FDI, Innovation and within Firm Inequality: Evidence from Hungary

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Abstract

Previous studies showed that foreign investment and export increases inequality in developing countries. This increase is mostly driven by the growth of across-firm wage differentials. We estimate the effect of FDI on within-firm inequality using a high-quality Hungarian linked employer-employee database. We show that FDI increases the returns to abstract tasks and does not affect the returns to routine tasks and face-to-face tasks. This process leads to increasing within-firm inequality. We investigate the potential mechanisms behind the results. We show that firms after FDI do not change the share of different tasks in production and implement more innovation right after FDI. The most likely explanation for the results is that firms change their technology in a skilled-biased way.

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1 Introduction

The traditional Heckscher-Ohlin model (Leamer, 1995; Stolper & Samuelson, 1941) predicts that reallocation of activities across countries decreases inequality in developing countries. According to the model, developed countries where high-skilled workers are abundant reallocate routine tasks with low skill requirements to developing countries. This reallocation increases the demand for routine tasks done by low-skilled workers in developing countries, and therefore, wage inequality should decrease. In contrast to the prediction of the Hecksher-Ohlin model, empirical results show that inequality in developing countries grows if their economy opens up through export or FDI (Basu & Guariglia, 2007; Bhandari, 2007; Figini & Görg, 2011; Goldberg & Pavcnik, 2007; Herzer et al., 2014). Recent papers explain this contradiction by increasing sorting of workers in developing countries. Sorting of workers increases because trade increases employment at high-paying firms (Arnold et al. 2009; Brown et al. 2006, 2010; Helpman et al., 2016) and these firms upgrade their workforce after entering international markets (Bernard & Jensen, 1997). In contrast to the results on across-firm wage differentials, we have only limited knowledge of the effect of international trade on within-firm inequality.

A better understanding of within-firm inequality could give new insights into the effect of international trade on developing economies. On the one hand, international trade can increase the demand for low-skilled workers and thus decrease within-firm inequality as predicted by the Hecksher-Ohlin model. On the other hand, international trade can increase inequality for several reasons. For example, the participation in international trade increases the market size of firms. If the size of the firms grows due to new market access, within-firm inequality can increase even if the technology of the firms does not change (Becker et al., 2019; Card et al., 2018). It is also possible that firms participating in international trade improve their technology and increase their relative demand for high-skilled workers compared to low-skilled workers. In this case, international trade increases wage differentials directly and not only through the sorting of workers.

We use Hungarian linked employer-employee data and a novel empirical strategy to estimate the effect of international trade on within-firm inequality. We contribute to the literature in two ways. First, we use an event study approach and control for worker selectivity to filter out the effect of worker sorting on wage inequality. Second, we investigate the potential mechanisms leading to the increase of within-firm inequality.

In the main specification, we proxy the participation in international trade with foreign direct investment (FDI) for two reasons. First, firms most likely cannot control whether they are acquired one year earlier or later. Therefore, we can use an event study approach to estimate the causal effect of trade on within-firm inequality. Second, if a Hungarian firm is acquired, it can access the technology of the parent firm, so there is a larger chance of technology transfer than in the case of simple product export. Furthermore, 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 which need face-to-face interaction across workers. The importance of this empirical strategy is that it enables us to infer on the effect of FDI on skill demand directly. Finally, we extend our event study approach with firm and worker fixed effects as in (Abowd et al., 1999; Frıas et al., 2022) to control for selectivity in FDI and worker composition.

Our main results suggest that foreign acquisition increases the return to abstract tasks only and the return to face-to-face tasks, while routine tasks do not change. These changes in task returns increase wage inequality as high-paid workers do more than average abstract tasks. We find that one standard deviation increase in abstract tasks increases wages by 1.8 percent while the return to face-to-face skills does not change. The results are qualitatively similar if we restrict attention only to firms which switch ownership, and in the service and manufacturing sectors.

After presenting the main results, we turn to the possible mechanisms. Most importantly, we use an event study approach to show that firms conduct product and process innovation right after FDI, while they do not do more R&D activities than firms which are not acquired. This result provides suggestive evidence that acquired firms implement the technology of the parent firm. We further estimate how FDI affects the task composition within firms. If the labor market competition is imperfect and the firm-level labor supply of workers doing abstract tasks is steeper than the labor supply of other workers, then firms increasing the returns to abstract tasks should decrease the amount of abstract tasks in production (Card et al., 2018; Lindner et al., 2022). As opposed to this, we find that the share of abstract tasks does not change in the production function after FDI.

Besides the literature cited above, we contribute to the 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 export (Frıas et al., 2022) and FDI (Breau & Brown, 2011). We add to the literature by investigating the potential mechanisms which connect international trade to firm premiums.

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

We also contribute to the literature on the effect of FDI on within-firm differences. Firms from developed countries pay a higher wage premium for abstract tasks (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 the developed countries and skilled-biased in the developing countries (Lai & Zhu, 2007; Trefler & Zhu, 2010). We add to this literature by showing that firms in developing countries are more likely to innovate after FDI and thus they may change their technology in a skilled-biased way.

2 Institutional Background and Data

2.1 Institutional Background

On the top of the richness of the available data, Hungary is an excellent laboratory to estimate the wage impact of FDI. First, Hungary entered the European Union in 2004. The relatively low wage level of Hungary compared to old member states and the legal certainty of the EU common market induced large scale FDI in the last two decades. Second, the Hungarian employment protection institutions are similar to Anglo-Sacon countries and are relatively weak compared to most Western European countries. It is relatively easy to dismiss workers and wage bargaining is made mostly on the 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 (OECD, 2004) while industry-level agreements are rare (Neumann, 2006) This institutional circumstances enable foreign firms to adjust both employment and wages after investing in Hungary.

2.2 Data

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

The Admin 3 database contains administrative wage data for 50 percent random sample of the population in 2003 and follows the worker up until 2017. The data set 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. Besides the database contains information on the age, gender, 4-digit occupation codes of the worker and whether she works full or part time. The firm level data contains the corporate income tax returns for the universe of the incorporated firms collected by the National Tax and Customs Administration. We observe the balance sheet and income statements of firms on the 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 the Central European University.[1] The two dataset was merged by using probabilistic matching method based on the work of Card et al. (2016). More details about the dataset and the matching process can be found in the Appendix A.

We split the foreign firms into two groups. The first group includes firms that entered our dataset as domestic firm and were acquired during the observed period, for this group we further define pre-acquisition and post-acquisition years. The second group includes all other foreign firms, thus those that entered our dataset as foreign firm because they were acquired before 2003 or were established by greenfield investment

We use the Community Innovation Survey (CIS) to investigates the possible mechanisms behind our main findings. This data base is a biannual survey available in every EU countries and recent literature use 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 types) and on R&D activities of firms conducted in the year of the survey and in the previous two years. Every firm with more than 50 employees and a random sample of firms with less than 50 employees have participate in the survey. We can merge the CIS data base to the balance sheet data but we are not able to merge them to the administrative employment and wage data due to administrative restrictions.

2.3 Sample selection

Although the worker-level information is available on a monthly basis, the firm-level data is available only on a yearly level, thus we restrict our sample to one month (October) in every year. We further restrict our sample to workers that were employed by labor contract at a firm that has at least 5 employees at least once during the observed period and their occupation is known thus we can merge our tasks measure indexes. We only keep workers in our sample that work full-time (i.e. work at least

[1] The data set was created by researchers at Central European University from original data made available by OPTEN Kft.from funds the European Union provided in the framework of the research project POLBUSNETWORKS. The data set is work in progress. Although both OPTEN Kft. and researchers at Central European University made efforts to clean the data, neither can be held liable for any remaining errors.

36 hours per week) and has non-missing wage. We drop workers from our sample that has less than 2 observations. Furthermore, if a worker has more jobs at the same time, than we only use the job with the highest salary. We use the daily wage (monthly wage divided by the number of days worked) as our main right-hand side variable. The restricted sample contains 11,743,369 worker-year observations corresponding to 1,565,888 workers working at 102,183 firms.

37.6 percent of our worker-year observations works at foreign owned firm. 5.8 percent of our worker-year observations correspond to firms which was acquired between 2004 and 2017 and 36.2 percent to other foreign firms. The number of acquisitions per year varies between 100 and 400, see appendix Table 4.

2.4 Measurement of tasks

Like many studies on the the task content or skill requirement of jobs, we use the O*NET data to compute our task measures.[2]. 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 indexes, we rely on the work of Firpo et al. (2011). See Appnedix A for more details on the construction of our task measures. In the robustness section we show that our results are robust to use other methods to create the summary indexes.

Our first measure, "abstract", identifies tasks that require abstract cognitive skills, are likely to complements to computers while they do not need face-to-face interaction. Thus this tasks can be offshored while they cannot be automatized. Our second measure, "automatization", identifies routine and repetitive tasks which have the potential to be offshored or be substituted by automatization. Our last measure, "face-to-face interaction", identifies tasks that require cognitive skills but need personal interaction either between workers or between workers and customers. Thus this task are difficult to offshore or to be replaced by computers. See appendix A for more details about the construction of our task measurements.

The task measures indexes 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 a high level of information processing tasks from the worker and at the same time they are considered to be less routine tasks. All of them are statistically significant, suggesting that there is a link between the set of tasks that are required to fulfill a given occupation (see appendix table 3.

We follow the strategy of (Ebenstein et al., 2014; Hakkala et al., 2014) to calculate the firm level task use. We re-scale task measures to the 0-1 interval by dividing them with their maximum, instead of standardization[3]. Then we aggregate up the individual level task use on the firm level to compute the firm level task use:

$$Skilluse_{ojt} = \frac{\sum_i TaskMeasure_{oit}}{\sum_{o=1}^{3} \sum_i TaskMeasure_{oit}}, \tag{1}$$

where $TaskMeasure_{oit}$ means the amount of task o done by worker i at year t. Thus, the numerator means the total amount of task o used by firm j at year t. We normalize this value by the total amount of task used by the firms. So the $Skilluse_{ojt}$ measures the share of task o in firm production on the [0,1] scale.

2.5 Descriptive statistics

Table 1 Panel A shows the characteristics of the workforce by ownership type of the firm. Domestic firms employ more male and older workers than foreign firms. The average level of information task is lower at domestic firm than at foreign firms. While the average level of information task is also lower at acquired firms before the acquisition, it increases after the acquisition. The average level of face-to-face task is higher at domestic firms than at foreign firms. It does not change much after a foreign acquisition. The difference by ownership type between the average level of the easily automatized

[2] We use O*NET 20.1 released in October 2015, https://www.onetcenter.org/db$_{r}eleases.html$

[3] Note: the main results are qualitatively the same if we use this re-scaled measure of tasks to compute the return to tasks

tasks is small. Panel B of the same table shows 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 characteristics by firm type.

	Domestic	Pre-Acquisition	Post-Acquisition	Always Foreign
Panel A: Worker characteristics				
Male (%)	63.7	64.0	62.8	56.7
Age	40.9	39.1	40.5	38.3
	(10.9)	(10.8)	(10.9)	(10.4)
Abstract	-0.12	-0.05	0.05	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	0.01	0.01
	(0.94)	(0.98)	(1.02)	(1.09)
Observation	6,806,681	233,494	451,747	4,251,447
Panel B: Firm characteristics				
Employment	24.2	39.2	54.2	108.9
	(200.2)	(114.8)	(224.0)	(468.3)
Sales	566.5	1865.2	3136.9	7521.0
(million 2019Huf)	(5114.1)	(18549.0)	(29818.7)	(57831.9)
Manufacturing (%)	38.9	30.5	28.3	38.0
Service (%)	61.1	69.5	71.7	62.0
Observation	673,548	13,685	19,142	88,349

Task measures are standardized to have zero mean and standard deviation of one. Column (2) shows pre-acquisition years and Column (3) the post-acquisition years of acquired firms.The last column shows firms which are foreing in every observed years. Sales is in million 2019Huf. Standard deviations are in the parenthesis.

3 Return to Tasks

3.1 Methodology

We estimate the effect of FDI on skill returns by using OLS and fixed affect approach in a difference-in-difference setting:

$$\begin{aligned} lnw_{ijot} = \delta_1 * Foreign_{jt} + \delta_2 * Foreign_{jt} * TaskMeasure_o + \\ + \gamma_1 * X_{ijt} + s_{jt} + [\nu_i + f_j + f_j * t] + \epsilon_{ijt}, , \end{aligned} \tag{2}$$

where lnw_{ijot} denotes the logarithm of the daily wage of worker i working at firm j at occupation o in year t. $TaskMeasure$ is the task indexes defined above (standardized to have a mean of zero and a standard deviation of one).

$Foreign_{jt}$ is dummy denoting that the given firm is under foreign ownership at year t. The main coefficient of interest is δ_2 showing the effect of foreign acquisition on the return to tasks.

To control for selectivity in foreign ownership, we control for a the firm sales, employment of firms and whether the firm is exporting, and firm specific fixed effects (f_j) and firm specific time trend in wages ($f_j * t$). Furthermore we add industry-year fixed effects and (s_{jt}) and task-year interactions ($\alpha_t * TaskMeasure_o + s_{jt}$) for economic level trends in skill returns. Finally, we allow that tasks have different returns at firms firms before acquisition or firms which were foreign owned in every observed years compared to the task return of domestic firms. This way, we can identify the effect of FDI on skill returns using only within firm change of ownership.

As we control for individual fixed effect in our most preferred specification that is why δ_2 is identified from the wage change of three different worker group: (i) incumbent workers after acquisition and did not change occupation; (ii) incumbent workers workers who stayed at the firm after the acquisition and changed occupation; (iii) workers who arrived to the firm after the acquisition. See Appendix A3 and Table 5 for more detailed discussion and for the number of relevant cases.

First, we estimate the model simply without firm and worker fixed effects then we include firm-fixed effect (f_j) only (we exclude ν_i) and at last by including firm and worker fixed effects at the same time. By this strategy we can magnify how much the selectivity across firms affect the returns to skill after acquisition. As previous literature on FDI showed (Earle et al., 2018), foreign firms tend to cherry-pick the best firms. Furthermore, if firms screen workers ability better than domestic firms than the worker composition would improve after acquisition. Thus we would overestimate the causal effect of FDI on skill return without firm and worker fixed effect .

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:.

$$
\begin{aligned}
lnw_{ijot} = {} & \delta_1 * PostAcq_{jt} + \delta_s * PostAcq_{jt} * TaskMeasure_o + \\
& + \alpha * TaskMeasure_o * AllwaysForeign_j + \alpha_t * TaskMeasure_o + \\
& + \gamma_1 * X_{ijt} + s_{jt} + [\nu_i + f_j + f_j * t] + \epsilon_{ijt},
\end{aligned} \tag{3}
$$

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 2. There are one important changes compared 2. Now, the coefficient of $Foreign_j * TaskMeasure_o$ has time dimension. s is zero in the last year under domestic ownership thus δ_s shows the return of $TaskMeasure_o$ s year before or after this year. We normalize the δ_0 to zero, and negative (positive) s denotes the years before (before) our reference period. All else remain the same as in the previous equation.

3.2 Results

3.2.1 Foreign-ownership

Table 2 shows the estimated results of Equation 2 by including all three task measures in a single regression. The first column shows that firms pay a 9,9 percent higher wage to their workers after a foreign take-over but this difference drops and became insignificant once we control for selectivity in acquisitions with firm specific time trends.

Turning to the main variable of interest we find that, workers at foreign firms receive a higher return to abstract tasks. The first column shows that firms after a foreign take-over pay a 4 percentage point higher premium to abstract tasks after acqusistion. The premium drops by one-third as we take into account that foreign investors cherry-pick the best domestic firms, and the difference is 1.2 percent if we control for selectivity in work force. We do not find any evidence for foreign premium in the return to face-to-face and routine tasks. The parameter estimates are close to zero and they are insignificant.

Table 2: The effect of foreign acquisition on task returns

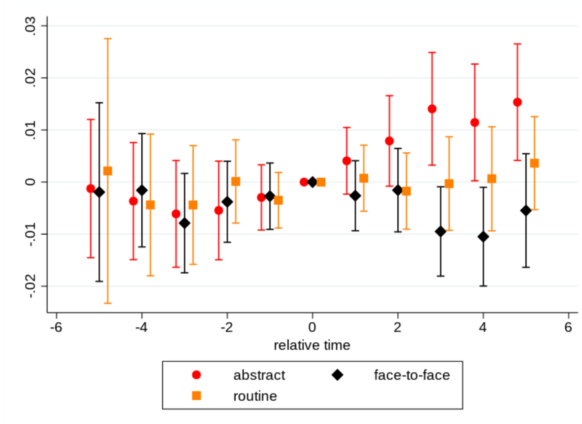
VARIABLES	(1) coef	se	(2) coef	se	(3) coef	se
Foreign	0.099***	(0.023)	0.009	(0.007)	0.015**	(0.007)
Foreign * Abstract	0.043***	(0.010)	0.029***	(0.007)	0.012***	(0.003)
Foreign * Face-to-face	-0.028***	(0.010)	-0.009	(0.007)	-0.001	(0.003)
Foreign * Routine	-0.027**	(0.013)	0.003	(0.009)	-0.001	(0.004)
Log Sales	0.031***	(0.003)	0.004***	(0.001)	0.004***	(0.001)
Log Employment	0.003	(0.006)	-0.004**	(0.002)	0.006***	(0.001)
Exporter	0.074***	(0.010)	-0.003	(0.002)	-0.002	(0.002)
Constant	7.358***	(0.035)	8.012***	(0.016)	9.152***	(0.015)
Sector * Year	Yes		Yes		Yes	
Firm FE			Yes		Yes	
Firm-level trend			Yes		Yes	
Worker FE					Yes	
Observations	11,743,369		11,743,369		11,743,369	
R-squared	0.577		0.763		0.922	

*** $p < 0.01, ** p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year fixed effects and their interaction with skill use indexes are included. We include a dummy indicating that the firm is acquired during our sampling period and a dummy showing that the firm was foreign owned at the beginning of the sample. We interact these dummies with the task measures. We further control for the gender and age of the worker, the size of the firm (measured by sales revenue, and employment), whether the firm is a public firm, exporting and 1 digit industry- year fixed effects. We further control for firm-level trends in the second column, and worker fixed-effects in the third column.

3.2.2 Event study approach

Figure 1 shows the results of estimating Equation 3 by including all the three task measures in a single regression. We estimate the model by including both firms and worker fixed effects and we further control for firm-specific trends. The red circles show the results for abstract processing tasks, the black diamonds for face-to-face contacts, and the orange squares for routine tasks. The parameters along with the results of the OLS and firm fixed-effects models can be found in Appendix Table 6. We do not find any evidence for pre-trend. The results confirm our earlier findings. A foreign takeover increases the return to abstract tasks that are do not need face-to-face interaction thus can be offshored (i.e. information processing). On the contrary, the return to cognitive tasks that are difficult to offshore (i.e. face-to-face interactions) does not change around the foreign acquisition. Finally the return to tasks that can be potentially substituted by new technologies (i.e. routine) are also unchanged.

Figure 1: The effect of foreign acquisition on task returns - event study approach.



$* * *p < 0.01, * * p < 0.05, *p < 0.1$
Standard errors are clustered at the firm level. Year fixed effects and their interaction with skill use indexes are included. We include a dummy indicating that the firm is acquired during our sampling period and a dummy showing that the firm was foreign owned at the beginning of the sample. We interact these dummies with the task measures. We further control for the gender and age of the worker, the size of the firm (measured by sales revenue, and employment), whether the firm is a public firm, exporting and 1 digit industry- year fixed effects. We further control for firm-level trends in the second column, and worker fixed-effects in the third column.

To sum up, the results show that after a foreign takeover the return to abstract tasks that are potentially complemented by computers and are relatively easy to offshore (i.e. abstract tasks) increases. On the contrary, the return to cognitive tasks that are difficult to offshore (i.e. face-to-face interactions) does not change around the foreign acquisition. While the return to tasks that are potentially substituted by new technologies and are relatively easy to offshore are also unchanged. These results are in line with the hypothesis that the skill premium increases after FDI

3.2.3 Heterogeneity and robustness checks

Only acquired firms Acquired and not acquired firms may be different in some unobserved factors even conditional on worker fixed effects and firm specific time trends in revenue. For example, it is possible that the return of tasks have different trends at acquired firms compared to not acquired firms for some unobserved reason. That is why we re-estimate slightly modified Equation 2 and Equation 3:

$$\begin{aligned} lnw_{ijot} = {} & \delta_1 * Foreign_{jt} + \delta_2 * TaskMeasure_o + \delta_3 * Foreign_{jt} * TaskMeasure_o \\ & \gamma_1 * X_{ijt} + s_{jt} + [f_j + f_j * t] + \epsilon_{ijt}, \end{aligned} \tag{4}$$

where lnw_{ijot} denotes the logarithm of the daily wage of worker i working at firm j at occupation o in year t. $TaskMeasure$ is the task indexed defined above (standardized to have a mean of zero and a standard deviation of one). We control for the firm sales, employment of firms and whether the firm is exporting, and firm specific fixed effects (f_j) and firm specific time trend in wages ($f_j * t$). Furthermore we add industry-year fixed effects and (s_{jt}). We cannot control for worker fixed effects in this regression because we restrict attention to the 3121 firms which change ownership in our sample thus we cannot observe enough worker transition between firms.

The main coefficient of interest is δ_3 showing the difference between the return to tasks at acquired firm when they are under domestic and foreign ownership. As $Foreign$ changes from 0 to 1 within a firm, this interaction term varies within the firm and the worker spell: it turns from zero to the value of the task requirement index of the occupation the worker is employed. In case when firm fixed effects are included, this parameter is identified from (i) workers who stayed with the firm after the acquisition and did not change occupation; (ii) workers who stayed at the firm after the acquisition and changed occupation; (iii) workers who arrived to the firm after the acquisition. See See Table 5 for the number of cases.

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.

$$\begin{aligned} lnw_{ijot} = \delta_1 * Foreign_{jt} + \delta_s * Foreign_j * TaskMeasure_o + \\ \gamma * X_{ijt} + \alpha_t * TaskMeasure_o + s_{jt} + \\ [f_j + f_j * t] + \epsilon_{ijt}, \end{aligned} \tag{5}$$

where lnw_{ijot} denotes the logarithm of the daily wage of worker i working at firm j at occupation o in year t. $TaskMeasure$ is the task indexed defined above (standardized to have a mean of zero and a standard deviation of one). We control for time varying firm characteristics measuring the size of the firm, namely sales revenue and employment, add a dummy for male workers, and age dummies (X_{ijt}). s_{jt} are sector-year interactions, f_j are firm fixed effects and $f_j * t$ are firm-specific trends.

As the aim of the analysis is to measure the change in the return to different tasks, we include leads and lags of the acquisition interacted with the task measures. We leave out the interaction term with the year of the acquisition δ_0. Now we have more than one δ_s parameters. Like before, s have a negative values before acquisition and positive values afterwards. If there is no pretend before acquisition than we expect that δ_s are zero for negative s. While δ_s parameters are different from zero for positive s, if foreign acquisition has an impact on the returns to task.

The results, show in in Table 3, are similar to the main specification. Foreign firms pay higher return on abstract tasks with 2.8 percent, even after controlling for firm specific time trends. We do not see a wage premium for the other to tasks, face-to-face interaction and routine tasks.

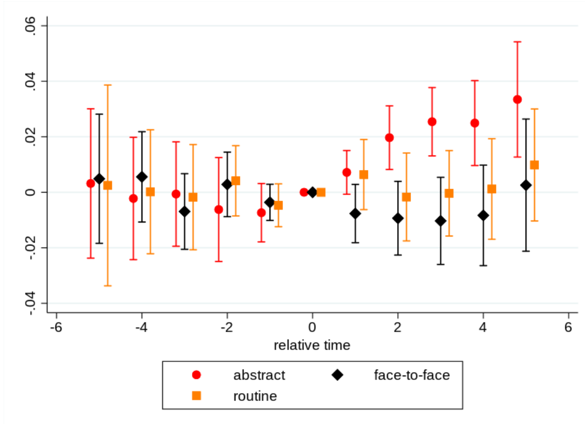
Finally, the event study results in Figure 2 show that there is no pre-trend in task returns before acquisition (the point estimates can be found in Appendix Table 7. We see that the return to abstract tasks increases in the first three years after acquisition and remains roughly constant afterwards. In contrast to this, we do not see significant change in the return of face-to-face or routine tasks after acquisition.

Table 3: The effect of foreign acquisition on task returns- only acquired firms

	(1)		(2)	
VARIABLES	coef	se	coef	se
Foreign	0.082***	(0.016)	0.006	(0.006)
Foreign * Abstract	0.035***	(0.010)	0.028***	(0.007)
Foreign * Face-to-face	-0.021**	(0.010)	-0.007	(0.007)
Foreign * Routine	-0.018	(0.013)	0.001	(0.009)
Log Sales	0.059***	(0.007)	0.004**	(0.002)
Log Employment	0.012	(0.009)	-0.011**	(0.005)
Exporter	0.083***	(0.017)	-0.010	(0.006)
Sector*Year	Yes		Yes	
Firm FE			Yes	
Firm-level trend			Yes	
Observations	685,241		685,241	
R-squared	0.505		0.719	

$***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year fixed effects and their interaction with skill use indexes are included. We further control for the size of the firm (measured by sales revenue, and employment), whether the firm is a public firm, and whether participate in exporting and 1 digit industry dummies and their interaction with the year dummies are also included. We further control for the gender and age of the worker. We further control for firm-level trends in the second column.

Figure 2: Only acquired firm, event study approach



$***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year fixed effects and their interaction with skill use indexes are included. We further control for the size of the firm (measured by sales revenue, and employment), whether the firm is a public firm, and whether participate in exporting and 1 digit industry dummies and their interaction with the year dummies are also included. We further control for the gender and age of the worker. We further control for firm-level trends.

Sectoral Comparison In this section, we compare the change in the return to tasks in the manufacturing sector and those that take place in the service sector around an acquisition. The reason for this is that many firms in service sector provide related business services to their parent company, thus the effect of FDI on the return to task might differ compared to the manufacturing sector. First, we re-estimate the Equation 2 with a slightly modification. We estimate the return to the different tasks separately for the service and manufacturing sector. Then, we use the event study approach to investigate the dynamics in the return of tasks (e.g. we re-estimate Equation 3).

Table 4 presents the effect of foreign ownership separately by sectors. The first column shows that the acquired firms in manufacturing sector pay 11.7 percent, while those in the service sector pay 7.9 percent more than Hungarian firms and the difference between the two sectors is statistically not significant. However, if we control for selectivity in FDI and worker composition, than the difference drops by about 80 percent and became insignificant in both of the sectors. We also see that the return to abstract tasks is higher at foreign firms in both of the sectors. The return to face-to-face tasks is slightly larger at in the manufacturing sector than in service sector, while the return of face-to-face tasks and routine tasks are close to zero and insignificant in both of the sectors. Finally, Figure 1 uses event study approach to show that the dynamics of task returns are similar in both sector.

Table 4: Sectoral comparison of the return to tasks.

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign * Manufacturing	0.117***	(0.035)	0.016	(0.010)	0.021	(0.013)
Foreign * Service	0.079***	(0.021)	0.000	(0.010)	0.009	(0.007)
Foreign * Manuf. * Abstract	0.043***	(0.013)	0.039***	(0.008)	0.012***	(0.004)
Foreign * Service * Abstract	0.043***	(0.014)	0.023**	(0.009)	0.012***	(0.005)
Foreign * Manuf * F2F	-0.011	(0.012)	-0.014	(0.009)	0.003	(0.005)
Foreign * Service * F2F	-0.026**	(0.012)	-0.004	(0.011)	-0.001	(0.004)
Foreign * Manuf. * Routine	0.003	(0.016)	0.011	(0.014)	0.000	(0.004)
Foreign * Service * Routine	-0.056***	(0.013)	-0.005	(0.012)	-0.002	(0.006)
Log Sales	0.031***	(0.003)	0.004***	(0.001)	0.004***	(0.001)
Log Emplosment	0.004	(0.006)	-0.004**	(0.002)	0.006***	(0.001)
Exporter	0.070***	(0.009)	-0.003	(0.002)	-0.002	(0.002)
Constant	7.363***	(0.035)	8.015***	(0.016)	9.151***	(0.015)
Sector*Year	Yes		Yes		Yes	
Firm FE			Yes		Yes	
Firm-level trend			Yes		Yes	
Worker FE					Yes	
R-squared	0.579		0.763		0.922	
Observations	11,743,369		11,743,369		11,743,369	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year fixed effects and their interaction with skill use indexes are included. We further control for the size of the firm (measured by sales revenue, and employment), whether the firm is a public firm, and whether participate in exporting and 1 digit industry dummies and their interaction with the year dummies are also included. We further control for the gender and age of the worker. We further control for firm-level trends.

4 Underlying Mechanisms

There are several mechanisms which can change the return of tasks after acquisition. We investigate three specific channels in this section: (i) technological change through innovation, (ii) Change of task composition in production (iii) change in firm size and task specialization

Technological change through innovation. Hungarian firms may get access to the more developed and skill biased technology of the parent firms after acquisition. Thus, Hungarian firms may improve their technology in a skill biased way after FDI. The relevance of this channel is supported by (Lindner et al., 2022) who showed that firm level innovation results in the increase of within firm inequality.

To test this hypothesis, we investigate the effect of FDI on innovation in event study approach. For this purpose, we restrict attention to firms which we observe in CIS and we run the following regression:

$$innov_{jt} = delta_s * Acquired_j + \gamma_1 * X_{jt} + f_j + \nu_t + \epsilon_{jt}, \tag{6}$$

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 in every second years only, we restrict s to even numbers. s takes the value 0 in the years of acquisition and one year before. We control for size, productivity, share of workers with college and high school diploma, for firm fixed effects f_j and year fixed effects ν_t.

The results are shown in Figure 3b. Panel A shows that the probability of process innovation increases with 7 percentage points in the year of FDI why it does not differ significantly from not-acquired firms before or after innovation. Similarly, panel B shows that the probability of introducing a new product is higher in the year of FDI than in other years. In contrast to this, we do not find evidence

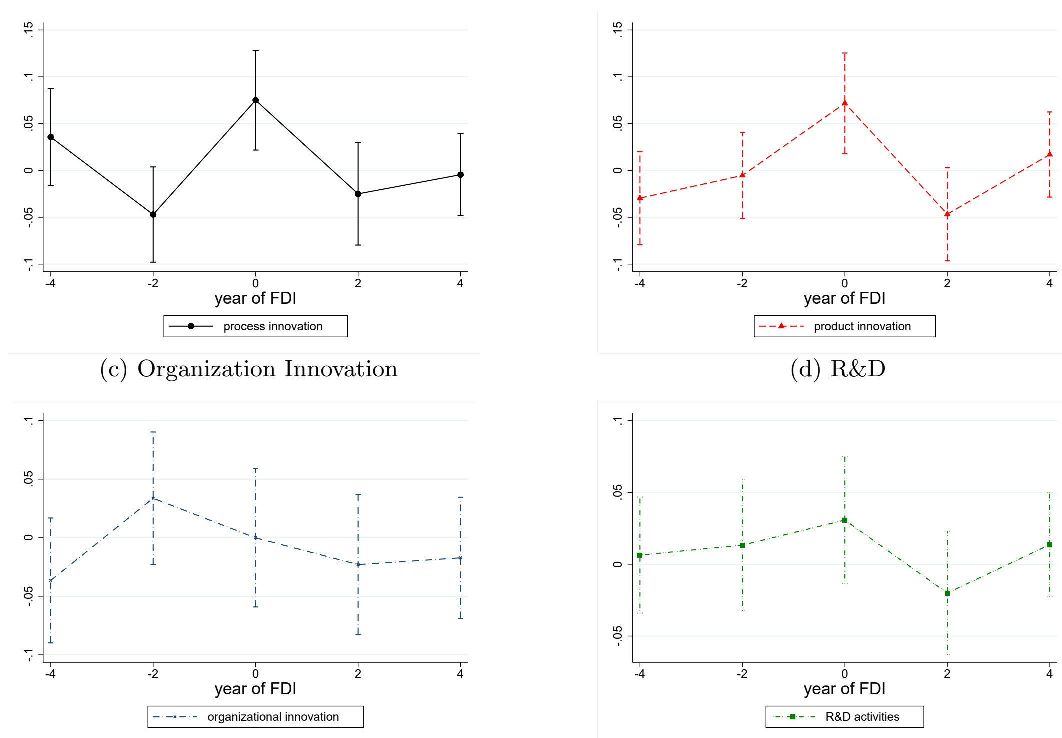
Figure 3: Innovation

(a) Process Innovation

(b) Product Innovation

(c) Organization Innovation

(d) R&D



that firms introduce organizational innovation (Panel C) or conduct more R&D activities after FDI than not acquired firms. The additional product and process innovation with lack of additional R&D effort provides suggestive evidence, that firms after FDI innovate through technology implementation instead of developing new technology.

Change of task composition in production. The within firm returns of tasks can change after FDI even if the technology of firms do not changes after acquisition. For sake of argument, assume that the labor market is oligopsonistic 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 the a Hicks-neutral technology change decreases the share of abstract tasks has an opposite effect of the task return and the amount of task use. Thus the share of cognitive task should decrease in production if the return to cognitive tasks increases (Lindner et al., 2022).

To test this hypothesis, we use the firm level task measure introduced in Section 2.4 and estimate the following model:

$$Skilluse_{jt} = \alpha * Foreign_{jt} + \beta * X_{jt} + [f_j + f_j * t] + s_{jt} + \epsilon_{ijt}, \tag{7}$$

where $skilluse_{jt}$ denotes the firm-level skill use indexes at firm j in year t. Our main independent variable is $Foreign_{jt}$ dummy that is equal one if the firm is majority foreign owned. We control for time-varying firm-level characteristics (such as size, number of employment and a dummy indicating that the firm is owned by the state or local government). s_{jt} are sector-year interactions, f_j are firm fixed effects, and we further include firm level trends ($f_j * t$). In our preferred specification case when firm fixed effects are included, the parameter of $Foreign_{jt}$ is identified from ownership change. We use the size of the firm (measured by the number of employees) as weights in the regression.

Table 5 presents how the firm-level task usage differs after acquisition. Panel A presents the results for abstract tasks, B for face-to-face contacts, while C for routine tasks. In the case of the abstract tasks, we see that firms use 0.2 percentage point more of this type of tasks after the acquisition than before. This small positive effect even halves as we take into account the selectivity in FDI (includes firm fixed effects). In the case of the face-to-face contacts, the estimate of parameters are zero and insignificant. Foreign firms tend to use less routine tasks according to the Panel C in the Table 5, and the effect is robust to the inclusion of firm fixed effects. However, the estimate parameter (0.1 percentage point) is very close to zero.

To sum up, we do not find evidence that firms after acquisition change the composition of tasks used at production in an economically significant magnitude. We use event study style analysis in Appendix Figure 2Figure 4 and show that there is no pre-trend in task composition and acquired firms do not change their task composition significantly on the longer term either.

Table 5: The effect of foreign ownership on task composition

	(1)		(2)	
	OLS		FirmFE	
VARIABLES	coef	se	coef	se
Panel A: Abstract tasks				
Foreign	0.002***	(0.001)	0.001*	(0.000)
R-squared	0.293		0.893	
Panel B: Face-to-face tasks				
Foreign	-0.000	(0.000)	0.000	(0.000)
R-squared	0.271		0.874	
Panel C: Routine tasks				
Foreign	-0.001**	(0.001)	-0.001**	(0.000)
R-squared	0.227		0.872	
Observations	794,724		794,724	
Sector*Year	Yes		Yes	
Firm FE			Yes	
Firm-level trend			Yes	

$***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level.

Change in firm size and task specialization (Becker et al., 2019) showed that larger firms have 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 to smaller firms. This mechanism implies in our case, that the number of occupations increases after FDI and the higher return of abstract task reflects only the task specialization at high paid occupations.

We formally test this hypothesis by estimating the following regression:

$$OCC_{jt} = \alpha * Foreign_{jt} + \beta * X_{jt} + [f_j + f_j * t] + s_{jt} + \epsilon_{ijt}, \tag{8}$$

where 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 8.

The results are shown in Table 6. In line with (Becker et al., 2019), the table shows that that larger firms use more occupations. According to Column (2), the number of occupations grow with 0.37 if the size of the firm growths by 10 percent. Similarly, the number of occupations increases with 0.07 if the firm starts to export. In contrast to this, we do not find evidence that the number of occupations changes after FDI to a large extent. Panel B highlights that the Herfindahl index of occupations remains unchanged after acquisition. The estimated parameter of the foreign dummy is close to zero (-0.006) and statistically not significant. We use event study style analysis show that there is no pre-trend in the number of occupation and the Herfindahl index at acquired firms and that the acquisition has no effect on these measures, see Appendix Figure 8-Figure 9.

Table 6: The effect of foreign ownership on task specialization.

	(1)		(2)	
	OLS		FirmFE	
VARIABLES	coef	se	coef	se
Panel A: Number of occupations				
Foreign	0.186	(0.137)	0.108**	(0.050)
Log Sales	-0.107***	(0.010)	-0.010**	(0.005)
Log Employment	3.758***	(0.048)	1.326***	(0.023)
Exporter	0.923***	(0.032)	0.072***	(0.010)
R-squared	0.520		0.963	
Panel B: Herfindhal index				
Foreign	-0.001	(0.005)	-0.006	(0.004)
Log Sales	-0.009***	(0.001)	-0.002***	(0.000)
Log Employment	-0.116***	(0.001)	-0.108***	(0.001)
Exporter	-0.066***	(0.002)	-0.005***	(0.001)
R-squared	0.269		0.806	
Observations	794,724		794,724	
Sector*Year	Yes		Yes	
Firm FE			Yes	
Firm-level trend			Yes	

$***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level.

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

5 Conclusion

In this paper we investigated the effect of foreign acquisitions on within firm inequality in Hungary. We found that foreign acquisition increases the task returns of abstract tasks while it does not change the return of face-to-face and routine tasks. This change in task returns leads to the increase of within firm inequality within firms as relatively highly paid workers do more abstract tasks.

We investigated the possible mechanisms behind this empirical facts. We found that firm after foreign acquisition conduct more process and product innovation but do not increase their R&D activities. We did not find evidence that firms changes the task composition of the production function or task specializations.

The most likely interpretation of these results is that firms changes their production firms in a skilled biased way by implementing new technology. This interpretation implies that foreign direct investment is an important driver of skilled biased technological change in developing countries such as Hungary.

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A Appendix

A.1 Data

A.1.1 Matching of ownership information

The information on the nationality of the owner comes from the administrative firm register. The data was provided by the Central European University. The firm register contains information on the nationality of the firm owner, and the balance sheet of the firm 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 data sets. We use the following variables for matching which we observe in both data sets: (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 employment. We use a multi-step matching procedure following the strategy of (Card et al., 2016). We apply exact matching at each step, and sequentially relaxes the number of variables that have to match exactly. Firms that are matched at one step and validated are removed from both data sets before moving to the next step.

STEP 1: We do exact matching based on the seven common variable described above on yearly level. If we found a perfect match at 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 consider the matches as invalid match and treat the firms as unmatched firms. Once a potential match was found 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 of the data sets. We consider a match to be valid, only if the deviation in annual sales between the two data sets is less than 10%, or in cases with a larger deviation in any one year, if the values in all other years were exactly the same in both data sets. STEP 2: We exclude firms from the sample that were matched and validated in STEP 1, and we relax the number of variables used in the matching process. At this stage we use different set of variables to find the exact match. We use year, 2 digit industry code and annual sales revenue to find perfect matches and any variables of the following: 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 the pairs in which a firm was matched to different firms in different years, and only consider firms as a matched pairs if we could validate the matching by using the annual sales revenue. After finding and validating the matched pairs, we exclude them from both data sets before STEP 3

STEP 3: We exclude firms from the sample that were matched and validated in STEP 1 or STEP 2, and we relax the number of variables used in the matching process. At this stage we use different set of variables to find the exact match. We use year and 2 digit industry code to find perfect matches and any two variables of the following: 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 the pairs in which a firm was matched to different firms in different years, and only consider firms as a matched pairs if we could validate the matching by using the annual sales revenue.

A.1.2 Construction of Task measurements

The information on the task contents of occupation comes from the O*NET which uses the SOC code. We follow the work of (Hardy et al., 2018) to translate the SOC nomenclature to ISCO nomenclature. Than we use the crosswalk[4] provided by the Hungarian Central Statistical Office to translate the ISCO codes to Hungarian nomenclature (called FEOR). The FEOR coding is based on the ISCO nomenclature and enables one-to-one matches for 80 percent of four digit occupation codes.

We rely on the work of (Firpo et al., 2011) to construct task measures from O*NET data. The O*Net provides information on the "importance" and "level" for each required work activities and "frequency" of five categorical levels of each work context. We assign a Cobb-Douglas weight of two thirds to "importance" and one third to "level" in using a weighted sum for work activities. For work contexts, we multiply the frequency by the value of the level. Equation 9 summaries our method. Each task measure for occupation "o" is computed as:

$$TaskMeasure_o = \sum_{n=1}^{N} IMP_n^{2/3} * LEV_n^{1/3} + \sum_{m=1}^{M} F_k * V_k, \tag{9}$$

[4] https://www.ksh.hu/docs/osztalyozasok/feor/fordkulcs$_{i}sco_{f}eor.pdf, date of download: 06.02.2023$

where N denotes the number of work activity elements and M denotes the number of work context element used to define the given task measure index. IMP corresponds to the "importance" and LEV to the "level" of the given work activity. We re-scale the summary indexes to 0-1 interval by dividing them by their maximum. In the robustness check section we show that our results are robust to constructing the task indexes in a different way. Table 1 details the task that are used to create the summary indexes.

Although the three indexes are linked, they are conceptually different. For example "Software developer" (FEOR 2142) required 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) required 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 easily be automatized. Even though "Client (customer) information clerk" (FEOR 4224) requires frequent face-to-face contact, they also have a large amount of routine tasks. Appendix Table 2 shows 3 examples of occupations from each quantile of the distribution of the given index and the average index value within the quantile. For example "Early childhood educator", "Ornamental plants, flowers and tree nursery gardener", and "Roofer" are three examples of the occupation that has the lowest value on the abstract task index.

Table 3 shows the relationship between the three indexes in a more structured way. The table shows, that there is a positive correlation between the amount of abstract and face-to-face task across occupation. While in occupations where people do more routine tasks they also tend to do relatively less abstract and face-to-face tasks.

Table 1: Summary of the indexes.

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 public
	coaching and developing others
	face-to-face discussion
Automation	
	degree of automation
	importance of repeating same task
	structured versus unstructured work
	pace determined by speed of equipment
	spend time making repetitive motion

note: by Firpo, Fortin and Lemieux, 2011

Table 2: Occupation example from the distribution of the indexes.

decile	FEOR	occupation	value
		information	
	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)	
		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	
		automation	
	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	

The table shows three example from each quantile of the unweighted distribution of the given index.

Table 3: Correlation between indexes.

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

Number of observation is 11,799,844.

A.1.3 Number of observations used for identification

Table 4 shows the number of acquired firms by years. We observe more than hundred acquisition every year. The number of acquisitions was the highest between 2007 and 2010 where the number of acquisitions where more than 300. We observe less acquisitions at the beginning and at the end of the observed years.

See Table 5 shows the for the number of individual observations relevant for the identification of the wage effect. In the whole data base, we have 11,8 million worker-year observations which come from 1.5 million separate workers. From these observations, 685 thousand 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 million worker transitions. In 605 thousand cases the worker changes firm and occupation at the same time. There are in total 227 thousand cases where either the worker left the domestic firm to start a new job at a foreign firm, or the firm where the worker was working changed ownership status. Workers changed occupation at the same time in about 66 percent of the cases. We observe 78 thousand cases where either the worker arrived to an acquired firm after the acquisition, or the worker working at an acquired firm, stayed with the the firm around the event. 36 percent of such worker changed occupation around this event.

Table 4: Number of acquisition per year.

year	Observation
2004	201
2005	234
2006	256
2007	389
2008	412
2009	300
2010	195
2011	245
2012	213
2013	153
2014	150
2015	122
2016	142
2017	109
Total	3,121

Table 5: Number of cases.

	No worker-year	No worker
all firm	11,743,369	1,565,888
never changed firm	4,579,722	670,805
changed firm at least once	7,163,647	895,083
Never changed occupation	3,362,441	575,641
Changed occupation at least once	8,380,928	990,247
Changed occupation within worker-firm spell	4,407,807	553,181
acquired firm	685,241	186,467
changed task measures within worker-firm spell (only acquired)	236,375	32,999

	No cases
Changed firm	1,005,412
- and occupation at the same time	605,087
domestic to foreign*	227,245
- and occupation	125,745
foreign to domestic*	197,265
- and occupation	109,590
workers who stayed with the firm after ownership change (do to fo OR fo to do)	114,186
- and change occupation	10,344
acquired firm	
workers that arrived after acquisition or incumbent workers around the acquisition	78,085
- and changed occupation	23,654
workers that arrive after the acquisition	35,827
- and changed occupation	20,654
workers who stayed at the firm around the acquisition	42,258
- and changed occupation	3,000

*ownership change can happen in two ways: either the firm has been acquired, or the worker changed firm. As from our perspective an occupation change is only relevant if any of our three task measures changes. Thus we define an event to be changed in the occupation only if any of our three task measures also changes irrelevant of the change in the occupation code.

A.2 Results

This section contains the point estimates shown in the figures in the main text.

A.2.1 Wage effect

This section contains the point estimates shown in the event study figure (Figure 1.

Table 6: Fullsample, eventstudy, All in one.

VARIABLES	(1) coef	se	(2) coef	se	(3) coef	se
Acquired * Abstract	0.013	(0.013)	-0.007	(0.010)	0.002	(0.005)
(<t-5) * Abstract	-0.009	(0.022)	0.001	(0.015)	-0.009	(0.008)
(t-5) * Abstract	0.007	(0.017)	0.003	(0.013)	-0.001	(0.007)
(t-4) * Abstract	0.004	(0.014)	-0.002	(0.010)	-0.004	(0.006)
(t-3) * Abstract	0.006	(0.013)	-0.001	(0.009)	-0.006	(0.005)
(t-2) * Abstract	0.005	(0.013)	-0.006	(0.009)	-0.005	(0.005)
(t-1) * Abstract	-0.006	(0.007)	-0.005	(0.005)	-0.003	(0.003)
(t+1) * Abstract	0.023***	(0.007)	0.005	(0.004)	0.004	(0.003)
(t+2) * Abstract	0.021**	(0.008)	0.015***	(0.005)	0.008*	(0.004)
(t+3) * Abstract	0.034***	(0.011)	0.021***	(0.006)	0.014**	(0.006)
(t+4) * Abstract	0.035***	(0.012)	0.022***	(0.007)	0.011**	(0.006)
(t+5) * Abstract	0.061***	(0.015)	0.032***	(0.008)	0.015***	(0.006)
(t+6) * Abstract	0.050***	(0.016)	0.027***	(0.009)	0.008	(0.007)
(t+7) * Abstract	0.050***	(0.013)	0.037***	(0.009)	0.013**	(0.006)
(>t+7) * Abstract	0.047***	(0.014)	0.039***	(0.010)	0.008	(0.007)
Other Foreign * Abstract	0.071***	(0.007)	0.046***	(0.006)	0.021***	(0.002)
Acquired * Face-to-face	0.005	(0.010)	0.006	(0.008)	-0.003	(0.005)
(<t-5) * Face-to-face	-0.019	(0.016)	0.002	(0.009)	-0.002	(0.007)
(t-5) * Face-to-face	-0.002	(0.016)	0.006	(0.010)	-0.002	(0.009)
(t-4) * Face-to-face	-0.005	(0.013)	0.004	(0.007)	-0.002	(0.006)
(t-3) * Face-to-face	-0.004	(0.012)	-0.008	(0.006)	-0.008	(0.005)
(t-2) * Face-to-face	0.002	(0.011)	0.002	(0.006)	-0.004	(0.004)
(t-1) * Face-to-face	0.006	(0.006)	-0.005	(0.004)	-0.003	(0.003)
(t+1) * Face-to-face	-0.035***	(0.008)	-0.009	(0.006)	-0.003	(0.003)
(t+2) * Face-to-face	-0.023***	(0.009)	-0.014*	(0.007)	-0.002	(0.004)
(t+3) * Face-to-face	-0.033***	(0.011)	-0.019**	(0.008)	-0.009**	(0.004)
(t+4) * Face-to-face	-0.025**	(0.011)	-0.019***	(0.007)	-0.010**	(0.005)
(t+5) * Face-to-face	-0.025**	(0.011)	-0.011	(0.009)	-0.005	(0.006)
(t+6) * Face-to-face	-0.006	(0.013)	0.001	(0.010)	-0.002	(0.006)
(t+7) * Face-to-face	-0.009	(0.012)	0.002	(0.010)	0.001	(0.006)
(>t+7) * Face-to-face	-0.005	(0.016)	0.010	(0.016)	0.008	(0.007)
Other Foreign * Face-to-face	-0.004	(0.010)	0.007	(0.006)	0.001	(0.002)
Acquired * Routine	-0.007	(0.011)	-0.018***	(0.006)	-0.007**	(0.003)
(<t-5) * Routine	-0.022	(0.019)	-0.009	(0.013)	0.000	(0.008)
(t-5) * Routine	-0.001	(0.024)	-0.001	(0.020)	0.002	(0.013)
(t-4) * Routine	-0.021	(0.016)	-0.004	(0.012)	-0.004	(0.007)
(t-3) * Routine	-0.007	(0.014)	-0.005	(0.010)	-0.004	(0.006)
(t-2) * Routine	-0.000	(0.011)	0.003	(0.006)	0.000	(0.004)
(t-1) * Routine	0.005	(0.007)	-0.006*	(0.004)	-0.003	(0.003)
(t+1) * Routine	-0.009	(0.010)	0.005	(0.007)	0.001	(0.003)
(t+2) * Routine	-0.015	(0.009)	-0.003	(0.008)	-0.002	(0.004)
(t+3) * Routine	-0.018	(0.011)	-0.002	(0.009)	-0.000	(0.005)
(t+4) * Routine	-0.020	(0.012)	-0.001	(0.008)	0.001	(0.005)
(t+5) * Routine	-0.009	(0.014)	0.008	(0.007)	0.004	(0.005)
(t+6) * Routine	-0.006	(0.014)	0.008	(0.008)	-0.000	(0.005)
(t+7) * Routine	-0.003	(0.015)	0.014	(0.009)	0.000	(0.006)
(>t+7) * Routine	-0.020	(0.017)	0.009	(0.011)	-0.008	(0.006)
Other Foreign * Routine	-0.048***	(0.007)	-0.045***	(0.006)	-0.020***	(0.002)
Log Sales	0.031***	(0.003)	0.004***	(0.001)	0.004***	(0.001)
Log Employment	0.003	(0.007)	-0.004***	(0.002)	0.006***	(0.001)
Exporter	0.074***	(0.010)	-0.003	(0.002)	-0.002	(0.002)
Constant	7.358***	(0.035)	8.013***	(0.016)	9.151***	(0.015)
Sector*Year	Yes		Yes		Yes	
Firm FE			Yes		Yes	
Firm-level trend			Yes		Yes	
Worker FE					Yes	

$***p < 0.01, **p < 0.05, *p < 0.1$ We estimate Equation 3 Standard errors are clustered at the firm

A.2.2 Heterogeneity

This section contains the point estimates shown in the event study figure (Figure 2.

Table 7: Acquired, eventstudy, All in one.

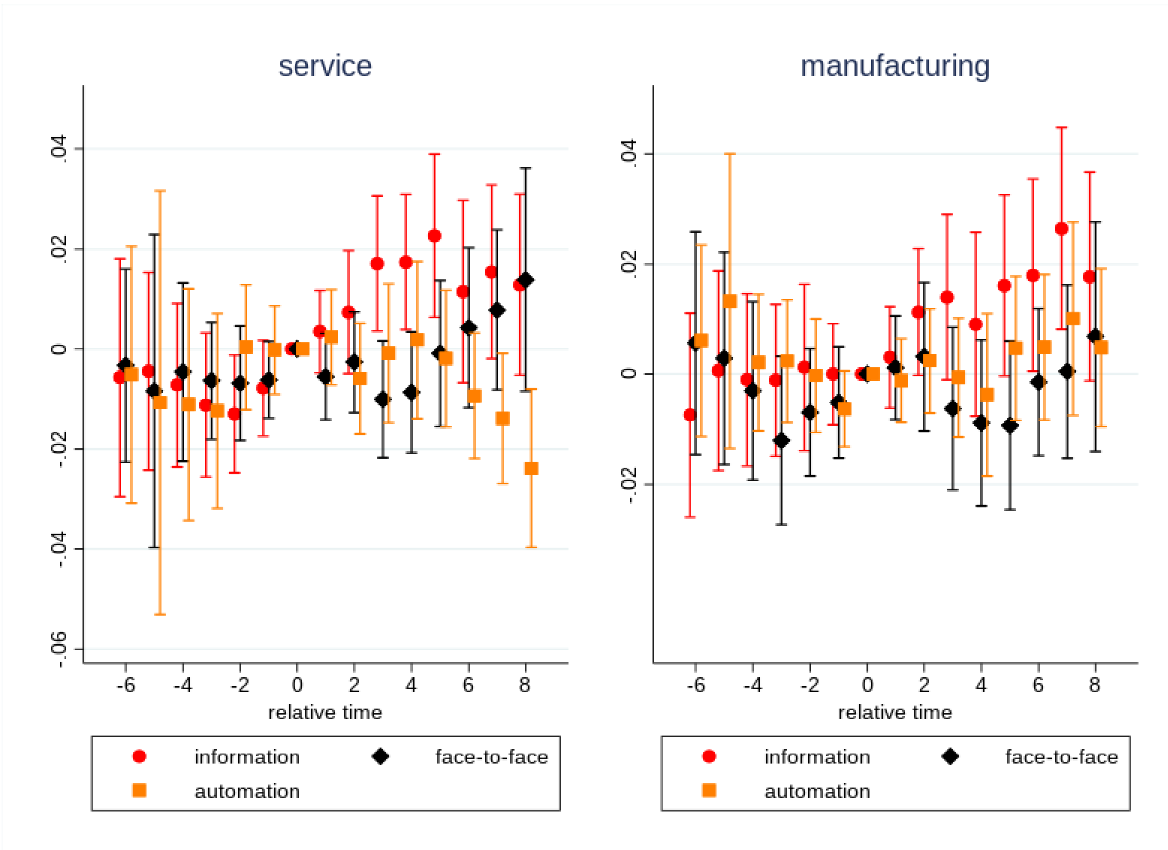
	(1)		(2)	
VARIABLES	coef	se	coef	se
(<t-5) * Abstract	-0.008	(0.021)	0.001	(0.016)
(t-5) * Abstract	0.003	(0.016)	0.003	(0.014)
(t-4) * Abstract	0.008	(0.013)	-0.002	(0.011)
(t-3) * Abstract	0.009	(0.012)	-0.001	(0.010)
(t-2) * Abstract	0.005	(0.011)	-0.006	(0.010)
(t-1) * Abstract	-0.003	(0.007)	-0.007	(0.005)
(t+1) * Abstract	0.017***	(0.007)	0.007*	(0.004)
(t+2) * Abstract	0.024***	(0.009)	0.020***	(0.006)
(t+3) * Abstract	0.038***	(0.011)	0.025***	(0.006)
(t+4) * Abstract	0.039***	(0.012)	0.025***	(0.008)
(t+5) * Abstract	0.064***	(0.014)	0.033***	(0.011)
(t+6) * Abstract	0.055***	(0.015)	0.029**	(0.014)
(t+7) * Abstract	0.043***	(0.016)	0.037**	(0.015)
(>t+7) * Abstract	0.039**	(0.019)	0.038*	(0.020)
(<t-5) * Face-to-face	-0.038**	(0.018)	-0.001	(0.010)
(t-5) * Face-to-face	-0.014	(0.017)	0.005	(0.012)
(t-4) * Face-to-face	-0.014	(0.013)	0.006	(0.008)
(t-3) * Face-to-face	-0.010	(0.011)	-0.007	(0.007)
(t-2) * Face-to-face	-0.004	(0.010)	0.003	(0.006)
(t-1) * Face-to-face	-0.000	(0.006)	-0.004	(0.003)
(t+1) * Face-to-face	-0.022***	(0.007)	-0.008	(0.005)
(t+2) * Face-to-face	-0.012	(0.009)	-0.009	(0.007)
(t+3) * Face-to-face	-0.019	(0.012)	-0.010	(0.008)
(t+4) * Face-to-face	-0.003	(0.012)	-0.008	(0.009)
(t+5) * Face-to-face	-0.002	(0.013)	0.003	(0.012)
(t+6) * Face-to-face	0.022	(0.016)	0.018	(0.015)
(t+7) * Face-to-face	0.028*	(0.016)	0.020	(0.017)
(>t+7) * Face-to-face	0.038*	(0.023)	0.032	(0.024)
(<t-5) * Routine	-0.018	(0.019)	-0.005	(0.013)
(t-5) * Routine	0.000	(0.022)	0.002	(0.018)
(t-4) * Routine	-0.012	(0.015)	0.000	(0.011)
(t-3) * Routine	0.000	(0.013)	-0.002	(0.010)
(t-2) * Routine	0.007	(0.009)	0.004	(0.006)
(t-1) * Routine	0.004	(0.007)	-0.005	(0.004)
(t+1) * Routine	0.008	(0.008)	0.006	(0.006)
(t+2) * Routine	-0.004	(0.010)	-0.002	(0.008)
(t+3) * Routine	-0.007	(0.011)	-0.000	(0.008)
(t+4) * Routine	-0.003	(0.013)	0.001	(0.009)
(t+5) * Routine	0.005	(0.015)	0.010	(0.010)
(t+6) * Routine	0.009	(0.017)	0.009	(0.014)
(t+7) * Routine	0.010	(0.020)	0.012	(0.017)
(>t+7) * Routine	-0.004	(0.025)	0.006	(0.024)
Constant	7.059***	(0.100)	8.083***	(0.047)
Sector*Year	Yes		Yes	
Firm FE			Yes	
Firm-level trend			Yes	
Worker FE				
Observations	685,241		685,241	
R-squared	0.507		0.719	

$***p < 0.01, **p < 0.05, *p < 0.1$ We estimate Equation 5 Standard errors are clustered at the firm level. Year fixed effects and their interaction with skill use indexes are included. We further control for the size of the firm (measured by sales revenue, and employment), whether the firm is a public firm, and whether participate in exporting and 1 digit industry dummies and their interaction with the year dummies are also included. We further control for the gender and age of the worker. We further control for firm-level trends in the second column

A.2.3 Wage return of tasks by industry

We re-estimate Equation 3 by allowing acquisition to have different effect in the manufacturing and the service sector. Figure 1 shows the results, while Table 8 shows the parameter estimates.

Figure 1: Effect of FDI on task returns by industry



	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
	(13)	(14)	(7)	(8)	(11)	(12)
VARIABLES	OLS	se	coef	se	coef	se
Aquired * Information * Service	0.032**	(0.015)	-0.011	(0.014)	0.004	(0.007)
$< (t-5)$ * Information * Service	-0.025	(0.022)	-0.008	(0.016)	-0.006	(0.012)
(t-5) * Information * Service	-0.029	(0.021)	-0.006	(0.015)	-0.004	(0.010)
(t-4) * Information * Service	-0.002	(0.017)	-0.010	(0.013)	-0.007	(0.008)
(t-3) * Information * Service	0.002	(0.015)	-0.007	(0.011)	-0.011	(0.007)
(t-2) * Information * Service	-0.000	(0.015)	-0.014	(0.012)	-0.013**	(0.006)
(t-1) * Information * Service	-0.006	(0.011)	-0.008	(0.009)	-0.008	(0.005)
(t+1) * Information * Service	0.017*	(0.010)	0.002	(0.005)	0.003	(0.004)
(t+2) * Information * Service	0.014	(0.013)	0.014*	(0.008)	0.007	(0.006)
(t+3) * Information * Service	0.029*	(0.017)	0.023***	(0.009)	0.017**	(0.007)
(t+4) * Information * Service	0.035**	(0.015)	0.029***	(0.009)	0.017**	(0.007)
(t+5) * Information * Service	0.068***	(0.018)	0.040***	(0.012)	0.023***	(0.008)
(t+6) * Information * Service	0.058***	(0.020)	0.033**	(0.014)	0.012	(0.009)
(t+7) * Information * Service	0.042**	(0.018)	0.039***	(0.014)	0.015*	(0.009)
$> (t+7)$ * Information * Service	0.029	(0.023)	0.041**	(0.016)	0.013	(0.009)
Re-Acquired * Information * Service	-0.037	(0.026)	-0.029**	(0.014)	-0.009	(0.006)
Other Foreign * Information * Service	0.155***	(0.010)	0.061***	(0.012)	0.033***	(0.004)
Aquired * Face-to-face * Service	0.041***	(0.013)	-0.003	(0.012)	-0.009	(0.007)
$< (t-5)$ * Face-to-face * Service	-0.053***	(0.019)	-0.012	(0.014)	-0.003	(0.010)
(t-5) * Face-to-face * Service	-0.037	(0.024)	-0.011	(0.017)	-0.008	(0.016)
(t-4) * Face-to-face * Service	-0.024	(0.018)	-0.004	(0.010)	-0.005	(0.009)
(t-3) * Face-to-face * Service	-0.005	(0.014)	-0.004	(0.007)	-0.006	(0.006)
(t-2) * Face-to-face * Service	-0.010	(0.013)	0.001	(0.007)	-0.007	(0.006)
(t-1) * Face-to-face * Service	-0.006	(0.009)	-0.007	(0.004)	-0.006	(0.004)
(t+1) * Face-to-face * Service	-0.037***	(0.011)	-0.011	(0.008)	-0.006	(0.004)
(t+2) * Face-to-face * Service	-0.030***	(0.012)	-0.014	(0.010)	-0.003	(0.005)
(t+3) * Face-to-face * Service	-0.036**	(0.014)	-0.016	(0.012)	-0.010*	(0.006)
(t+4) * Face-to-face * Service	-0.035**	(0.014)	-0.012	(0.012)	-0.009	(0.006)
(t+5) * Face-to-face * Service	-0.039**	(0.016)	0.003	(0.014)	-0.001	(0.007)
(t+6) * Face-to-face * Service	-0.020	(0.019)	0.016	(0.016)	0.004	(0.008)
(t+7) * Face-to-face * Service	-0.021	(0.019)	0.020	(0.019)	0.008	(0.008)
$> (t+7)$ * Face-to-face * Service	-0.017	(0.029)	0.032	(0.029)	0.014	(0.011)
Re-Acquired * Face-to-face * Service	0.028	(0.023)	0.005	(0.018)	0.000	(0.006)
Other Foreign * Face-to-face * Service	0.023*	(0.014)	-0.008	(0.010)	-0.001	(0.003)
Aquired * Automation * Service	-0.019	(0.016)	-0.013	(0.010)	-0.005	(0.005)
$< (t-5)$ * Automation * Service	-0.027	(0.025)	-0.019	(0.018)	-0.005	(0.013)
(t-5) * Automation * Service	-0.013	(0.041)	-0.025	(0.038)	-0.011	(0.022)
(t-4) * Automation * Service	-0.012	(0.025)	-0.017	(0.020)	-0.011	(0.012)
(t-3) * Automation * Service	0.003	(0.023)	-0.018	(0.017)	-0.012	(0.010)
(t-2) * Automation * Service	0.019	(0.015)	0.000	(0.009)	0.000	(0.006)
(t-1) * Automation * Service	0.013	(0.014)	-0.004	(0.006)	-0.000	(0.005)
(t+1) * Automation * Service	0.007	(0.015)	0.006	(0.011)	0.002	(0.005)
(t+2) * Automation * Service	-0.021	(0.015)	-0.008	(0.014)	-0.006	(0.006)
(t+3) * Automation * Service	-0.032*	(0.017)	-0.009	(0.014)	-0.001	(0.007)
(t+4) * Automation * Service	-0.036**	(0.016)	-0.008	(0.012)	0.002	(0.008)
(t+5) * Automation * Service	-0.043**	(0.019)	-0.011	(0.009)	-0.002	(0.007)
(t+6) * Automation * Service	-0.035*	(0.019)	-0.014	(0.009)	-0.009	(0.006)
(t+7) * Automation * Service	-0.036*	(0.019)	-0.010	(0.009)	-0.014**	(0.007)
$> (t+7)$ * Automation * Service	-0.058**	(0.025)	-0.017	(0.011)	-0.024***	(0.008)
Re-Acquired * Automation * Service	0.096***	(0.019)	0.023**	(0.010)	0.008	(0.005)
Other Foreign * Automation * Service	-0.053***	(0.013)	-0.033***	(0.007)	-0.018***	(0.003)

cont. next page

Table 8: Fullsample, eventstudy, All in one.

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Aquired * Information * Manufact	-0.032*	(0.018)	-0.008	(0.013)	-0.003	(0.007)
$< (t-5)$ * Information * Manufact	0.013	(0.032)	0.006	(0.021)	-0.007	(0.009)
(t-5) * Information * Manufact	0.034	(0.025)	0.004	(0.020)	0.001	(0.009)
(t-4) * Information * Manufact	0.017	(0.022)	0.002	(0.016)	-0.001	(0.008)
(t-3) * Information * Manufact	0.022	(0.020)	0.006	(0.015)	-0.001	(0.007)
(t-2) * Information * Manufact	0.013	(0.020)	0.003	(0.014)	0.001	(0.008)
(t-1) * Information * Manufact	0.001	(0.008)	-0.005	(0.005)	-0.000	(0.005)
(t+1) * Information * Manufact	0.013	(0.010)	0.010*	(0.005)	0.003	(0.005)
(t+2) * Information * Manufact	0.037***	(0.011)	0.024***	(0.008)	0.011*	(0.006)
(t+3) * Information * Manufact	0.054***	(0.016)	0.036***	(0.009)	0.014*	(0.008)
(t+4) * Information * Manufact	0.037*	(0.020)	0.031***	(0.010)	0.009	(0.009)
(t+5) * Information * Manufact	0.050**	(0.020)	0.050***	(0.015)	0.016*	(0.008)
(t+6) * Information * Manufact	0.052**	(0.020)	0.056***	(0.015)	0.018**	(0.009)
(t+7) * Information * Manufact	0.071***	(0.023)	0.070***	(0.016)	0.026***	(0.009)
$> (t+7)$ * Information * Manufact	0.085***	(0.024)	0.077***	(0.015)	0.018*	(0.010)
Re-Acquired * Information * Manufact	-0.072***	(0.019)	-0.052***	(0.012)	-0.009	(0.007)
Other Foreign * Information * Manufact	0.033***	(0.009)	0.035***	(0.006)	0.014***	(0.002)
Aquired * Face-to-face * Manufact	-0.007	(0.015)	0.019**	(0.009)	0.007	(0.005)
$< (t-5)$ * Face-to-face * Manufact	0.037	(0.030)	0.021	(0.014)	0.006	(0.010)
(t-5) * Face-to-face * Manufact	0.022	(0.026)	0.021	(0.013)	0.003	(0.010)
(t-4) * Face-to-face * Manufact	0.013	(0.021)	0.007	(0.011)	-0.003	(0.008)
(t-3) * Face-to-face * Manufact	-0.002	(0.019)	-0.014	(0.011)	-0.012	(0.008)
(t-2) * Face-to-face * Manufact	0.003	(0.017)	-0.007	(0.011)	-0.007	(0.006)
(t-1) * Face-to-face * Manufact	0.013	(0.011)	-0.009	(0.006)	-0.005	(0.005)
(t+1) * Face-to-face * Manufact	0.000	(0.011)	-0.007	(0.005)	0.001	(0.005)
(t+2) * Face-to-face * Manufact	0.003	(0.017)	-0.012	(0.012)	0.003	(0.007)
(t+3) * Face-to-face * Manufact	-0.008	(0.018)	-0.019*	(0.010)	-0.006	(0.008)
(t+4) * Face-to-face * Manufact	0.005	(0.018)	-0.024**	(0.011)	-0.009	(0.008)
(t+5) * Face-to-face * Manufact	0.003	(0.019)	-0.029**	(0.014)	-0.009	(0.008)
(t+6) * Face-to-face * Manufact	0.016	(0.019)	-0.013	(0.013)	-0.001	(0.007)
(t+7) * Face-to-face * Manufact	0.015	(0.021)	-0.014	(0.015)	0.000	(0.008)
$> (t+7)$ * Face-to-face * Manufact	0.003	(0.029)	-0.013	(0.022)	0.007	(0.011)
Re-Acquired * Face-to-face * Manufact	-0.003	(0.020)	0.001	(0.015)	-0.010*	(0.006)
Other Foreign * Face-to-face * Manufact	-0.054***	(0.009)	0.023***	(0.005)	0.006***	(0.002)
Acquired * Automation * Manufact	-0.010	(0.013)	-0.021***	(0.008)	-0.009**	(0.004)
$< (t-5)$ * Automation * Manufact	0.001	(0.026)	0.003	(0.018)	0.006	(0.009)
(t-5) * Automation * Manufact	0.020	(0.019)	0.021	(0.016)	0.013	(0.014)
(t-4) * Automation * Manufact	-0.011	(0.016)	0.010	(0.011)	0.002	(0.006)
(t-3) * Automation * Manufact	-0.005	(0.015)	0.006	(0.009)	0.002	(0.006)
(t-2) * Automation * Manufact	-0.009	(0.013)	0.004	(0.008)	-0.000	(0.005)
(t-1) * Automation * Manufact	-0.003	(0.009)	-0.009**	(0.004)	-0.006*	(0.004)
(t+1) * Automation * Manufact	-0.010	(0.007)	0.004	(0.004)	-0.001	(0.004)
(t+2) * Automation * Manufact	-0.005	(0.009)	0.003	(0.007)	0.002	(0.005)
(t+3) * Automation * Manufact	0.004	(0.012)	0.007	(0.009)	-0.001	(0.006)
(t+4) * Automation * Manufact	-0.005	(0.016)	0.002	(0.012)	-0.004	(0.008)
(t+5) * Automation * Manufact	0.010	(0.016)	0.020*	(0.012)	0.005	(0.007)
(t+6) * Automation * Manufact	0.012	(0.018)	0.023*	(0.013)	0.005	(0.007)
(t+7) * Automation * Manufact	0.018	(0.023)	0.031*	(0.018)	0.010	(0.009)
$> (t+7)$ * Automation * Manufact	0.013	(0.025)	0.031	(0.020)	0.005	(0.007)
Re-Acquired * Automation * Manufact	-0.030	(0.028)	-0.016	(0.021)	0.002	(0.006)
Other Foreign * Automation * Manufact	-0.039***	(0.008)	-0.048***	(0.008)	-0.020***	(0.002)
R-squared	0.554		0.764		0.922	
Observations	11,743,369		11,743,369		11,743,369	
Sector*Year	Yes		Yes		Yes	
Firm FE			Yes		Yes	
Firm-level trend			Yes		Yes	
Worker FE					Yes	

A.2.4 Change of task composition in production

Figure 2: Change of task composition in production - Share of abstract task usage around the acquisition

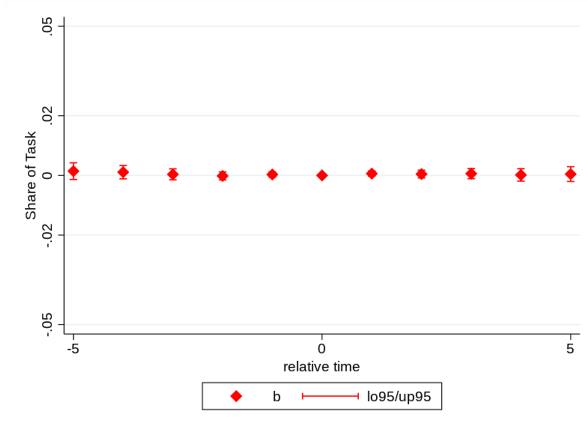


Figure 3: Change of task composition in production - Share of face-to-face task usage around the acquisition

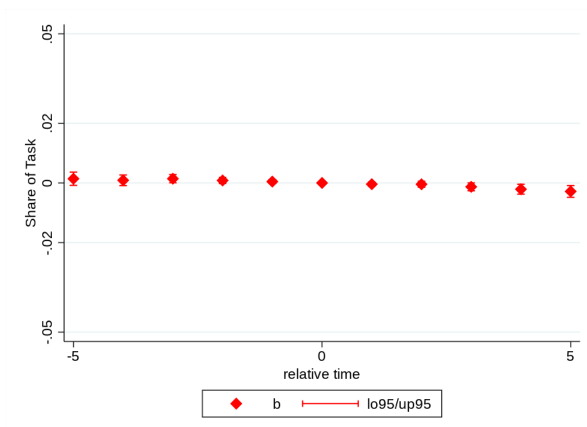
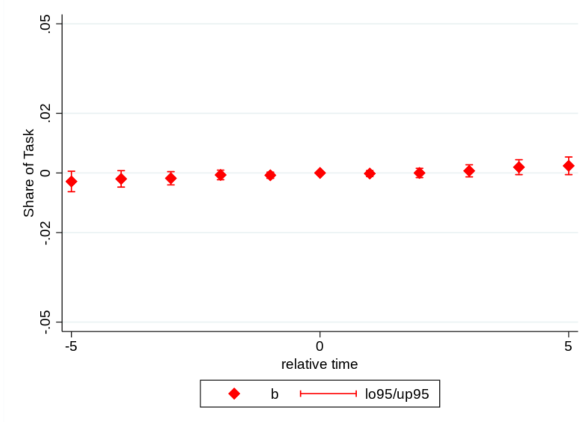


Figure 4: Change of task composition in production - Share of routine task usage around the acquisition



We re-estimate Equation 8 and Equation 6 on the sub-sample of acquired firms. In Table 9 the first column shows the results in the case of the OLS model, while the second column corresponds to the firm fixed effect model. The first panel shows the estimated parameters in the case of the abstract tasks, the second panel corresponds to the face-to-face tasks and the last panel to the routine tasks. The parameter estimates are very small in magnitude. Thus we conclude that firms do not change the composition of tasks used at production in an economically significant magnitude after a foreign take-over. Figure 5-Figure 7 shows the results for the event study approach. The figures confirm that there is no composition effect. The parameter estimates of the Fixed effect model together with the parameter estimates of the OLS model can be found in the column (3) and (4) of the Appendix Table 10-Table 12.

Table 9: Composition effect, Acquired Firm, foreign results.

	(1)		(2)	
	OLS		Firm FE	
VARIABLES	coef	se	coef	se
	Panel A: Abstract			
Foreign	0.003***	(0.001)	0.001**	(0.000)
R-squared	0.329		0.891	
	Panel B: Face-to-face			
Foreign	-0.000	(0.000)	0.000	(0.000)
R-squared	0.259		0.860	
	Panel C: Routine			
Foreign	-0.003***	(0.001)	-0.001***	(0.000)
R-squared	0.224		0.858	
Observations	32,827		32,827	
Sector*Year	Yes		Yes	
Firm FE			Yes	
Firm-level trend			Yes	

$***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level.

Figure 5: Change of task composition in production - Share of abstract task usage around the acquisition, acquired firm subsample only

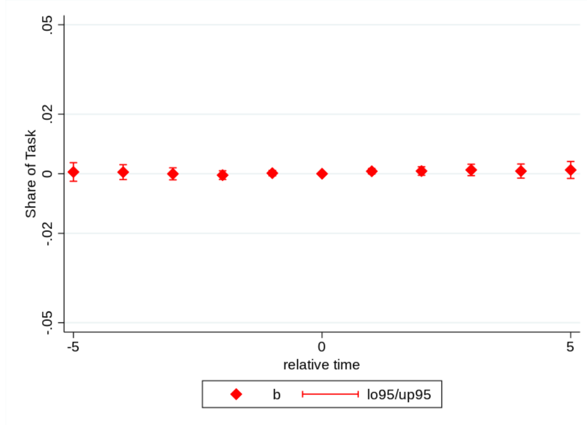


Figure 6: Change of task composition in production - Share of face-to-face task usage around the acquisition, acquired firm subsample only

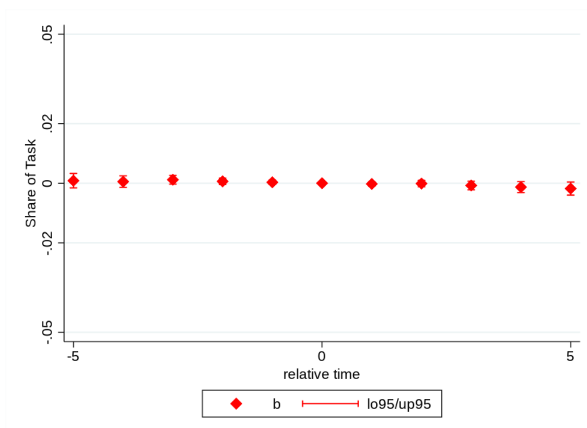


Figure 7: Change of task composition in production - Share of routine task usage around the acquisition, acquired firm subsample only

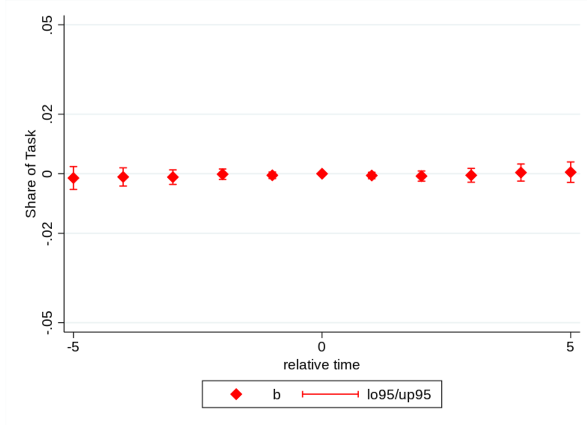


Table 10: Composition effect - Share of abstract tasks around the foreign acquisition

	Full Sample				Acquired			
	(1)		(2)		(3)		(4)	
VARIABLES	coef	se	coef	se				
(<t-5)	0.001	(0.001)	0.001	(0.002)	-0.001	(0.001)	-0.001	(0.002)
(t-5)	0.001	(0.001)	0.001	(0.001)	-0.000	(0.001)	0.001	(0.002)
(t-4)	0.001	(0.001)	0.001	(0.001)	-0.001	(0.001)	0.001	(0.001)
(t-3)	0.001	(0.001)	0.000	(0.001)	-0.000	(0.001)	-0.000	(0.001)
(t-2)	0.001*	(0.001)	-0.000	(0.001)	0.000	(0.001)	-0.000	(0.001)
(t-1)	0.001	(0.000)	0.000	(0.000)	0.001	(0.000)	0.000	(0.000)
(t+1)	-0.000	(0.000)	0.001	(0.000)	0.001	(0.001)	0.001*	(0.000)
(t+2)	0.001	(0.001)	0.000	(0.001)	0.002***	(0.001)	0.001	(0.001)
(t+3)	0.001**	(0.001)	0.001	(0.001)	0.003***	(0.001)	0.001	(0.001)
(t+4)	0.002**	(0.001)	0.000	(0.001)	0.004***	(0.001)	0.001	(0.001)
(t+5)	0.002***	(0.001)	0.000	(0.001)	0.005***	(0.001)	0.001	(0.001)
(t+6)	0.002**	(0.001)	-0.000	(0.001)	0.005***	(0.001)	0.001	(0.002)
(t+7)	0.002**	(0.001)	-0.000	(0.002)	0.006***	(0.001)	0.001	(0.002)
(>t+7)	0.004***	(0.001)	0.000	(0.002)	0.008***	(0.001)	0.000	(0.002)
Acquired	0.005***	(0.001)						
Other Foreign	0.010***	(0.000)						
Constant	0.314***	(0.001)	0.340***	(0.000)	0.322***	(0.002)	0.348***	(0.002)
Sector*Year	Yes		Yes		Yes		Yes	
Firm FE			Yes				Yes	
Firm-level trend			Yes				Yes	
Observations	794,724		794,724		32,827		32,827	
R-squared	0.293		0.893		0.331		0.892	

$***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level.

Table 11: Composition effect - Share of face-to-face tasks around the foreign acquisition

	Full Sample				Acquired			
	(1)		(2)		(3)		(4)	
VARIABLES	coef	se	coef	se				
(<t-5)	0.000	(0.001)	0.002	(0.001)	0.000	(0.001)	0.001	(0.002)
(t-5)	-0.000	(0.001)	0.001	(0.001)	-0.000	(0.001)	0.001	(0.001)
(t-4)	0.000	(0.001)	0.001	(0.001)	0.000	(0.001)	0.001	(0.001)
(t-3)	0.001	(0.001)	0.001**	(0.001)	0.001	(0.001)	0.001	(0.001)
(t-2)	0.000	(0.000)	0.001	(0.001)	-0.000	(0.000)	0.001	(0.001)
(t-1)	-0.000	(0.000)	0.000	(0.000)	-0.000	(0.000)	0.000	(0.000)
(t+1)	-0.000	(0.000)	-0.000	(0.000)	0.000	(0.000)	-0.000	(0.000)
(t+2)	-0.000	(0.000)	-0.000	(0.001)	0.000	(0.000)	-0.000	(0.001)
(t+3)	-0.001	(0.000)	-0.001*	(0.001)	-0.000	(0.001)	-0.001	(0.001)
(t+4)	-0.001	(0.000)	-0.002**	(0.001)	-0.000	(0.001)	-0.001	(0.001)
(t+5)	-0.001***	(0.001)	-0.003***	(0.001)	-0.001	(0.001)	-0.002	(0.001)
(t+6)	-0.001**	(0.001)	-0.003***	(0.001)	-0.001	(0.001)	-0.002	(0.001)
(t+7)	-0.002**	(0.001)	-0.004***	(0.001)	-0.001	(0.001)	-0.003*	(0.002)
(>t+7)	-0.002**	(0.001)	-0.004***	(0.002)	-0.001	(0.001)	-0.003	(0.002)
Acquired	0.000	(0.000)						
Other Foreign	-0.000**	(0.000)						
Constant	0.356***	(0.000)	0.351***	(0.000)	0.354***	(0.001)	0.350***	(0.001)
Sector*Year	Yes		Yes		Yes		Yes	
Firm FE			Yes				Yes	
Firm-level trend			Yes				Yes	
Observations	794,724		794,724		32,827		32,827	
R-squared	0.271		0.874		0.259		0.860	

$***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level.

Table 12: Composition effect - Share routine tasks around the foreign acquisition

	Full Sample				Acquired			
	(1)		(2)		(3)		(4)	
VARIABLES	coef	se	coef	se	coed	se	coef	se
(<t-5)	-0.002	(0.001)	-0.003	(0.002)	0.001	(0.001)	-0.001	(0.002)
(t-5)	-0.001	(0.001)	-0.003	(0.002)	0.001	(0.001)	-0.001	(0.002)
(t-4)	-0.001	(0.001)	-0.002	(0.001)	0.001	(0.001)	-0.001	(0.002)
(t-3)	-0.002*	(0.001)	-0.002	(0.001)	-0.001	(0.001)	-0.001	(0.001)
(t-2)	-0.001	(0.001)	-0.001	(0.001)	-0.000	(0.001)	-0.000	(0.001)
(t-1)	-0.001	(0.001)	-0.001	(0.001)	-0.000	(0.001)	-0.001	(0.001)
(t+1)	0.000	(0.001)	-0.000	(0.001)	-0.001	(0.001)	-0.001	(0.001)
(t+2)	-0.001	(0.001)	-0.000	(0.001)	-0.002***	(0.001)	-0.001	(0.001)
(t+3)	-0.001	(0.001)	0.001	(0.001)	-0.003***	(0.001)	-0.001	(0.001)
(t+4)	-0.001	(0.001)	0.002	(0.001)	-0.004***	(0.001)	0.000	(0.001)
(t+5)	-0.001	(0.001)	0.002	(0.002)	-0.004***	(0.001)	0.001	(0.002)
(t+6)	-0.000	(0.001)	0.004*	(0.002)	-0.004***	(0.001)	0.001	(0.002)
(t+7)	-0.000	(0.001)	0.004**	(0.002)	-0.005***	(0.001)	0.002	(0.002)
(>t+7)	-0.002**	(0.001)	0.004*	(0.002)	-0.008***	(0.002)	0.002	(0.003)
Acquired	-0.005***	(0.001)						
Other Foreign	-0.009***	(0.000)						
Constant	0.330***	(0.001)	0.309***	(0.000)	0.324***	(0.002)	0.302***	(0.002)
Observations	794,724		794,724		32,827		32,827	
R-squared	0.227		0.872		0.226		0.858	
Sector*Year	Yes		Yes		Yes		Yes	
Firm FE			Yes				Yes	
Firm-level trend			Yes				Yes	

$***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level.

A.2.5 Change in firm size and task specialization

The event study analysis confirm our finding, that foreign acquisition does not have an effect on task specialization. Figure 8-Figure 9 show the effect of a foreign takeover on the composition of firm-level task usage. We do not find any evidence for pre-trend, and the parameter estimates corresponding to the post-acquisition periods are also insignificant and small. The parameter estimates of the Fixed effect model together with the parameter estimates of the OLS model can be found in the first two column of the Appendix Table 10-Table 12.

Figure 8: Number of occupation codes around the acquisition

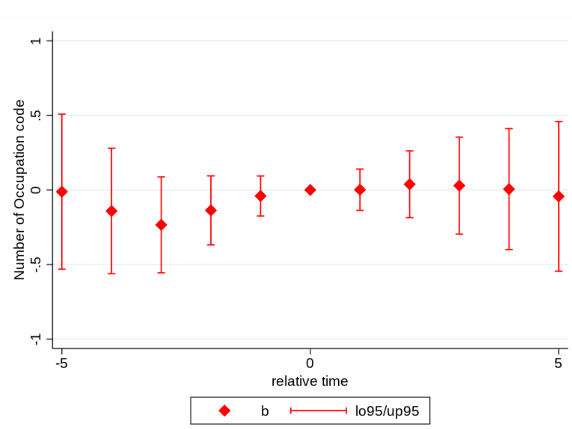
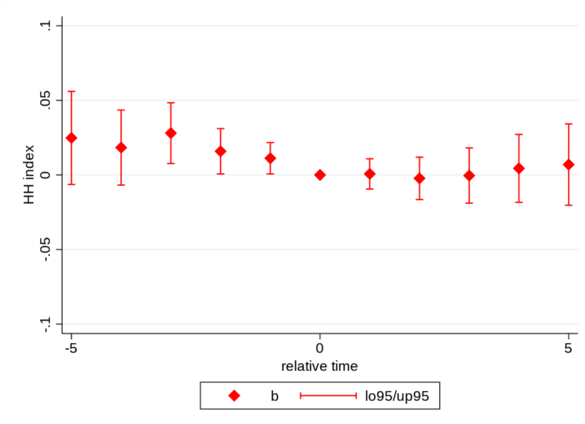


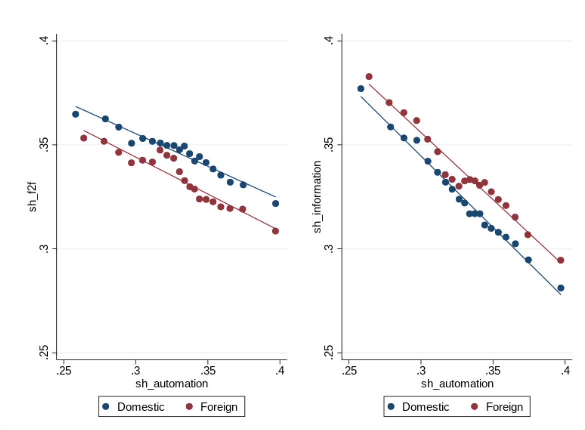
Figure 9: HH index around the acquisition



A.2.6 Composition effect - additional details

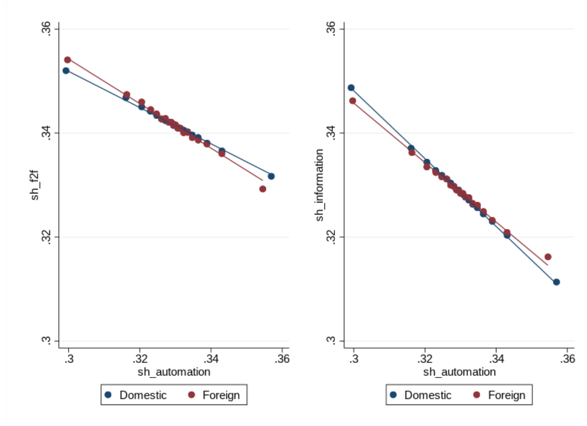
Figure 10 shows the relationship between the firm-level usage of different types of task by ownership. On the one hand, the more routine task a firm use, the lower is the share of face-to-face and routine tasks. On the other hand, at any level of routine tasks, foreign firms use fewer face-to-face task and more abstract tasks. As soon as we control for firm fixed effects the differences by ownership types disappears, see Figure 11. This figures also suggest that firms do not change the share of routine of cognitive tasks after acquisition.

Figure 10: Variance in firm level task usage (share)



Firm seize measured by the number of employees used as weights. Firm level task usage calculated by using the Formula 1.

Figure 11: Variance in firm level task usage (share)



Firm seize measured by the number of employees used as weights. Firm level task usage calculated by using the Formula 1.