
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: This Table compares the effect of foreign acquisition on task return by sectors. In particular, it shows the parameter estimates of Equation (5), in which the dependent variable is the logarithm of the daily wage of worker i working at firm j in year t. We introduce a dummy variable indicating whether a firm operates in the service industry, and interact it with the *Foreign* dummy and the task measures. Additionally, we include a triple interaction term involving all three variables. We estimated the model on our "Acquired Sample" (more details in Section 3.1). Year fixed effects and their interaction with task use indices are included in every regression. We further control for the gender and age of the worker, and whether the firm is a public firm, and 1-digit industry fixed effects. In the second column, we further control for firm-specific fixed effects. Column (3) uses the two-stage difference-in-differences method suggested by (Gardner et al., 2024). Standard errors are clustered at firm level. *** $p < 0.01, **p < 0.05, *p < 0.1$.

Table C.21: The effect of foreign ownership on firm size and task composition by industry - Re-estimation of Table 4 by comparing the service and manufacturing sectors

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
			Panel A: Firm size			
Foreign	0.155***	(0.055)	-0.014	(0.025)	-0.014	(0.036)
Service * Foreign	0.129**	(0.060)	0.132***	(0.030)	0.170***	(0.044)
Constant	3.062***	(0.063)	2.893***	(0.005)	2.777***	(0.011)
Observations	29,187		29,187		27,778	
R-squared	0.074		0.772		0.009	
			Panel B: Abstract tasks			
Foreign	0.002**	(0.001)	0.001	(0.001)	0.001	(0.001)
Service * Foreign	0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)
Constant	0.332***	(0.002)	0.338***	(0.000)	0.336***	(0.000)
Observations	29,187		29,187		27,778	
R-squared	0.320		0.796		0.001	
			Panel C: Face-to-face			
Foreign	-0.001	(0.001)	0.001	(0.000)	0.001***	(0.001)
Service * Foreign	-0.000	(0.001)	-0.001**	(0.001)	-0.002***	(0.001)
Constant	0.321***	(0.001)	0.324***	(0.000)	0.324***	(0.000)
Observations	29,187		29,187		27,778	
R-squared	0.265		0.742		0.001	
			Panel D: Routine			
Foreign	-0.002	(0.001)	-0.001	(0.001)	-0.002*	(0.001)
Service * Foreign	-0.000	(0.002)	0.002*	(0.001)	0.002*	(0.001)
Constant	0.347***	(0.002)	0.338***	(0.000)	0.339***	(0.000)
Observations	29,187		29,187		27,778	
R-squared	0.234		0.740		0.001	
Year	YES		YES		YES	
Industry	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: This Table shows the effect of foreign ownership on task composition by industry. In particular, it shows the parameter estimates of Equation (7), in which the dependent variables are the firm-level task use indices (see Section 3.2). We incorporate the service dummy and interact it with our main independent variable, the foreign-ownership dummy. The model is estimated on our "Acquired Sample" (for more details, see Section 3.1). We control for a set of year dummies and 1-digit industry dummies in column (1), while in column (2) we further add firm-specific fixed effects to the model. Column (3) uses the two-stage difference-in-differences method following Gardner et al. (2024). Standard errors are clustered at firm level. $***p < 0.01, **p < 0.05, *p < 0.1$

C.8 Alternative task measures

In the main analysis, we follow Firpo et al. (2011) in constructing task measure indices. Here, we re-scale each task measure to reflect its percentile rank in 2003, following the approach of Autor et al. (2003), Deming and Kahn (2018), and Ottaviano et al. (2013). The re-scaled indices range from 0 to 1, representing their relative position in the distribution of each task among all workers in 2003. Here, the abstract task index is 1 for workers with the highest task use, 0.5 for the median workers, etc. To create our summary indices, we take the average of the corresponding re-scaled indices. We use the same survey questions as in the main analysis (see Appendix Table A.2) and re-estimate Equation (5) and (7).

Table C.22 shows that foreign firms pay a higher return to abstract tasks even if we use the rank of workers in the distribution of tasks instead of the composite index. According to Column (1), a 10 percent increase in the rank of abstract tasks corresponds to 0.53 percent larger wages. As in the main results, foreign firms pay a high return to abstract tasks even if we control firm fixed effects in Column (2) or apply the two-stage fixed effect estimation proposed by Garner et al. (2024) in Column (3). Figure C.5 on the event study analysis shows similar patterns to the main analysis.

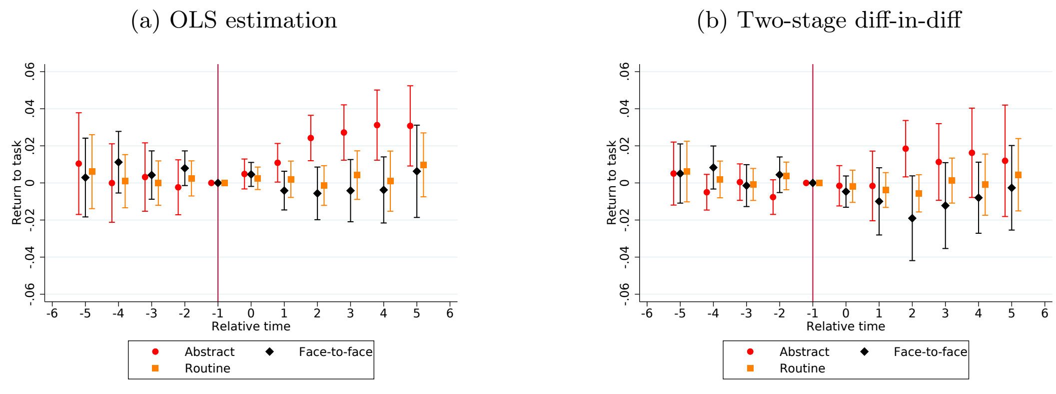
Finally, Table C.23 and Figure B.3 confirm that the task composition estimates are also robust to changing the task definition.

Table C.22: The effect of foreign acquisition on task returns - Re-estimation of Table 2 using alternative task measures

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign	0.161***	(0.034)	0.030***	(0.010)	0.005	(0.017)
Foreign * Abstract	0.053***	(0.013)	0.024***	(0.009)	0.019*	(0.010)
Foreign * Face-to-face	-0.018	(0.012)	-0.007	(0.006)	-0.011	(0.013)
Foreign * Routine	-0.023	(0.015)	-0.005	(0.007)	0.001	(0.008)
Constant	7.912***	(0.064)	8.060***	(0.030)	7.902***	(0.011)
Observations	628,487		628,487		592,292	
R-squared	0.439		0.702			
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE	NO		YES		YES	

Note: This Table shows the effect of foreign acquisition on task returns by using an alternative method to create our summary task indices. In particular, we use the same questions as in the main part of the text (see Table A.2) and re-scale these measures so that they equal the percentile rank in 2003 by following the work of Autor et al. (2003), Deming and Kahn (2018), and Ottaviano et al. (2013). The re-scaled indices are between 0 and 1, and represent the relative importance of that task among all workers in 2003. To construct our summary indices, we take the average of the corresponding re-scaled indices. The Table shows the parameter estimates of Equation (5), in which the dependent variable is the logarithm of the daily wage of worker i working at firm j in year t. We estimated the model on our "Acquired Sample" (more details in Section 3.1). The main independent variables are these summary task indices interacted with a dummy denoting foreign ownership. Year fixed effects and their interaction with task use indices are included in every regression. We further control for the gender and age of the worker, and whether the firm is a public firm, and 1-digit industry fixed effects. In the second column, we further control for firm-specific fixed effects. Column (3) uses the two-stage difference-in-differences method suggested by (Gardner et al., 2024). Standard errors are clustered at firm level. *** $p < 0.01, **p < 0.05, *p < 0.1$.

Figure C.5: The effect of foreign acquisition on task returns using alternative task measures – event study approach



Note: The Figure shows the effect of foreign acquisition on task returns by using an alternative method to construct our summary task indices. In particular, we use the same questions as in the main part of the text (see Table A.2) and re-scale these measures so that they equal the percentile rank in 2003 by following the work of Autor et al. (2003), Deming and Kahn (2018), and Ottaviano et al. (2013). The re-scaled indices are between 0 and 1, and represent the relative importance of that task among all workers in 2003. To construct our summary indices, we take the average of the corresponding re-scaled indices. The Figure shows the parameter estimates of event study Equation (6), in which the dependent variable is the logarithm of the daily wage of worker i working at firm j in year t. The model is estimated on the "Acquired Sample" (more details in Section 3.1). The main independent variables are the task indices (see more in Section 3.2) interacted with event years capture the time relative to the event of the foreign acquisition. Year fixed effects and their interaction with task use indices are included. We further control for the gender and age of the worker, whether the firm is a public firm, and 1-digit industry fixed effects. We further control for firm-specific fixed effects. The bars show 95% confidence intervals and standard errors are clustered at firm level.

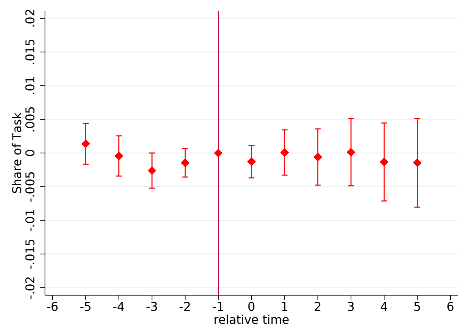
Table C.23: The effect of foreign ownership on task composition using alternative task measures - Re-estimation of Table 4

VARIABLES	(1) coef	se	(2) coef	se	(3) coef	se
Panel A: Abstract						
Foreign	0.007***	(0.002)	0.001	(0.001)	0.001	(0.001)
Constant	0.317***	(0.001)	0.319***	(0.000)	0.314***	(0.001)
Observations	29,189		29,189		27,780	
R-squared	0.318		0.792		0.000	
Panel B: Face-to-face						
Foreign	-0.003**	(0.001)	-0.000	(0.001)	0.000	(0.001)
Constant	0.292***	(0.001)	0.292***	(0.000)	0.293***	(0.000)
Observations	29,189		29,189		27,780	
R-squared	0.280		0.741		0.000	
Panel C: Routine						
Foreign	-0.004***	(0.002)	-0.000	(0.001)	-0.000	(0.001)
Constant	0.391***	(0.001)	0.389***	(0.000)	0.390***	(0.001)
Observations	29,189		29,189		27,780	
R-squared	0.234		0.752		0.000	
Year	YES		YES		YES	
Industry	YES		YES		YES	
Firm FE	NO		YES		YES	

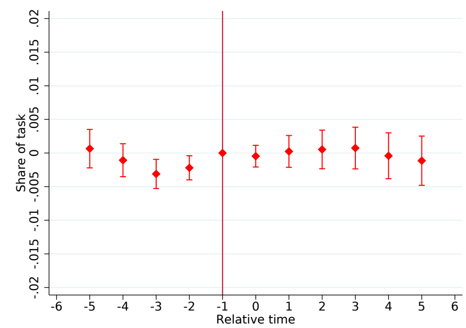
Note: This Table shows the effect of foreign ownership on task composition by using an alternative method to construct our summary task indices. In particular, we use the same questions as in the main part of the text (see Table A.2) and re-scale these measures so that they equal the percentile rank in 2003 by following the work of Autor et al. (2003), Deming and Kahn (2018), and Ottaviano et al. (2013). The re-scaled indices are between 0 and 1, and represent the relative importance of that task among all workers in 2003. To construct our summary indices, we take the average of the corresponding re-scaled indices. The Table shows the parameter estimates of Equation (7), in which the dependent variables are firm-level task use indices calculated by using these alternative summary task measures. The main dependent variable is the foreign-ownership dummy. The model is estimated on our "Acquired Sample" (for more details, see Section 3.1). We control for a set of year dummies and 1-digit industry dummies in column (1), while in column (2) we further add firm-specific fixed effects to the model. Column (3) uses the two-stage difference-in-differences method following Gardner et al. (2024). Standard errors are clustered at firm level.
$***p < 0.01, **p < 0.05, *p < 0.1$

Figure C.6: The effect of foreign ownership on the task composition of the firm by using alternative task measures - Event study approach

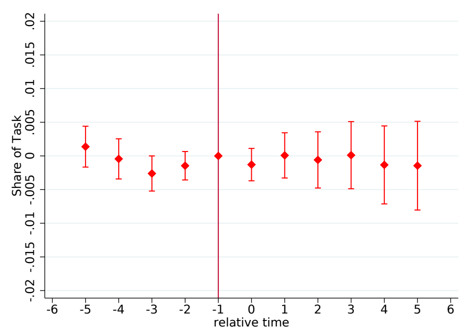
(a) Abstract task



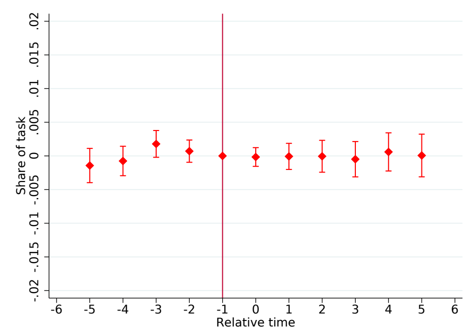
(b) Abstract task, two-stage DID



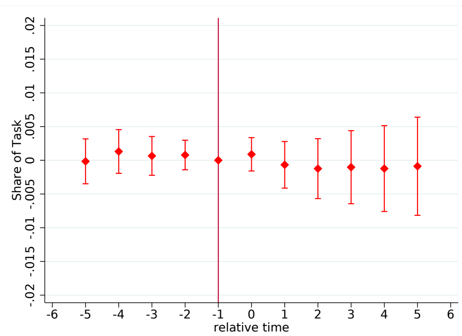
(c) Face-to-face task



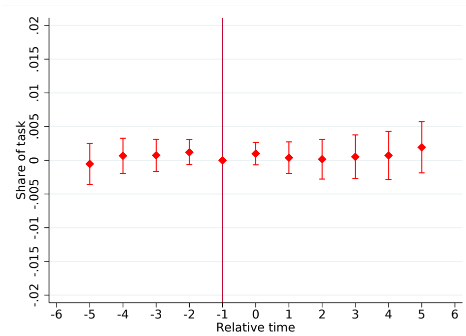
(d) Face-to-face task, two-stage DID



(e) Routine task



(f) Routine task, two-stage DID



Note: The Figure shows the effect of foreign ownership on the task composition in firm's production around the event of the foreign acquisition by using alternative method to construct the task indices. In particular, we use the same questions as in the main part of the text (see Table A.2) and re-scale these measures so that they equal the percentile rank in 2003 by following the work of Autor et al. (2003), Deming and Kahn (2018), and Ottaviano et al. (2013). The re-scaled indices are between 0 and 1, and represent the relative importance of that task among all workers in 2003. To construct our summary indices, we take the average of the corresponding re-scaled indices. The Figure shows the parameter estimates of Equation 8, in which the dependent variables are the firm-level task use indices. Relative times capture the time relative to the onset of CHC. The figure shows the share of each task in the production relative to the share in the last year under domestic ownership. We control for industry fixed effects (s_j), year dummies (τ), and add firm fixed effects (f_j) as a robustness check. All else remains the same as in Equation (7). Figure (b), (d) and (f) show the change of task composition in production using the two-stage difference-in-differences method proposed by Gardner et al. (2024).