Growing Inequality:
a Novel Integration of
transformations research

Co-funded by the Horizon 2020 programme
of the European Union

D4.3 Impacts of offshoring for local workers in Bulgaria and Hungary

WP4 Globalisation: Impact on skills and inequality

Authors: Balázs Reizer, Attila Gáspár, Rita Petö, Marcel Smolka and Boris Georgiev

Associate Work Package: WP4

Lead Beneficiary: KRTK & EUF

WP leader: RUG

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement number 101004494 — The contents of this publication are the sole responsibility of the GI-NI project Consortium and do not necessarily reflect the opinion of the European Union.

Document Summary

Document type:	*Report*
Title:	Impacts of Offshoring for Local Workers in Bulgaria and Hungary
Author/s:	*Balázs Reizer, Attila Gáspár, Rita Petö, Marcel Smolka and Boris Georgiev*
Reviewer/s:	*Ruud Gerards, Bart Los*
Date:	*March 28, 2024*
Document status:	*Submitted*
Keywords:	*Offshoring, FDI, processing firms, import prices, firm heterogeneity, worker heterogeneity, wages*
Version:	*1.0*
Document level:	*Public*

Summary

This report consists of three papers, focusing on the implications of the increased role that countries in Eastern Europe have started to play in the European and global economy after their accession to the European Union. As opposed to the majority of studies in the existing literature, these papers do not study the consequences for firms and their workers in countries from which firms offshored parts of their activities to Eastern Europe, but analyse the consequences for firms and workers in the Eastern European countries themselves. Two papers study the case of Hungary, one paper focuses on Bulgaria.

Firms are becoming increasingly international. Over the last decade, exports and imports grew faster than GDP in virtually every country in the world. In addition to trading physical goods and services, international investment of firms is growing rapidly as well. By 2023, foreign direct investment (FDI) by firms amounted to more than two percent of global GDP. These aspects of globalisation have had a huge impact on labour markets on all continents and regions therein. Many studies, for instance, show that globalisation increased GDP and the average wage in developing countries, but at the cost of higher inequality.

This report investigates the effect of globalisation on emerging economies in Eastern Europe regarding three aspects. First, the paper by Gáspár and Reizer examines the effects of differences in domestic input prices on firm performance and employment in Hungary. Previous studies revealed that the devaluation of domestic currencies hurts importing firms. In this case, the production costs of importing firms increase, compared to the production costs of other firms that do not import but rely on domestically purchased inputs only. As a consequence, importing firms raise prices and lose market share compared to other firms in the same industry. However, these studies assumed that domestic prices are the same for every firm. The paper challenges this assumption by using The Hungarian Material Expense Survey. We show that there is significant heterogeneity in the growth of domestic input prices even within narrowly defined industries. Furthermore, the prices of domestically produced inputs go up if the price of similar imported products increases. Some firms replace their domestically produced inputs with imported alternatives if the prices of domestic inputs increase. However, firms cannot completely mitigate the negative effect of domestic shocks by imports. The paper shows that the growth of domestic input prices causes a decrease in employment, especially among blue-collar workers, and increases the relative wage of white-collar

workers and hence the overall wage inequality within firms. These results have implications for the determination of exchange rate policies. Previous policy recommendations assumed that changes in exchange rates affect firms through the change in import and export prices. In other words, the devaluation of the domestic currency boosts export at the cost of increasing import prices. In contrast, we showed that the growth of import prices also hurts firms that operate only in the domestic markets by using close alternatives of imported products, too. Thus the actual costs of devaluation of the domestic currencies puts a larger burden on firms than previously thought, and increases wage inequality between blue-collar and white-collar workers.

The second paper (by Petö and Reizer) investigates the effect of foreign direct investment (FDI) on wage inequality in a Hungarian context. The quality of the Hungarian data allows us to estimate the mechanisms through which FDI affects the labour market of developing countries in much more detail than previous studies. We show evidence that foreign acquirers cherry-pick relatively large and high-paying domestic firms. After the acquisition, these high-paying firms further increase wages and employment, leading to greater wage inequality at the national level. However, we find a wage increase only in the case of white-collar workers, who conduct more complex and abstract tasks if we filter out the composition effects caused by cherry-picking. As opposed to this, the wages of blue-collar workers carrying out more routine tasks do not increase. We present a lot of evidence showing that more advanced technologies of the parent company get implemented at the premises of acquired firms. For example, the acquired firms are more likely to innovate in cooperation with foreign business partners, they import more machines, and start to produce more expensive and higher quality product varieties. These results show that foreign direct investment has a major role in technology transfer to developing countries. Many of these technologies are favourable for white-collar workers, but less so for blue-collar workers. The results challenge the widespread opinion that firms from developed countries outsource only low-quality and simple jobs to developing countries. Even if the outsourced activities do not have an extremely large skill requirement compared to the average job in developed countries, they require a lot of high-skilled work compared to the tasks conducted in the average job in emerging countries like Hungary. These findings also imply that emerging Eastern European countries should increase the education and skill level of their workers to tap the full potential of FDI.

In the third paper (by Georgiev and Smolka), a novel and detailed firm-product level data set from Bulgaria over the period 2008-2015 is explored. It focuses on differences between firms in two radically different production regimes: (i) production on the firm's own account ("own-manufacturing"); and (ii) production on behalf of another firm ("processing trade"). As it turns out, this distinction is very different from the question of whether a firm is in foreign or domestic ownership. Processing trade can be seen as the flip side of offshoring. By offshoring we mean the relocation of certain parts of a fragmented production process abroad to low-wage countries. Over the last several decades, many firms in the U.S. and Western Europe have become increasingly involved in offshoring. To do so, firms need to form linkages with local suppliers abroad. Our knowledge of these suppliers is limited, however. Evidence about them is scarce and derives mainly from China. More generally, we have an incomplete understanding of the effects of offshoring on the economies of offshoring destinations.

We merge several micro-level data sets from Bulgaria (an important offshore destination in Europe) to shed some light on these issues. Importantly, our data allow us to draw a sharp line at the firm-product level between "ordinary" manufacturing firms, and firms conducting narrow processing activities for foreign headquarters. These processing firms do not hold property rights in the production process, the input materials used, and the final good produced. Nor are they responsible for the sourcing of inputs, the R&D activities, or the activities related to marketing, distribution, and sales. Instead, they carry out well-defined production tasks against payment of a manufacturing service fee from the headquarter. Processing firms in Bulgaria, thus, play a fundamental role in enabling firms in Western Europe to move production offshore.

The nature and detail of our data allow us to study the selection of firms (and products) into processing trade in a convincing way by focusing on transitions between production regimes. We can also distinguish between processing trade on behalf of a foreign headquarter, and processing trade for a domestic (Bulgarian) headquarter. Finally, we can study within-firm changes following processing trade with respect to a variety of outcome variables, including sales, the occupational composition of employment, wages, and exports.

We generate two sets of results. First, we find that firms sorting into processing trade are bigger and more productive than firms producing on their own account. They are also much more specialised in actual production tasks (which is reflected in higher labour and wage bill shares of blue-collar workers compared with the average firm), and they choose their most important product rather than a peripheral product for processing trade. Importantly, these observations are true *before* firms take up processing trade, that is, they are not a result of processing trade. This implies that processing trade might play an even more important role for the Bulgarian economy than perhaps previously believed, as it concerns some of the biggest and best-performing firms in the manufacturing sector with arguably high levels of human capital. The second set of results concerns the effects of processing trade on various firm outcomes. We obtain three main results. First, we see that, while total firm sales do not change following processing trade, the composition of sales changes, away from the firm's own goods, and towards processing trade. Secondly, we find that both the level and the composition of the workforce change: processing firms hire more production workers, which raises the labour and wage shares of production workers as well as total employment of the firm. In other words, labour demand, and especially demand for production workers, rises among processing firms, with a non-negative effect on production wages. And finally, we find that firms exporting a certain good under a processing trade regime are more likely to start exporting their own goods to the same destination. This is evidence for positive spill-over effects of processing trade into the firm's own activities.

The three papers together give detailed insights into the consequences of various aspects of globalisation on labour market inequalities and other important characteristics of the economies of countries in Eastern Europe. These findings could have implications for a wide range of policies facilitating international business activity and collaboration, related to e.g. education, investment and exchange rates. An important message from the second and third paper is that policymakers in offshore destination countries who are concerned with growth *and* wage inequality face a trade-off. More research into this issue is definitely needed, but our findings suggest that attracting production activities only, without trying to get technology by the parent firms transferred, could reduce wage inequality. Growth and development, however, are promoted by technology transfer, which tends to be skill-biased against production workers.

Index

Processing Firms

Domestic input prices, trade shocks, and firm growth

Attila Gáspár*and Balázs Reizer *†

March 26, 2024

Abstract

The impact of international price fluctuations on firm outcomes is well-attested in the literature. We know less how these effects compare to firm-level changes in the prices of domestic intermediate inputs, which are usually assumed to be homogeneous and have no cross-sectional variation across firms. We use a new Hungarian database with information on product-level intermediary inputs to compare the effect of domestic input price changes to price changes in upstream and downstream international markets on firm-level outcomes. We find that a one standard deviation increase in exposure to domestic costs has about the same employment effect as a one standard deviation increase in exposure to foreign currency fluctuations in the firm's export market. Our results suggest that firms' employment reactions to these effects, though similar in magnitude, are different in terms of their composition and have different effects on within-firm inequality. Consequently, the implications for policy are also different.

Acknowledgments: We thank Ruud Gerards and Bart Los for the valuable comments. This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement number 101004494.

*Centre for Economic and Regional Studies, Institute of Economics (KRTK-KTI). Contact: gaspar.attila@krtk.hun-ren.hu

†Corvinus University Budapest, Hungary. Contact: balazs.reizer@krtk.hun-ren.hu

1 Introduction

Export and import price fluctuations alter the relative position of firms participating in international trade compared to one another, and relative to firms operating only in the domestic market. Devaluation of the domestic currency, for example, will favor those firms that import some of their inputs, relative to those firms that rely on domestic inputs and those firms that export their output. Understanding the impact of exchange rates and domestic price fluctuations is a central question in research on international trade.

The literature on the impact of international price movements (see Auboin and Ruta 2013 for a review) uses country-firm-product level customs data to analyze the export-import activity of firms. These data enable the precise measurement of the impact of exchange rate shocks at the firm level. Using firm-level variation in the effective exchange rates has been shown to greatly enhance the fit between trade theory and trade data [Dai and Xu, 2017]. In the meantime, the same papers usually assume that firms use the same composite domestic intermediate input for production, besides capital and labor even though they are otherwise quite heterogeneous in their exposure to exchange rate fluctuations. The reason for this choice of convenience is that product-level data on domestic input use are scarce.

The assumption of a single homogeneous domestic input is problematic for many reasons. First of all, we do not know how firms can react to the change of domestic input prices compared to the change of import prices even though most of the firms use only domestic inputs. Second, domestically produced and imported inputs may be substitutes. For example, if the price of an imported input goes up (either because of currency devaluation, trade barriers, or industrial policy), some importers might switch to domestically produced substitutes. As a result, the increased demand for domestic inputs will raise the input prices of non-importing firms as well. Third, some firms may start to export products that were previously sold domestically if the domestic currency is devalued. This change in export behavior may have a negative effect on the domestic consumers of the firms. Despite the importance of domestic inputs, we have minimal information on how their prices affect firms.

In this paper, we contrast the effect of international price fluctuations (both on the markets of imported inputs and exported products) to the effect of heterogeneous domestic input cost fluctuations on firms. Our main contribution is that we construct a measure of firm-level domestic cost shocks using a novel Hungarian database that contains firm- and product-level information on intermediate input use. We can link these data to almost complete-coverage firm-level export and import data, and exhaustive administrative data on the firms' balance sheet and workers. Importantly, we link these different data sets using firm-level administrative identifiers, thus we can avoid more noisy, name or address-based matching techniques that are ubiquitous in the literature. Thus we can simultaneously capture firm-level heterogeneity in export prices, imported input prices, and domestic input prices.

We first closely replicate the results from Dai and Xu [2017] who build an empirical model to study the impact of firm-level exchange rate fluctuations on employment in China. They argue that this impact is realized through three different channels. The first is the import cost channel: an exchange rate appreciation makes imported inputs cheaper, which on the one hand pushes firms to substitute labor for foreign inputs (substitution effect); on the other hand it increases firms' total output thus increasing its demand for labor (scale effect). The second is the export price channel: appreciation of foreign currency makes the firms' output more expensive abroad, and the reduced demand abroad translates to reduced labor demand at home. The third is the import competition channel: a currency appreciation pushes imported product prices down, which in turn decreases output and labor demand for domestic firms that compete with imported goods on the domestic market. We estimate this model on Hungarian data between 2005 and 2020 and contrast our results to theirs. Our results are qualitatively similar, but not identical, as Hungary is a small and open economy so its international trade activity differs from that of China in both its scale and in its structure.

Next, as our main contribution, we present an extended empirical framework that allows firm-level heterogeneity in domestic input price fluctuations and we estimate its impact on employment. We first show that domestic inputs are indeed substitutes for imported inputs. Hence, they need to be taken into account to have a clear picture of the impact of foreign price fluctuations as well. Then we estimate their with the inclusion of a fourth channel, firm-specific domestic cost fluctuations. We quantify the relative importance of export prices, import costs, and domestic costs in the reallocation of labor in the study period. Finally, we look at the reduced-form relative impact of foreign exchange rate fluctuations and domestic price fluctuations on a range of other firm-level outcomes. These include measures of workforce composition and inequality, productivity, and trade. We find that a one standard deviation increase in exposure to domestic costs has about the same employment effect as a one standard deviation increase in exposure to foreign currency fluctuations in the firm's export market (an almost 3 percent reduction in employment by the firm). The composition effects are, however, different: when firms find it more profitable to substitute domestic labor for imported inputs, average wages and the share of part-time workers decrease; when firms' products become cheaper on the export markets, they are more likely to hire skilled and blue-collar workers; on the other hand, domestic cost increases mostly hurt blue-collar and part-time workers.

Our identification strategy is identical to Dai and Xu [2017]. We calculate the changes in firm-level effective exchange rates for exported goods and imported inputs. We calculate these by weighting bilateral real exchange rate fluctuations between Hungary and country k between t-1 and t by the firm-level export share to (import share from) country k in t-1, then add these up for all countries where the firm exports to (imports from). Similarly, calculate a firm-level change in the domestic input price by calculating the domestic price change for about 150 product categories between t-1 and t then calculate the average price change for each firm weighting by their input use in t-1. Using export shares, import shares, and product category shares in t-1 to calculate the expected exposure to exchange rate and domestic price fluctuations in t alleviates endogeneity concerns in t.

We contribute to the literature on the effect of export and import price changes on firm outcomes. Early studies showed that exchange rate changes affect employment and wages in export-oriented industries [Goldberg et al., 1999, Campa and Goldberg, 2001, Hua, 2007]. Recent studies using firm-level data confirmed that within the industry, exporters gain in employment compared to importers if the domestic currency devalues [Nucci and Pozzolo, 2010, Ekholm et al., 2012, Dai and Xu, 2017, Kaufmann and Renkin, 2018]. In addition, appreciation of the currency decreases the demand for low-skilled [Kaiser and Siegenthaler, 2016] and temporary workers [Yokoyama et al., 2021] because firms replace them with imported inputs. Our contribution is to show that firms adjust the composition of the workforce differently when they face domestic cost pressures.

Lastly, we contribute to the literature on the relationship between firm-level intermediate input and export prices. Amiti and Konings [2007] showed that firm productivity increases if the price of imported inputs decreases. Papers on the subject showed that firms that export products at a higher price also import more expensive inputs [Greenaway et al., 2010, Manova and Zhang, 2012, Fan et al., 2015, Bastos et al., 2018a, Carranza et al., 2020] because of quality upgrading. Closest to our paper are the findings of [Bastos et al., 2018b] who showed that export prices and domestic intermediate input prices are also positively correlated. We add to the literature by investigating the relationship between domestic input prices and other firm outcomes.

2 Theoretical framework and empirical strategy

Dai and Xu [2017] derive firm-level labor employment growth from a model where firms combine labor with inputs from many countries (including their own) to produce goods which that they can sell in any of those countries (again, including their own). In the model, domestic and imported inputs are imperfect substitutes which are combined with a CES aggregator function. Then, the composite input is combined with labor in a Cobb-Douglas production function. They arrive at the following expression for employment growth at firm i of country n:

$$\Delta \ln L_{in} = (\alpha_n - \bar{\eta}_n^M)\phi_{in}\Delta IMFEER_i - \beta_n \chi_{in} \Delta EXFEER_i - \gamma_n (1-\chi_{in})\Delta IMPEER_j + \lambda_n.$$

In the above equation, α_n, β_n, γ_n are functions of demand elasticities in country n, $\bar{\eta}_n^M$ is the average exchange rate pass through into the relative price of imported inputs; while ϕ_i is import intensity of the firm,[1] and χ_i is the export intensity of the firm.[2] IMFEER, EXFEER and IMPEER are the firm-specific import, exchange and import-penetration exchange rates, respectively. These are defined as follows:

$$\Delta IMFEER_i = \sum_k \omega_{ink}^M \Delta \ln e_{nk},$$

$$\Delta EXFEER_i = \sum_k \omega_{ink}^X \Delta \ln e_{nk},$$

$$\Delta IMPEER_j = \sum_k M_{kn} \Delta \ln e_{nk},$$

where $\ln e_{nk}$ is the change in the natural logarithm of the real exchange rate between countries n and k, and ω_{ink}^M (ω_{ink}^X) is the share of country k in the firm's total imports (exports), and M_{kn} is the import penetration ratio of country k in country n.[3] In this setting, the change of employment can be decomposed as the sum of three channels (the first three terms on the right

[1] $\phi_i = \frac{\sum_k IM_{ik}}{TCi}$ - the sum of imports from all countries, divided by the total costs of the firm,

[2] $\chi_{in} = \frac{\sum_k EX_{ik}}{SALESi}$ - the sum of exports to all countries, divided by the total sales of the firm,

[3] $M_{jk} = \sum_k \left(\frac{IM_{jk}}{DOMSALE_j + \sum_k IM_{jk}} \right)$ - the share of imports from country k in the total sales in the firms' industry j.

in Equation 2). The first is the import cost channel, the sign of which is ambiguous: if country n's currency gains value over the currency of country k, imports from k become cheaper; thus the firm may opt to substitute labor for imported inputs on one hand (negative substitution effect), and may employ more people if it can scale up production in the new environment (positive scale effect). The second is the export price channel: a currency appreciation makes exports less competitive, so the firm will cut labor demand to meet a lower product demand. The third is the import competition channel: if the currency appreciates against country k, and k is a country to which the firms' industry is open, then output in the industry becomes cheaper, so the firm will produce less output.

Importantly, in this setup λ_n captures the "equilibrium relationship between domestic prices (wages and domestic input price) and the exhange rates of all [of the home country's] trading partner countries", representing "a co-movement between exchange rates and factor prices determined in general equilibrium" (page 57 in Dai and Xu 2017). In their setting they use time fixed effects to absorb these economy-wide relationships. This follows from assuming that firms in country n face the same average domestic input price ($\bar{V}_n^*$ in Equation A12 in Appendix A1).

Our main contribution is that we relax this assumption and allow λ_n to vary across firms, in particular, we will assume that λ_n depends on domestic prices that observe firm-level heterogeneity:

$$\lambda_{in} = (1 - \phi_{in})\Delta DOMIPI_i + \lambda'_n.$$

The Domestic Input Price Index of firm i ($DOMIPI_i$) is defined as

$$\Delta DOMIPI_i = \sum_m \mu_{im} \Delta \ln V_{nm},$$

where μ_{im} is the share of inputs used by the firm from material input group m in its total spending on material inputs, and $\Delta \ln V_{nm}$ is the change of the log prices in the output of domestic firms in input group m. In what follows, we are going to re-estimate the main results from Dai and Xu [2017] to assess the impact of domestic and foreign cost changes and output prices on firm employment allowing for variation in the domestic input price index, and then we look at a set of alternative outcomes. In order to do this, we first present background information and our data.

The main equation that we estimate looks as follows:

$$\Delta \ln Y_{it} = \beta_0 + \beta_1 \phi_{i,t-1} \Delta IMFEER_i t + \beta_2 \chi_{i,t-1} \Delta EXFEER_i t +$$

$$+\beta_3(1-\chi_{i,t-1})\Delta IMPEER_jt + \beta_4(1-\phi_{i,t-1})\Delta DOMIPI_{it} + \nu_j + \lambda_t' + \epsilon_{it}$$

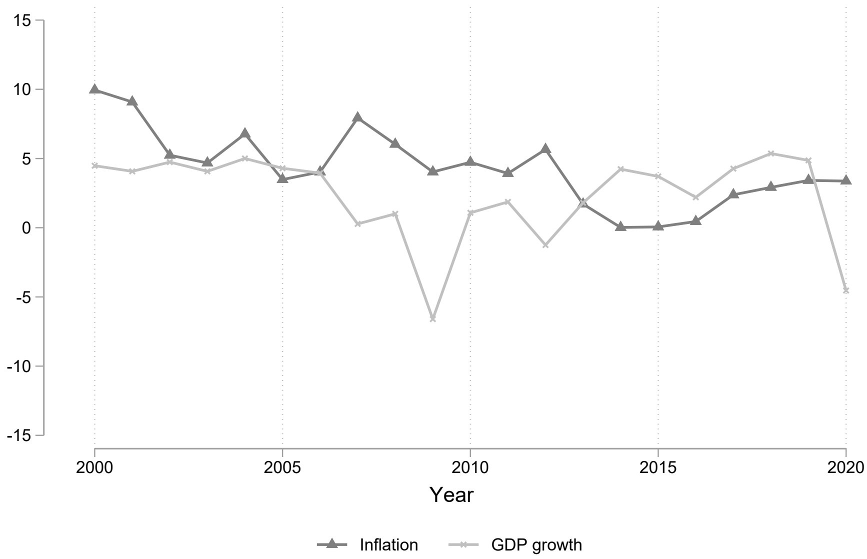
$\Delta \ln Y_{it}$ is the dependent variable of interest, which in the main specification is the change of employment at firm i between time $t-1$ and t. $\Delta IMFEER_it$ and $\Delta EXFEER_it$ are the changes in the firm-specific import and export effective exchange rates; $\Delta IMPEER_jt$ is the industry-specific import penetration ratio. To mitigate endogeneity concerns, we use $\omega^{X,M}$, M_{kn} and μ_{im} weights from $t-1$ when constructing these measures; for the same reason, we also use the lagged values of χ_i and ϕ_i (export and import intensity of the firm, relative to total sales and total costs, respectively). ν_j are industry-level fixed effects, the aim of which is to capture industry-level trends in employment. λ_t' are time-fixed effects. As the material use survey that we rely on to construct $DOMIPI_i$ is conducted every five years, the time unit of the analysis is also going to be five years.

3 Hungarian background and data

Hungary provides an ideal setting for studying firm responses to price adjustments. It is a small and open economy in Central Eastern Europe, with trade accounting for 149% of its GDP in 2005 according to World Bank data. A member state of the European Union since 2004, Hungary's biggest trading partners are other EU countries. Germany alone accounted for 30% of Hungarian exports and 27% of its imports in 2005 [WB:, 2023].

In the early 2000s, Hungary enjoyed low and decreasing inflation along with robust GDP-growth and a stable foreign exchange rate (see Figures 1 and 2). Growth, however, was driven partly by fiscal spending which became unsustainable by 2006. The effect of subsequent contractionary policies was then exacerbated by the Great Recession. As a consequence of these events, between 2005 and 2010 GDP mostly did not grow or even shrink (in 2008), and the currency suffered a substantial loss of value against the Euro (as much as 20% between December 2005 and the trough in March 2009).

Figure 1: Main macroeconomic indicators of Hungary, 2000-2020



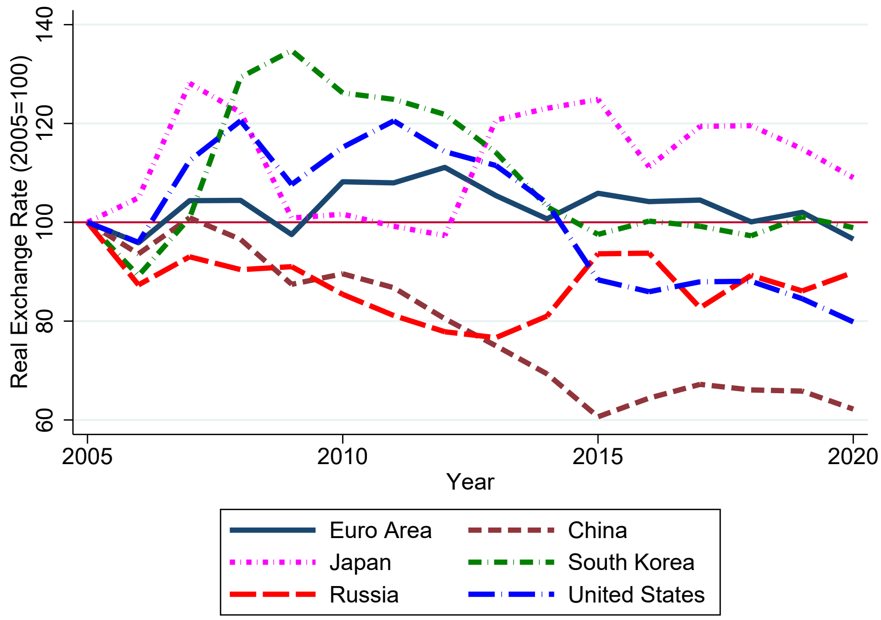
Notes: The figure plots changes in the consumer price index and the growth rate of gross domestic product between 2000 and 2020. Source: ECB [2023]

As our paper follows that of Dai and Xu [2017], it is important to highlight the most important, big-picture differences between the two settings. First and foremost, they look at China, which is either the biggest or the second-biggest economy in the world. Also, China is still considerably more closed to international trade than Hungary is (China's international trade relative to its GDP peaked at 64.5% in 2006, and stood at 37.3% in 2021, see WB: 2023). So their example is relatively closer to the textbook model of a large and closed economy, while ours is very close to that of a small and open one.

Besides the obvious ramifications regarding the sample size, studying a small and open economy also has two other peculiarities that we have to keep in mind. First, similarly to other small open economies Amiti et al. [2014], Hungarian firms either operate only on the domestic market, or they import and export heavily at the same time. Second, Hungarian firms usually export from and import to similar countries (mostly, to the Single European Market). This means that firm-specific effective import and export exchange rates are more correlated. We highlight these facts in Panels A and B of Figure 3. Panel A is a binned scatterplot (with each bin representing 1% of the data) showing the relationship between the share of imported inputs and the share of exports in sales at the firm level. It shows that import intensity explains (together with 4-digit industry fixed effects) more than half of the variation in export intensity, so firms that import are mostly the ones that also export. Panel B is a binned scatterplot (with each bin representing 1% of the data) showing the relationship between the firm-specific effective export and import exchange rates. Positive values correspond to a real currency appreciation over a five-year term, while negative values correspond to a currency depreciation. We also plot vertical and horizontal lines at zero. The reason for this is to show that the overwhelming majority of the firms who experienced an appreciation of their effective export exchange rate also experienced an (offsetting) appreciation of their import exchange rate.

Given these differences between the two empirical settings, while our estimated parameters should be qualitatively in line with the model predictions, important quantitative differences are to be expected compared to Dai and Xu [2017].

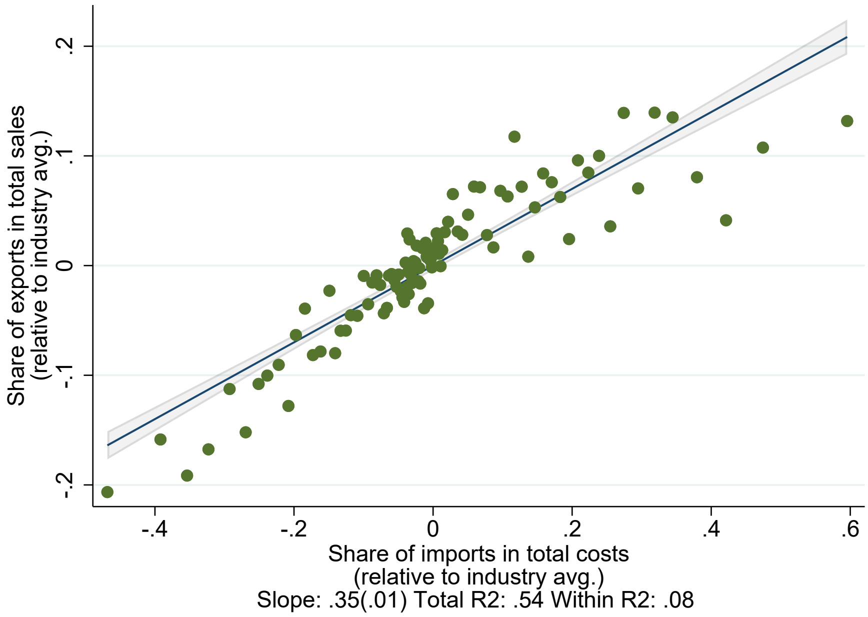
Figure 2: Real exchange rates



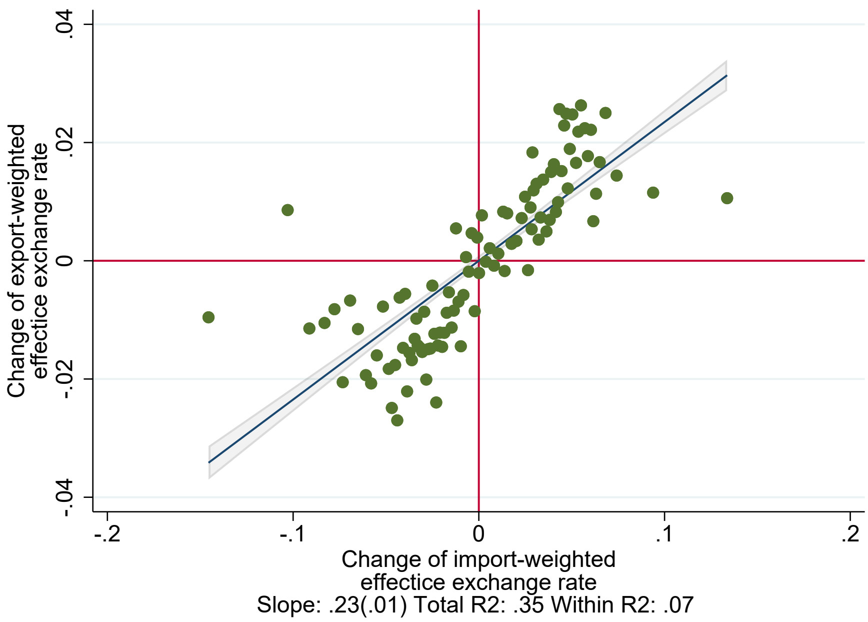
Notes: The figure plots real exchange rates against HUF for currencies of some of the most important trading partners of Hungary, 2005 to 2020 (Source: Darvas [2021])

Figure 3: Openness of Hungarian firms

Panel A: Export exposure as a function of import exposure of firms



Panel B: Export-weighted exchange rates as a function of import-weighted exchange rates of firms



Notes: Panel A is a binned scatterplot showing the relationship between the share of imported inputs and the share of exports in sales at the firm level. Panel B is a binned scatterplot showing the relationship between the firm-specific effective export and import exchange rates.

3.1 Data

We link five distinct administrative data sources for our empirical analysis, spanning the time period between 2005 and 2020. The data are available on-site in the secure data room of the Hungarian Central Statistical Office (HCSO). Our main data set is administrative balance sheet data based on tax declaration forms. We link this to input and output prices from surveys conducted by the HCSO (the Material and Service Use Survey, the PRODCOM survey, and firm-level export-import statistics), and a separate administrative data set on employees (Admin3). We link the data sets using an anonymized identifier which is generated by the HCSO and allows for perfect matching of the data at the firm level. In this section, we introduce the data sets one by one and then define the variables used in our empirical analysis. Finally, we present descriptive statistics on the data.

Balance Sheet Database, BSD consists of administrative tax declaration forms provided by the National Tax and Customs Administration. The declaration forms contain detailed information on the balance sheet and income statements between 2002 and 2020 of the universe of firms that practice double-entry bookkeeping. The database comprises balance sheet information for all years when the firms were active. Therefore, we can compute the change of revenue and employment and total factor productivity[4] between 2005 and 2020 without sample attrition.

The **Material and Service Use Survey, MSUS** collects data on the material and service expenditure of a sample of firms every five years; we have access to the years 2005, 2010, and 2015. Firms have to participate in the survey if their material expense exceeds HUF 500 million (€2.03 million at the 2005 average exchange rate). Firm-level inputs are categorized into 120 distinct categories and firms report total material expenditure in each category, but no quantities and unit prices are provided. To get around this problem, we derive domestic price indices from the PRODCOM database. The two data sets are linked through CPA codes of the input groups (Statistical Classification of Products by Activity).

PRODCOM (short for Production Communautaire) collects firm-level data on domestic sales and exports at the product level. This survey is requested by Eurostat and is available in every EU country. In the Hungarian version, all manufacturing firms have to participate if they employ at least 20 people; smaller manufacturing firms are represented by a random sample. Firms whose activity is primarily not in manufacturing participate if they made at least HUF 500 million from selling manufacturing goods (€2.03 million at the 2005 average exchange rate).

[4] We use the TFP estimator proposed by [Ackerberg et al., 2015].

The **Export-Import Database (ExIm)** of the HCSO contains firm-product level export and import statistics (prices and quantities as well). For trade outside the European Union, the database covers the universe of firms and their exported and imported products. For international trade within the European Union, firms have to report their export and import quantities as well as their prices by product and country if their total exports and imports are above a specific threshold. The threshold was HUF 100 million (€ 402,000) for exports and HUF 40 million (€ 161,300) for imports in 2005. The HCSO monitors on the basis of administrative value-added tax records whether firms exceed the thresholds. As a consequence, the coverage of the database is close to complete, and it accounts for 93-97 percent of total export and import value.[5]

Admin3 data set We use administrative social security data to estimate the effect of price changes on wage inequality and worker composition (for a detailed data description see [Sebők, 2019]). The database comprises wage and occupation (four-digit ISCO code) information on a random 50 percent sample of the Hungarian population and balance sheet data for the employer. We use the database to compute the average wage and within-firm wage inequality measures. In contrast to the other databases used in the study, this database does not share the same anonymized firm identifier. That is why we follow the strategy of Card et al. [2016] and use balance sheet information and statistical matching to connect the wage information of Admin3 and MSUS. The matching procedure is explained in detail by Boza and Reizer. This data set is only available until 2017.

Price Index Data Darvas [2021] provides real effective exchange rates for 178 countries for the whole study period, covering the overwhelming majority of the trading partners of Hungary (the exceptions being some active conflict zones with no inflation or exchange rate data, and some overseas regions of major countries).

3.2 Sample and summary statistics

Given that the MSUS survey is only available to us in 2005, 2010, and 2015, we can only construct the base-year material use weights (μ_{im}) for these three years, the effective time dimension of our sample is $t-1 \in \{2005, 2010, 2015\}$ and $t \in \{2010, 2015, 2020\}$. We exclude firm observations (similarly to Dai and Xu 2017) with less than 8 employees; missing or negative sales, capital or intermediate inputs; state-owned enterprises; and firms whose trade activity

[5] https://www.ksh.hu/apps/meta.objektum?p_lang=HU&p_menu_id=110&p_almenu_id=104&p_ot_id=100&p_obj_id=BFAA

in the BSD and the ExIm data sets are inconsistent with one another. We set the export and import value to zero for firm-year observations where no such activity was reported.

Our main outcome variable, as in Dai and Xu [2017] is $\Delta \ln L_{it}$, the change in the natural logarithm of the number of employees between t and $t-1$. The data comes from BSD. Besides this, in Section 4.3 we look at a range of alternative outcome variables on firm-level outcomes. These are defined as follows:

- ΔDomestic sales: Percentage change of domestic sales. The sources are the BSD and the ExIm data sets.

- ΔImport/export quantity: quantity index of exports and imports by the firm. For every product group we calculate the natural logarithm of the quantity exported (imported) in years $t-1$ and t. Next, we calculate the difference at the firm-product level, then calculate a firm-level value-weighed average growth rate. We can calculate this index only for firms that imported/exported similar products over time.

- ΔValue added: Change in the natural logarithm of value added. The data comes from BSD.

- ΔDomestic price: Price index of domestic sales. The sources are the BSD and the PRODCOM data sets.

- ΔTFP: Change in the Ackerberg et al. [2015] TFP estimate. The data comes from BSD.

- ΔLog(wage): Change in the natural logarithm of the average compensation of employees. The data comes from BSD and Admin3.

- ΔPart-time share: Change in the share of part-time workers. The data comes from BSD and Admin3.

- ΔCollege share: Change in the share of employees with a college degree. The data comes from BSD and Admin3.

- ΔUnskilled share: Change in the share of employees without a high school diploma. The data comes from BSD and Admin3.

- ΔSd(wage): Change in the relative standard deviation of wages. The data comes from BSD and Admin3.

- Δp90/p50: Change in the ratio of the average compensation of the top earning decile of employees to the median earners. The data comes from BSD and Admin3.

Table 1 shows descriptive statistics of the main right- and left-hand side variables. The first two rows show that about 20% of the studied firms participated in international trade as exporters, and about 19% percent of firms imported inputs. Hungarian firms mostly experienced a real depreciation of their currency against their trading partners (an about 2.5 and 2.7 percent decrease in exports and imports, respectively, and a roughly 0.9 percent decrease in the import penetration exchange rate).

Table 1: Descriptive statistics

Variable	Mean	Sd.	5^{th} pctl.	95^{th} pctl.	N	
$\chi(Exportintensity)$	.204	.317	0	.922	8355	[1,2]
$\phi(Importintensity)$	.193	.248	0	.712	8355	[1,2]
$\Delta EXFEER_{it}$	-.025	.067	-.13	.072	8355	[1,2]
$\Delta IMFEER_{it}$	-.027	.079	-.142	.086	8355	[1,2]
$\Delta IMPEER_{jt}$	-.009	.024	-.052	.023	8355	[1,2]
$\Delta DOMIPI_{it}$	.149	.278	-.146	.652	8355	[1,3,4]
$\phi_{t-1} \times \Delta IMFEER_{it}$	-.007	.025	-.052	.028	8355	[1,2]
$\chi_{t-1} \times \Delta EXFEER_{it}$	-.009	.029	-.067	.023	8355	[1,2]
$(1-\chi_{t-1}) \times \Delta IMPEER_{jt}$	-.005	.015	-.028	.013	8355	[1,2]
$(1-\phi_{t-1}) \times \Delta DOMIPI_{it}$	.119	.31	-.102	.567	8355	[1,2,3,4]
$\Delta \ln \bar{W}_{it}$	.301	.259	-.062	.739	4976	[5]
$\Delta UnskilledShare_{it}$	.032	.169	-.171	.345	4976	[5]
$\Delta WhiteCollarShare_{it}$	.017	.139	-.178	.235	4976	[5]
$\Delta PartTimeShare_{it}$	.02	.118	-.1	.186	4976	[5]
$\Delta \ln L_{it}$	.01	.558	-.813	.794	8229	[1]
$\Delta \ln VA_{it}$	.027	.769	-1.154	1.099	8355	[1]
$\Delta \ln TFP_{it}$	-.005	.634	-1.042	.952	8355	[1]
$\Delta ImportQ_{it}$	.563	1.839	-.814	3.694	8355	[1,2]
$\Delta ExportQ_{it}$	.726	2.299	-.716	5.966	8355	[1,2]

Notes: The table shows descriptive statistics. Data sources: [1] BSD,[2] ExIm,[3] MSUS,[4] PRODCOM, [5] Admin3

4 Results

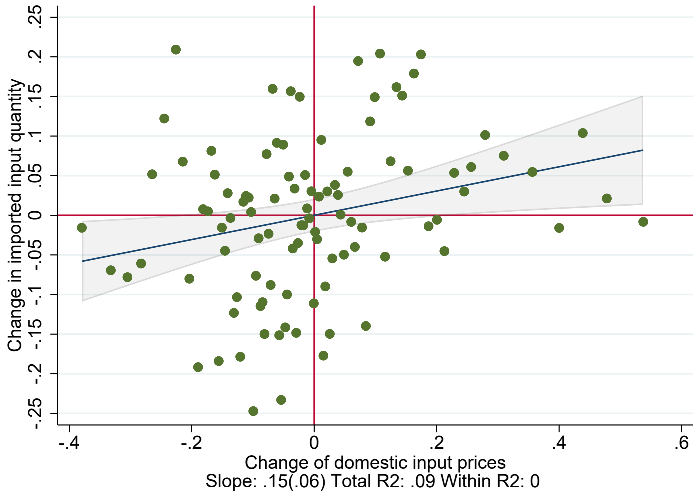
4.1 Motivating evidence

First, we show two pieces of motivating evidence, which serve a dual purpose: first, they serve as reality checks showing that our domestic input price indices indeed measure what they set out to measure. Second, they make the case that cross-firm heterogeneity in domestic input prices - though often assumed away - affects the firms' participation in international trade.

We start the empirical analysis by showing that the change in domestic prices indeed affects the composition of firm-level inputs. For this purpose, we investigate the relationship between domestic prices and the change in the quantity of inputs imported by the firm, holding the import exchange rate fixed. If imported and domestic inputs are substitutes, we expect that firms that face an increase in domestic prices start to import more. To show this, we order firms by the change of domestic import prices, and group them into 100 equally sized bins. Then we compute the average change in the volume of imported inputs (holding import exchange rates fixed, and including year and industry fixed effects).

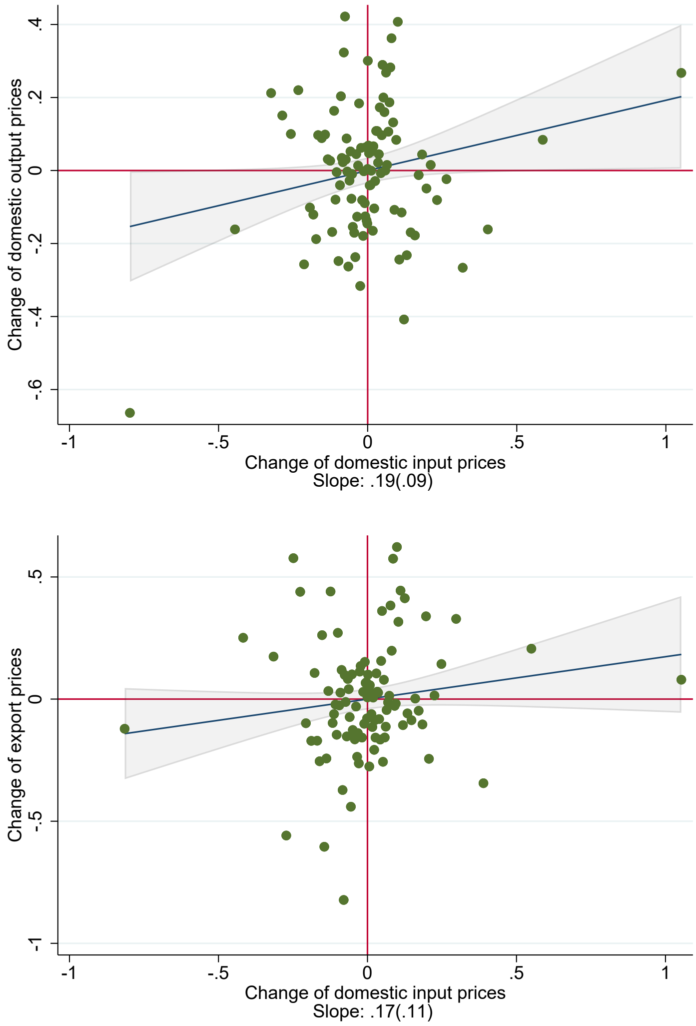
Figure 5 shows that firms with above-average input price growth increased their import compared to firms with below-average domestic input price growth. In particular, a 1 percent increase in domestic prices is associated with a 0.15 percent increase in imported input quantities over a five-year term. This suggests that imported and domestic inputs are substitutes to some extent.

Figure 4: Domestic prices and imported input quantities



Notes: The figure shows the relationship between the change in the imported input quantities and the change in domestic input prices. The message of the figure is that firms start to import more when domestic prices increase.

Figure 5: The relationship between the domestic input prices and output prices



Notes: The figure shows the relationship between changes in output prices and changes in domestic input prices. In Panel A the vertical axis corresponds to the change in the domestic output price, in Panel B the vertical axis corresponds to the export output price. The figure illustrates that heterogeneity of domestic costs is among the factors that determines both foreign and domestic output pricing.

Next, we test whether domestic input prices are correlated with output prices in the foreign and domestic markets. This tests to what extent heterogeneous domestic prices pass through into output prices. For this purpose, we order firms by the change of domestic input prices and make equally sized bins. Then, we compute the average change of domestic output prices (Panel A) and export output prices (Panel B). Figure 5 suggests that firms whose domestic input prices grew more than average indeed had higher output prices; unsurprisingly, the relationship is more precisely estimated for pass-through into domestic prices.

4.2 Baseline results

Table 4.2 shows our baseline results upon estimating Equation 2. We estimate it using either 4-digit industry fixed effects, which are proposed by Dai and Xu (columns 1 and 3) and using 2-digit industry fixed effects (columns 2 and 4), to accommodate for the fact that we have a substantially smaller sample. First we estimate the model without the inclusion of firm-specific domestic costs (columns 1 and 2), and then with their inclusion (columns 3 an 4) to see if it affects the estimates of the other coefficients.

The signs of our estimated exchange rate coefficients are consistent with the three expected channels of pass-through. The coefficient on $\Delta IMFEER$ is always close to zero and insignificant; positive when 2-digit fixed effects are included (broad industry categories), and negative when 4-digit industry fixed effects (fine-grained categories) are used. The model predicts that import costs have two effects on employment: the substitution effect is negative (firms substitute labor for imported inputs when these become cheaper), and the scale effect is positive (access to cheaper inputs allows firms to scale up their production, thus eventually demand more labor). In the Chinese case study, the scale effect won this tug-of-war, and their significant point estimates were between 0.16 and 0.21, depending on the specification (Dai and Xu 2017, Table 4 on p. 60). In our Hungarian example, the scale effect and the substitution effect seem to cancel each other out, with the substitution effect being perhaps (slightly) larger than the other.

Our coefficients on $\Delta EXFEER$ are negative and strongly significant in all specifications: if the currency appreciates against the export markets, Hungarian firms' products become more expensive abroad, consequently also reducing firms' labor demand. It is important to see how strong this effect is: for a firm that exports all its output ($\chi = 1$), a 1 percent evaluation of the currency induces a 0.88 to 0.96 percent reduction in employment. The effect is three times larger than in the Chinese example (where the corresponding coefficient is -0.32).

The coefficients on $\Delta IMPEER$ are negative, as expected: an appreciation of the currency drives down the prices in industries heavily penetrated by foreign competitors, driving down the demand for the products of domestic producers in the same industry. The effect, is, however, insignificant in all cases. Again, the point estimates are much larger than in the Chinese example (which is around -0.1).

The differences in the effect sizes and significance levels between the Hungarian and the Chinese examples are consistent with what we would expect to be the differences between a small and open, and a large and relatively more closed economy. Substitution of labor with imported inputs is easier in the Common European Market while scaling up production is harder, potentially due to constraints on specialized labor, so the scale effect and the substitution effect cancel each other out in the import cost channel. More specialized export-oriented firms are more sensitive to export market fluctuations, so the export price channel is more pronounced. Finally, the economy is smaller so there are just not that many industries where there are readily available domestic producers, so the import competition channel is insignificant; though where there are such domestic producers, they suffer more from the competition (so the coefficient is larger on average).

Now that we have established that our results on the pass-through of firm-specific exchange rates are consistent with theoretical predictions, we turn to the effect of domestic costs. The coefficient on firm-specific domestic cost changes is around -0.09; meaning that a one percent increase in domestic costs reduces employment by about 0.09 percent. Importantly, however, domestic cost changes are exhibiting much more variation than exchange rates. From Table 1 we see that the standard deviation of export currency exposure is 0.029, while the standard deviation of domestic cost exposure is 0.31. Thus a one standard deviation increase in export exchange rate exposure has a comparable effect on employment than a one standard deviation increase in exposure to domestic costs ($0.029 \times -0.09 = 0.0261$ vs $0.31 \times -0.09 = 0.0279$). This means that in the Hungarian case, variation in domestic costs is an important channel in determining changes in employment, as are (export) exchange rate dynamics. Perhaps because of the small and open economy nature of our empirical setting, however, the effect of domestic costs on employment is decoupled from the effect of currency fluctuations: including domestic costs does not change the other parameter estimates in the statistically distinguishable way.

We check whether our estimates are heterogeneous along the dimension of firm size. To do this, we slice the sample at the median average employment and estimate Equation 2 for below- and above-median-sized firms. The results are presented in columns 5 and 6 of Table 4.2, respectively. The signs of all coefficients are the same, except for the import-weighted effective exchange rates: here, the effect is positive for small firms, and negative for large firms, though none of the estimates are statistically distinguishable from zero. It seems that small firms are more heavily affected by the scale effect, while large firms from the substitution effect, but not by a large margin. Another interesting feature is that the export cost channel is stronger for smaller firms. In comparison, the domestic cost channel is smaller for larger firms, and the coefficient on the other of the two is insignificant in both cases. Our interpretation is that small firms are more specialized, and export to fewer markets, so they cannot as effectively absorb exchange rate shocks by, for example, switching markets. On the other hand, large firms are more likely to export and import more at the same time (e.g. companies in the automotive industry mostly import the parts and export assembled cars), so currency fluctuations' effects offset one another. Consequently, these firms are relatively more responsive to domestic cost shocks (these firms probably chose Hungary as a location because of low domestic costs in the first place).

We now turn to estimating how these four channels affect outcomes other than employment.

Table 2: Baseline results

Dep. variable: $\Delta \ln L_{it}$	(1)	(2)	(3)	(4)	(5)	(6)
$\phi_{i,t-1}\Delta IMFEER_{it}$	-0.103	0.00588	-0.0619	0.0544	0.480	-0.177
	(0.278)	(0.292)	(0.276)	(0.289)	(0.492)	(0.423)
$\chi_{i,t-1}\Delta EXFEER_{it}$	-0.956***	-0.926***	-0.920***	-0.884***	-1.284***	-0.484
	(0.254)	(0.243)	(0.255)	(0.243)	(0.423)	(0.341)
$(1-\chi_{i,t-1})\Delta IMPEER_{jt}$	-0.465	-0.502	-0.426	-0.453	-0.587	-0.546
	(0.599)	(0.671)	(0.595)	(0.657)	(0.969)	(0.851)
$(1-\phi_{i,t-1})\Delta DOMIPI_{it}$			-0.0856**	-0.0966**	-0.0706	-0.126***
			(0.0428)	(0.0459)	(0.0530)	(0.0382)
Firm- specific domestic costs	No	No	Yes	Yes	Yes	Yes
Industry FE	4-digit	2-digit	4-digit	2-digit	2-digit	2-digit
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All firms	All firms	All firms	All firms	Small firms	Large firms
Observations	8,192	8,226	8,192	8,226	4,166	4,108
R-squared	0.081	0.034	0.082	0.036	0.047	0.054

Notes: The table reports OLS estimation results of Equation 2. The dependent variable is change in the logarithm of employment over a 5-year period. ϕ: import intensity, χ: export intensity; $\Delta IMFEER$, $\Delta EXFEER$, $\Delta IMPEER$, $\Delta DOMIPI$ are firm-specific import, export and import penetration exchange rates and the domestic input price index, respectively. Columns (1) and (2) are our estimates of the main specifications from Dai and Xu [2017]; Columns (3) and (4) are our main specifications which include the firm-specific domestic input prices. Columns (5) and (6) split the sample of Column (4) into firms of below- and above-median employment. Columns (1) and (4) include 4-digit industry fixed effects, the rest use 2-digit industry fixed effects. Standard errors are clustered at the industry level. $*$: Significant at 10%. $**$: Significant at 5%. $***$: Significant at 1%.

4.3 Alternative outcomes

Next, we estimate Equation 2 with alternative outcome variables. The goal of this exercise is to better understand how firms react to a changing foreign and domestic cost environment. The first set of outcomes that we look at describe the changing composition of the workforce (change in the average wage, the share of unskilled, white-collar, and part-time workers); the second set comprises of productivity and trade-related measures (change in value-added, total factor productivity, and quantity indices of export and import).

Columns 1 to 4 of Table 4.3 show the results on worker composition. The effect on wages confirms that the substitution effect dominates the import cost channel: if the currency appreciates against the countries from where their imports come, firms substitute domestic labor for more imported inputs, and this depresses wages (Column 1); in this case, the laid-off are more likely to be part-time workers, so their share decreases (Column 4). On the other hand, when the currency appreciates against countries where their products are exported, firms are more likely to lay off the unskilled (Column 2) and white-collar workers (Column 3). However, when firms decrease employment because of an increase in domestic costs, they are more likely to retain white-collar and part-time workers (Columns 3 and 4). This suggests that not all cost-induced employment adjustments are identical in practice and firms optimize not just the scale, but the composition of the workforce as well. This also means that employment adjustments have different impact on firm-level wage inequality, when the underlying reasons are different. In Columns 5 and 6 the outcome variables are the change in the relative standard deviation of wages within the firm, and the change in the pay ratio of the top income decile and the median earner at the firm. The results show that when firms lay off people because they substitute labor for inputs upon a currency appreciation (first row), firm-level wage inequality tends to decrease; while inequality increases if the currency appreciates towards the export markets, and thus firms suffer a negative demand shock (second row). Similarly, firm-level wage inequality tends to increase when firms are experiencing an increase in domestic input costs (fourth row).

Finally, in Table 4.3 we look at the relative impact of domestic and foreign price shocks on trade and productivity. These results are in line with the mechanics of our model, and serve as a reality check. Trade responses are in line with expectations: the firm level volume imports increase when the currency appreciates towards countries from where firms are importing inputs; imports decrease when the currency appreciates against export markets, as the higher price drives down product demand, and thus the demand for imported inputs. Similarly, firms import less inputs, when the currency appreciates against their foreign competitors on the domestic market. The coefficient is marginally insignificant on domestic costs, but it is quantitatively very similar to the slope of the line in Figure 5, so it seems that firms are more likely to import inputs when their domestic costs increase. When the outcome is the index of export volume (Column 2), the coefficients are insignificant due to a limited sample size, but their sign is mostly in line with predictions. The effects on value added and total factor productivity are also largely mechanical: If the currency appreciates towards input markets, firm will rely on imported inputs more and thus add less value to their production (Column 3). Meanwhile, if the currency appreciates towards export markets, firms face lower product demand, but apparently cut employment more excessively, leading to an increase in productivity (Column 4). We see no significant effect of the domestic cost channel on any of these measures.

Table 3: Effects on worker worker composition

	(1)	(2)	(3)	(4)	(5)	(6)
Dep variable:	$\Delta \ln \bar{W}$	$\Delta Unskilled$	$\Delta WhiteCollar$	$\Delta PartTime$	$\Delta RelativeSD$	$\Delta p90/p50$
$\phi_{i,t-1}\Delta IMFEER_{it}$	-0.471***	-0.133	0.00619	-0.223***	-0.569***	-0.625
	(0.176)	(0.123)	(0.0938)	(0.0662)	(0.207)	(0.522)
$\chi_{i,t-1}\Delta EXFEER_{it}$	-0.0784	-0.228**	-0.124*	0.0206	0.0382	0.719**
	(0.137)	(0.102)	(0.0663)	(0.0561)	(0.141)	(0.358)
$(1-\chi_{i,t-1})\Delta IMPEER_{jt}$	-0.248	-0.135	0.0517	0.228	0.355	0.949
	(0.286)	(0.248)	(0.181)	(0.168)	(0.293)	(0.733)
$(1-\phi_{i,t-1})\Delta DOMIPI_{it}$	0.00562	-0.00746	0.0148**	0.0139*	0.0264**	0.0315
	(0.0135)	(0.00538)	(0.00665)	(0.00718)	(0.0115)	(0.0258)
Firm- specific domestic costs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	4-digit	4-digit	4-digit	4-digit	4-digit	4-digit
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,888	4,888	4,888	4,888	5,088	5,087
R-squared	0.098	0.145	0.089	0.105	0.159	0.170

Notes: The table reports OLS estimation results of Equation 2 with alternative outcomes. The dependent variables are the change in the average log wage in the firm ($\Delta \ln \bar{W}$), the change in the share of the unskilled workers employed at the firm ($\Delta Unskilled$), the change in the share of white-collar workers at the firm ($\Delta WhiteCollar$), the change in the share of part-time workers at the firm ($\Delta PartTime$), the change in the relative standard deviation of wages at the firm ($\Delta RelativeSD$) and the change in the ratio of the 90th and the 50th income percentile at the firm ($\Delta p90/p50$), respectively.

Table 4: Effects on firm performance

Dep variable:	(1) ΔQ^{IM}	(2) ΔQ^{EX}	(3) ΔVA	(4) ΔTFP
$\phi_{i,t-1}\Delta IMFEER_{it}$	3.621**	-3.559	-0.730*	-0.428
	(1.410)	(2.529)	(0.397)	(0.351)
$\chi_{i,t-1}\Delta EXFEER_{it}$	-4.599***	-1.045	0.515	1.370***
	(1.381)	(1.961)	(0.379)	(0.320)
$(1-\chi_{i,t-1})\Delta IMPEER_{jt}$	-5.620*	-3.412	0.889	0.878
	(3.183)	(4.724)	(0.694)	(0.608)
$(1-\phi_{i,t-1})\Delta DOMIPI_{it}$	0.202	0.0251	-0.00993	0.0121
	(0.132)	(0.232)	(0.0306)	(0.0270)
Firm- specific domestic costs	Yes	Yes	Yes	Yes
Industry FE	4-digit	4-digit	4-digit	4-digit
Year FE	Yes	Yes	Yes	Yes
Observations	4,248	3,414	8,243	8,243
R-squared	0.165	0.169	0.083	0.079

Notes: The table reports OLS estimation results of Equation 2 with alternative outcomes. The dependent variables are change in the import quantity index (ΔQ^{IM}), the export quantity index (ΔQ^{EX}), value added and Ackerberg et al. [2015] TFP estimates (ΔTFP), respectivey

5 Discussion and conclusion

In this paper, we estimated the model of Dai and Xu [2017] using Hungarian data, and discussed how the mechanics of their model play out differently in a small and open economy, in contrast to a large and more closed one. Then we relaxed their assumption of homogeneous domestic inputs in production. Combining detailed data on firm-level input use and domestic prices, we calculated an index of firm-level domestic input price change and incorporated it into the same empirical setting.

We found that firm-level variation in domestic input prices is an important, and previously neglected channel that has an important role in determining firm-level variation in employment over time. We find that a one standard deviation increase in the firm level domestic cost index has about the same effect on employment as a one standard deviation change in firm-specific effective export exchange rates.

Changes in domestic and foreign input costs, as well as export prices, have quite different effect on worker composition and wage structure. Substitution of domestic labor for foreign inputs (the effect of a currency appreciation against input markets) decreases wages overall, but also wage inequality within the firm. A negative export demand shock (the effect of currency appreciation against export markets) tends to increase firm-level wage inequality, and so does a negative supply shock (the effect of an increase in domestic input costs).

This has important implications for policy. Our results suggest that different types of people fall out of employment when the firms are pressured by changing export prices, changing import prices, and changing domestic costs. Even if the net change in employment is similar in magnitude, different types of intervention are needed when those laid off are mostly part-time workers, or mostly unskilled.

References

European central bank, eurosystem - exchange rate of the hungarian forint, 2023. URL https://www.ecb.europa.eu/stats/policy_and_exchange_rates/euro_reference_exchange_rates/html/eurofxref-graph-huf.en.html.

Wits - hungary trade, 2023. URL https://wits.worldbank.org/CountrySnapshot/en/HUN/textview#:~:text=The%20top%20five%20countries%20to,partner%20share%20of%205.84%20percent.

D. A. Ackerberg, K. Caves, and G. Frazer. Identification properties of recent production function estimators. *Econometrica*, 83(6):2411–2451, 2015.

M. Amiti and J. Konings. Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. *American Economic Review*, 97(5):1611–1638, 2007.

M. Amiti, O. Itskhoki, and J. Konings. Importers, exporters, and exchange rate disconnect. *American Economic Review*, 104(7):1942–1978, 2014.

M. Auboin and M. Ruta. The relationship between exchange rates and international trade: a literature review. *World Trade Review*, 12(3):577–605, 2013.

P. Bastos, D. A. Dias, and O. A. Timoshenko. Learning, prices and firm dynamics. *Canadian Journal of Economics/Revue canadienne d'économique*, 51(4):1257–1311, 2018a.

P. Bastos, J. Silva, and E. Verhoogen. Export destinations and input prices. *American Economic Review*, 108(2):353–392, 2018b.

I. Boza and B. Reizer. Role of flexiblewage components in gender wage differences. *GI-NI Project Discusion Paper.*

J. M. Campa and L. S. Goldberg. Employment versus wage adjustment and the us dollar. *Review of Economics and Statistics*, 83(3):477–489, 2001.

D. Card, A. R. Cardoso, and P. Kline. Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women. *The Quarterly journal of economics*, 131(2):633–686, 2016.

J. E. Carranza, A. González-Ramírez, and A. Pérez. The quality and the destination of the colombian manufacturing exports. *The Journal of International Trade & Economic Development*, 29(3):247–271, 2020.

M. Dai and J. Xu. Firm-specific exchange rate shocks and employment adjustment: Evidence from china. *Journal of International Economics*, 108:54–66, 2017.

Z. M. Darvas. Timely measurement of real effective exchange rates. Technical report, Bruegel Working Paper, 2021.

K. Ekholm, A. Moxnes, and K. H. Ulltveit-Moe. Manufacturing restructuring and the role of real exchange rate shocks. *Journal of International Economics*, 86(1):101–117, 2012.

H. Fan, Y. A. Li, and S. R. Yeaple. Trade liberalization, quality, and export prices. *Review of Economics and Statistics*, 97(5):1033–1051, 2015.

L. Goldberg, J. Tracy, and S. Aaronson. Exchange rates and employment instability: Evidence from matched cps data. *American Economic Review*, 89(2):204–210, 1999.

D. Greenaway, R. Kneller, and X. Zhang. The effect of exchange rates on firm exports: The role of imported intermediate inputs. *The World Economy*, 33(8):961–986, 2010.

P. Hua. Real exchange rate and manufacturing employment in china. *China Economic Review*, 18(3):335–353, 2007.

B. Kaiser and M. Siegenthaler. The skill-biased effects of exchange rate fluctuations. *The Economic Journal*, 126(592):756–780, 2016.

D. Kaufmann and T. Renkin. Manufacturing prices and employment after the swiss franc shock. study on behalf of the state secretariat for economic affairs, seco. Technical report, KOF Studien, 2018.

K. Manova and Z. Zhang. Export prices across firms and destinations. *The Quarterly Journal of Economics*, 127(1):379–436, 2012.

F. Nucci and A. F. Pozzolo. The exchange rate, employment and hours: What firm-level data say. *Journal of International Economics*, 82(2):112–123, 2010.

A. Sebők. The panel of linked administrative data of cers databank. Technical report, Budapest Working Papers On The Labour Market, 2019.

I. Yokoyama, K. Higa, and D. Kawaguchi. Employment adjustments of regular and non-regular workers to exogenous shocks: evidence from exchange-rate fluctuation. *ILR Review*, 74(2):470–510, 2021.

FDI, technological progress and inequality: A task-based approach

Rita Pető[1] and Balázs Reizer[1,2]

[1] Centre for Economic and Regional Studies, Budapest, Hungary
[2] Corvinus University Budapest, Budapest, Hungary
March 26, 2024

Abstract

FDI is shown to increase growth at the cost of higher inequality. Inequality increases because investors cherry-pick the best firms and raise wages and employment at firms that pay high salaries even before FDI. However, we have limited knowledge of how FDI affects the wages conditional on selectivity. We use a high-quality linked employer-employee database from Hungary and an event study approach for identification. We estimate the effect of FDI on task returns to go beyond estimating wage growth by educational level. We show that FDI increases the returns to abstract tasks and does not affect the returns to routine tasks and face-to-face tasks. We also show that acquired firms improve product quality, innovate, and import more machines after FDI. The most likely explanation for the results is that firms change their technology in a skilled-biased way.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement number 101004494 and the European Research Council (ERC) under the grant agreement number 724501

1 Introduction

The global yearly FDI flows exceed more than 1000 billion dollars a year 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 is shown to increase 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 acquiring firms cherry-pick the best domestic firms and workers. In other words, FDI increases employment at high-paying firms (Arnold et al. 2009; Brown et al. 2006, 2010; Helpman et al., 2016) and firms upgrade their workforce after acquisition (Bernard & Jensen, 1997; Koch & Smolka, 2019). In contrast to this, we have only limited knowledge of how FDI affects individual wages if we filter out selectivity across firms and unobserved heterogeneity across workers.

A better understanding of the individual wage effect could give new insights into understanding the effect of FDI. On the one hand, FDI can increase the demand for low-skilled workers and thus decrease within-firm inequality as predicted by the Heckshe-Ohlin model (Leamer, 1995; Stolper & Samuelson, 1941). On the other hand, FDI can increase wage inequality within and between firms for several reasons. For example, FDI may provide access to foreign markets. If the size of the firms grows due to new market access, 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 FDI improves the technology of acquired firms and makes them more skill-biased at the same time. 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 how FDI affects wages by worker type. We contribute to the literature in two ways. First, we use an event study approach and control for firm and worker selectivity to filter out the effect of worker upgrading. Second, we investigate the potential mechanisms leading to the increase of within-firm inequality.

Our empirical strategy has two important strengths compared to previous papers. First, firms most likely cannot control whether they are acquired one year earlier or later while we control for selectivity in FDI with individual fixed effects and firm-specific fix trends. Therefore, we can use an event study approach to estimate the causal effect of FDI on wages. Second, 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 effect of FDI on task returns directly. Finally, we extend our event study approach with firm and worker fixed effects as in Abowd et al. 1999 and Frias et al. 2022 to control for selectivity in FDI and worker composition.

Our main results suggest that FDI increases the return to abstract tasks only. We find that FDI increases the return to abstract tasks by 1.6 percentage points while the return to face-to-face tasks or to routine tasks does not change. The results are qualitatively similar if we restrict attention only to firms that switch ownership, control for time-varying firm-level characteristics, and the export activity of firms. We also show that the effect is similar in the service and manufacturing sectors.

As the second step of the analysis, we investigate how FDI effects the composition of the workforce. We found the average share of abstract, routine, and face-to-face tasks remains the same after the FDI. These are crucial findings because (Card et al., 2018; Lindner et al., 2022) showed that the return of abstract tasks and their share in production should change in the opposite direction if the technology of the firm remains the same after FDI.

As the second step of the analysis, we investigate how FDI effects the composition of the workforce. We found the average share of abstract, routine, and face-to-face tasks remains the same after the FDI. Even though the share of tasks does not change on the average, we find evidence of task restructuring across workers. For this purpose, we compute the share of incumbent workers who are reassigned to a new occupation. We define occupational changes as upgrading (downgading) if the share of abstract tasks is higher (lower) in the new occupation than in the previous one. Then we show that both occupational upgrading and downgrading become more likely after FDI. These results complement the findings of (Koerner et al., 2023), who showed the same occupational restructuring at German firms that invest abroad. The finding that there is restructuring after acquisition without change in the share of the abstract task in production is a crucial finding because (Card et al., 2018; Lindner et al., 2022) showed that the price of abstract tasks and their share in production should change in the opposite direction if the technology of the firm remains the same after FDI.

This leads to the last part of the paper, where we examine the possible mechanisms. The most likely explanation for our empirical findings is that firms upgrade their technology in a skilled biased way after FDI and increase their relative demand for abstract tasks. We show a battery of suggestive evidence in line with this mechanism. First, we use an event study approach to show that firms are more likely to report innovation activities right after FDI. Furthermore, they are more likely to innovate in cooperation with foreign firms of their company group while the intensity of R&D activities does not change. This means in our interpretation that the acquired firm gets access to and implements the technology of the parent firm. Second, we show that acquired firms import more machinery after FDI which may be complements to abstract tasks and substitutes for routine tasks. Third, we show that acquired firms switch to the production of more expensive products which may be a sign of product quality upgrade. Additionally, we also show that the return to routine tasks decreases significantly after a foreign investment that is coming from high-income countries and does not change in other firms. This result is also in line with the hypothesis that firms get access to a skill biased technology from more advanced countries in this case.

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

An other possible mechanism is related to the change of monitoring costs. According to Lazear (2018) firm use incentive contracts to increase effort if they cannot monitor effort. It is possible that firms introduce incentive contracting and bonus payments to incentivize workers to do 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 the monitoring costs are higher if the distance between the home country of the investor and Hungary is larger. In contrast to this, we do not find evidence that the distance to the country of the investor affects the return of tasks.

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 that connect FDI 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). Many 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), 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

On top of the richness of the 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 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) 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).

The Admin 3 database contains administrative wage data for 50 percent random sample of the population between 2003 and 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 a 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 Appendix A.

[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.

We split the 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 includes all other foreign firms, thus those that 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 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 to participate in the survey. We can merge the CIS database to the balance sheet data but we are not able to merge them to 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 the Eurostat and is available in every country of the European Union. Most importantly, the database consists of information on wage elements (the base wage, bonuses, premia, and overtime payments) earned in May. Compared to most other countries, the Hungarian version is repeated every year and has a unique firm identifier that allows to merging of the data to 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 on the worker level. Firms with less than 50 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 5th, 15th, or 25th 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 the amount and unit value of import and export by country, year, and products. We match the data to the Balance Sheet record of the firm based on a unique firm identifier. We are not able to merge it with the administrative employment and wage data due to administrative restrictions.

3.1 Sample selection

We restrict our sample to one month (October) every year even though the worker-level information is available on a monthly basis because the firm-level data is available only on a yearly level. We further restrict our sample to workers that were employed by labor contract at a firm that has at least 10 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 who work full-time (i.e. work at least 36 hours per week) and has non-missing wage. We use the job with the highest salary only if a worker has more jobs at the same time, then. Our main right-hand side variable is the daily wage (monthly wage divided by the number of days worked). The restricted sample contains 11,957,372 worker-year observations corresponding to 1,845,958 workers working at 103,201 firms.

37.5 percent of our worker-year observations work at foreign-owned firms. 5.3 percent of our worker-year observations correspond to firms that were acquired between 2004 and 2017 and 36.6 percent to other foreign firms.

In the main part of the analysis, we focus on acquired firms only, firms for which we observe the pre- and post-acquisition periods. We have 2663 such firms. The number of acquisitions per year varies between 93 and 367, see appendix Table 6. In this subsample we have 628,331 worker-year observations, half of which correspond to foreign-owned years.

In our second sample, we keep all the firms even if they were foreign in every observed year or they were always domestic. The reason for this is that we use individual fixed effects in our robustness checks, where fixed effects are identified from the movement of workers between companies. If we would restrict the sample to specific firms than, we would not observe all worker movements and would underestimate the variance of worker fixed effects (Bonhomme et al., 2023).

3.2 Measurement of tasks

Like many studies on 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 Appenedix A for more details on the construction of our task measures. Later 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, and are likely to complement computers while they do not need face-to-face interaction. Thus these tasks can be offshored while they cannot be automatized. Our second measure, "automatization", identifies routine and repetitive tasks that 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 these tasks 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 5.

We follow Koerner 2023 to define up and downgrade of tasks. Although we know the workers' occupations monthly, we construct quarterly data by keeping February, May, August, and November from each year as the reference month. If an employee had more than one job, we only consider the job with the highest earnings. We also know the importance of abstract, routine, and face-to-face tasks for the given occupation based on our continuous task indicators detailed above. we define occupational upgrades (downgrades) as job switches accompanied by an increase (decrease) in the given task. For example, upgrading abstract tasks means that the new job involves more abstract tasks, and upgrading automation means that the new job involves more easily automatized tasks. Up and downgrades are only defined within worker-firm spells. (If the employee leaves the company and has a new occupation, we call it separation.) It is important to note that although we distinguish between three types of tasks, each of them varies between occupations, but not within. That is, upgrades and downgrades coincide with a change of occupation, and thus in most cases, the importance of all three tasks changes once, i.e. the downgrading of routine tasks is almost always accompanied by the up or downgrading of abstract tasks and tasks requiring personal contact.

We follow the strategy of Ebenstein et al. 2014 and Hakkala et al. 2014 to calculate the 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 the individual level task use on the firm level to compute the 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 done by worker i at year t at firm j. Thus, the numerator means the total amount of task n used by firm j at year t. So the $Taskuse_{njt}$ 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 to product variety and a residual price part running the following regression:

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

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

where the dependent variable is the price of product variety v produced by firm j at year t and exported to country c. The explanatory variables are year fixed effect, and product fixed effect P_v showing the economy-level average price of a variety v, country fixed effect P_c showing whether the firms export the products more expensively to the country c compared to other countries. In this setup, the residual price (ϵ_{jvt}) has a direct interpretation as well (Faber, 2014; Fieler et al., 2018). If ϵ_{jvt} is positive then the 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 P_{jt} variable increases within the firm between years, then it means that the firm sells relatively more expensive varieties compared to previous years. We define the firm-level country price (P_{ct}) similarly to equation 3 but use country fixed effects (P_c) in the denominator.

Finally, we define the 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 positive if firm j increases product quality between years.

3.4 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 tasks is lower at domestic firms than at foreign firms. The average level of information tasks is also lower at acquired firms before the acquisition than after the acquisition. The average level of face-to-face tasks 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 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 (%)	63.4	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	12.97	13.06
	(1.47)	(1.77)	(1.74)	(2.03)
Manufacturing (%)	39.2	30.7	28.4	37.8
Observation	678,140	13,775	15,412	92,304

Task measures are standardized to have zero mean and standard deviation of one. Column (2) shows pre-acquistion years and Column (3) the post-acquisition years of acquired firms. The last column shows firms that are foreign in every observed year. Standard deviations are in the parenthesis.

4 The effect of foreign acquisition on the return to tasks

4.1 Estimation Strategy

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

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

where lnw_{ijot} denotes the logarithm of the daily wage of worker i working at firm j at occupation o in year t. $TaskMeasure$ is the occupation-level task indexes defined above (standardized to have a mean of zero and a standard deviation of one). In the case of the present estimate, the sample includes only those companies that were acquired after 2003. These companies have two states: under domestic ownership and under foreign ownership. In the latter case, the $Foreign_{jt}$ dummy equals 1. The main coefficient of interest is δ_2 showing the effect of foreign acquisition on the return to tasks by comparing pre-acquisition years to post-acquisition years. We control for worker characteristics (X_{it}) in the model, such as age, its square, and gender, we further add industry (s_j) and year dummies (τ_t), and task-year interactions ($\tau_t * TaskMeasure_o$) to account for economic level trends in task returns.

We add to the model firm-specific fixed effects (f_j) and firm-specific time trends in wages ($f_j * t$) to control for selectivity in foreign ownership. First, we estimate the model without firm-specific fixed effects then we include firm-fixed effect (f_j) only then we add firm-specific trends to the model. By this strategy, we can quantify how much the selectivity across firms affects the returns to task after acquisition. The reason for this strategy is that previous literature on FDI showed (Earle et al., 2018), foreign firms tend to cherry-pick the best firms.

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 foreign acquisition interacted with the task measures:

$$lnw_{ijot} = \alpha_s * Foreign_j + \alpha_s * Foreign_j * TaskMeasure_o + \\ \gamma_1 * X_{ijt} + s_j + \tau_t + \tau_t * TaskMeasure_o + [f_j + f_j * t] + \epsilon_{ijt}, \tag{6}$$

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. 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 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 remains the same as in the previous equation.

4.2 Results

4.2.1 Foreign-ownership

Table 2 shows the estimated results of Equation 5 by including all three task measures in a single regression. The first column shows that firms pay 13.8 percent higher wages to their workers after a foreign take-over but this difference drops to about 1-1.5 percentage points once we control for selectivity in acquisitions.

Turning to the main variable of interest we find that, workers after a foreign acquisition receive a higher return to abstract tasks. The first column shows that firms after a foreign take-over pay a 4.9 percentage point higher premium to abstract tasks. The premium drops by one-third as we take into account that foreign investors cherry-pick the best domestic firms (second column), it further shrinks as we also take into account within firm trends (third column), but the parameter estimates remain significant and they are between 1.2 and 2.9 percentage points.

We do not find any evidence of 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

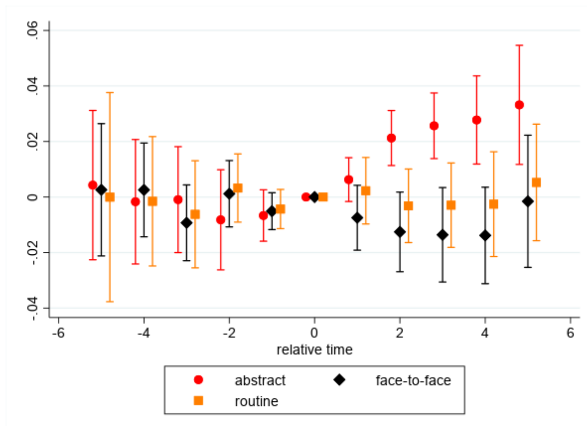
	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign	0.157***	(0.034)	0.031***	(0.011)	0.006	(0.007)
Foreign * Abstract	0.049***	(0.013)	0.029***	(0.007)	0.029***	(0.007)
Foreign * Face-to-face	-0.024*	(0.014)	-0.010	(0.007)	-0.008	(0.007)
Foreign * Routine	-0.017	(0.017)	0.006	(0.009)	0.002	(0.009)
Age	0.028***	(0.003)	0.025***	(0.001)	0.025***	(0.001)
Age Square	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Constant	7.915***	(0.063)	8.061***	(0.030)	8.074***	(0.032)
Observations	628,331		628,331		628,331	
R-squared	0.452		0.708		0.730	
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE			YES		YES	
Firm-trend					YES	

*** $p < 0.01, ** p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year-fixed effects and their interaction with task use indexes are included. 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. We further control for firm-specific fixed effects in the second, for firm-level trends in the third column.

4.2.2 Event study approach

Figure 1 shows the results of estimating Equation 6 by including all three task measures in a single regression. We estimate the model by including firm-specific fixed effects and trends. The red circles show the results for abstract tasks, the black for face-to-face contacts, and the orange for routine tasks. The parameters along with the results of the OLS and firm fixed-effects models can be found in Appendix Table 8. 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 do not need face-to-face interaction and 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) is 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 task use indexes are included. 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. We further control for firm-specific fixed effects and firm-level trends 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.

4.2.3 Heterogeneity analysis and the Robustness of the results

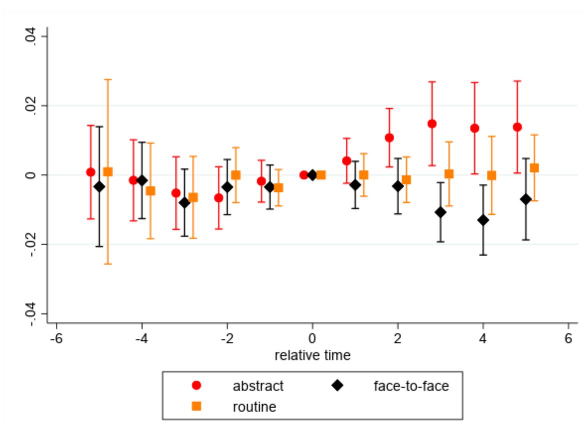
4.2.3.1 Worker selectivity Previous literature emphasized the importance of firm-level selectivity in the case of foreign acquisition, i.e. foreign firms tend to cherry-pick the best domestic firms, we come over this issue by (i) considering only acquired firms and comparing their behavior under domestic and foreign ownership, (ii) we included firm-specific fixed effects in the model. A second issue is that if firms screen workers' abilities better than domestic firms then the worker composition would improve after acquisition. Thus we would overestimate the causal effect of FDI on task return without firm and worker fixed effect. To be able to estimate the model with worker fixed effects, we keep all the firms even if they were foreign in every observed year or they were always domestic in our sample. The reason for this is that fixed effects are identified from the movement of workers between companies. If we restrict 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). For more details on the estimation strategy see Appendix Section A.2.2.1.

Appendix Table 9 shows the estimated results. As we mentioned in Section 3, there are two types of foreign firms: firms that were acquired during the sampling period ("acquired") and for which we observe pre- and post-acquisition period, and foreign firms that are either greenfield or were acquired before the sampling period ("other foreign") for them we do not observe pre-acquisition period. According to the estimation results, other foreign firms pay more than 40 percentage points, and even before the acquisition acquired firms pay almost 20 percentage points higher wages than domestic ones. Most of these differences are due to selectivity. As we look at acquired firms, we see that in the years under foreign ownership, they pay 15 percent higher wages than years under domestic ownership, and this gap drops dramatically to about 1-3 percent as we take into account firm- and worker level selectivity (column 2- column 4).

Turning to the variable of our main interest we find that, workers at other foreign firms receive a higher return to abstract tasks. The gap between domestic and other foreign firms in the return to abstract tasks shrinks as we take into account selectivity issues, but even in our preferred estimates, where we add firm and worker-specific fixed effects to the model together with firm-specific trend, the gap is significant and its about 2 percentage points. If we look at acquired firms, we see that the return to abstract tasks at these firms does not differ significantly from domestic firms when they are under domestic control. However, the return to abstract tasks jumps significantly when they are under foreign control. The effect is 1.2 percent if we control for selectivity in the workforce. We do not find any evidence of foreign premium in the return to face-to-face. In the case of routine tasks, foreign firms pay a lower return to these tasks than domestic firms, and this is true already before the acquisition takes place. While did not find any evidence that a foreign take-over would significantly alter the return to these tasks.

Figure 2 shows the results of estimating the event study model by including all three task measures in a single regression. We estimate the model by including both firm and worker fixed effects and we further control for firm-specific trends. The red circles show the results for abstract tasks, the black stands for face-to-face contacts, and the orange for for routine tasks. The parameters along with the results of the OLS and firm fixed-effects models can be found in Appendix Table 10. 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 do not need face-to-face interaction and 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) is also unchanged.

Figure 2: The effect of foreign acquisition on task returns - Event study approach - Controlling for worker-level selectivity



$***p < 0.01, **p < 0.05, *p < 0.1$
Standard errors are clustered at the firm level. Year-fixed effects and their interaction with task use indexes 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 sample. 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, 1-digit industry-fixed effect, and year fixed effects. We further control for firm-level trends and worker fixed-effects.

To sum up, these robustness check results confirm our previous findings and also confirms that our findings are not driven by firm or worker-level selectivity suggested by the literature.

4.2.3.2 Divestment We were silent in the previous chapters about that our main parameters are identified from comparing firm years under domestic and foreign management, and are not only identified from foreign take-overs but also from divestment activities. We have 628,331 person-year observations that can be associated with firms acquired during the observed period, 38 percent of these observation years are associated with pre-acquisition periods, 50 percent are associated with foreign ownership, and 12 percent are associated with divestment. In this robustness check we exclude all post-divestment years from our sample, and we re-estimate Equation 5 and Equation 6. The results can be found in Table 11 and Table 12, and in Figure 1. The results are robust to excluding post-divestment years from the sample. If anything, the increase in the return to abstract tasks is larger than previously and also significant. There is no robust effect for the other two task measures. The event study figures confirm these findings.

4.2.3.3 Additional control variables Foreign firms are larger in terms of the number of employees and sales revenue as well, they engage in export activities more often than domestic firms. Firms after a foreign acquisition started to increase in size and became exporters with a higher probability than domestic firms. Also, foreign investors may prefer to choose different locations depending on the local labor market attribute of the location than domestic ones, for example, locations with a higher skilled worker supply. All of these could drive our results. To rule out this scenario, we re-estimate equation 5 in Appendix Table 13 by controlling for the logarithm of the sales revenue, the logarithm of the number of employees, a dummy indicating that the firm participates in export activities and we further include county-year fixed effects to control for local labor market attributes in the first column. In the second column, we further add industry-year fixed effects to the model and industry-county-year fixed effects in the last column. The results are robust to these changes in the main specification, even the size of the parameters does not change.

4.2.3.4 Specific sub-samples First, we drop firm-years with less than 50 employees from our sample. The results are robust to this change (Panel A of Appendix Table 14).

Second, if after a foreign acquisition, the new owner would increase the wage of managers only for any reason, would leave the wage of other workers untouched, we would get similar results, as managers perform more abstract tasks and less routine tasks. This is somewhat contradicted by the fact that, according to Appendix Table 4, it is not (only) managers who perform a lot of abstract tasks, but to rule out this explanation completely, we have dropped managers from our sample and show that our results hold on this subsample as well (see Panel B of Appendix Table 14).

Last but not least, our sample was restricted 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 took place. The results hold on this subsample as well (see Panel C in Appendix Table 14), confirming that our results are driven only by workforce composition changes.

4.2.3.5 Export activity We further examine whether the fact that firms start to engage in export activities with a higher probability after a foreign takeover can explain our results. Entering the export market can change the labor demand at the firm along several dimensions as firms will face higher competition (HIVATKOZÁS). To examine this channel we include in our main regression (equation 5) a dummy variable that is 1 if the firm is exporting and zero otherwise, we also include the interaction term of this dummy with our task measure indexes.

The results are robust to these changes in the main specification (see Appendix Table 15. Exporter firms pay a lower return to face-to-face activities than non-exporting firms but this effect, but this effect disappears as we take into account worker selectivity. Firms engaged in exporting activities pay lower wages to routine tasks and this holds even after controlling for selectivity.

4.2.3.6 Sectoral comparison As many firms in the service sector provide related business services to their parent company, the effect of FDI on the return to task might differ in this sector compared to the manufacturing sector. To examine this, we re-estimate Equation 5 with a slight modification to be able to compare the return to the task in the Service and Manufacturing sectors: we include a dummy indicating that the firm operates in the Service industry and interact with it the foreign dummy and the task measures, and we further include the triple interaction term of the three variables. Appendix Table 16 summarizes our results. The return to abstract tasks increases after a foreign takeover in the manufacturing sector and there is no significant difference in the service sector. The return to the other tasks does not change after the takeover in any of the two sectors.

4.2.3.7 Alternative task measure In the main part of the analysis, we follow the work of Firpo et al. 2011 in constructing the task measure indexes. In this part, we re-scale each task measure so that it equals the percentile score in 2003 by following the work of Autor et al. 2003, Deming and Kahn 2018 and Ottaviano et al. 2013. The re-scaled indexes are between 0 and 1 and represent the relative importance of that task among all workers in 2003. To construct our summary indexes, we simply take the average of the re-scaled corresponding indexes. We use the same questions as in the main part of the text, see Table 3.

We replicate Table 2 by re-estimating Equation 5 using these new task measure indexes. The results are robust to calculate the indexes in an alternative way (see Appendix Table **??**).

4.2.3.8 Matched sample Foreign investors do not randomly select the range of domestic companies they acquire but rather cherry-pick the best domestic companies. This is confirmed by our descriptive statistics, acquired firms have more employees and higher sales revenue even before the acquisition than domestic firms (see Table 1). Although by including firm and worker fixed effects in our preferred model, we take this selection issue into account, and our event study approach further confirms that our findings are not driven by selectivity, in this section, we take additional steps to filter out the selectivity channel. We use propensity score matching to construct a control group as similar as possible to the group of acquired firms. We follow the work of Koerner et al. 2023 by using an iterative matching procedure to achieve a unique one-to-one matching of acquired and always domestic firms over the entire observation period (See Appendix A.1.1 for more details on the matching procedure). Since for each acquired firm, we match a single domestic firm at a precise year, we can assign the acquisition dates for the matched acquired firms as pseudo investment dates for the always domestic firms. This procedure allows us to run placebo regressions in which we show that placebo foreign investment does not, but only true foreign investments increase the return to abstract tasks.

In Columns (1) and (2) of Table 3, we replicate the results of Columns (1) and (2) of Table 9 by re-running Equation 5 on the matched sub-sample. We are unable to replicate the results of Column (3) of the same Table, as it includes worker fixed effects. In the matched sample, we do not observe the entire carrier of the workers, thus worker fixed effects would be biased. The results tell the same story as our main results, even the parameter estimates are very close.

Columns (3) and (4) of Table 3 are the same as the first two columns, but now we include a pseudo acquisition dummy for always domestic firms and we interact it with the task indexes. As we did a one-to-one matching of acquired and domestic firms on a specific year, we can assign the acquisition dates for the matched acquired firms as pseudo investment dates for the always domestic firms. Our $PlaceboPost$ dummy will be one for always domestic firms after the year of the pseudo investment. We do not find any evidence for an increase in the return to abstract tasks after a placebo investment, while there is a significant increase in the return to this task after a real investment. The parameter estimates are very close to what we found in the main analysis.
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 occupation-level task indexes defined above (standardized to have a mean of zero and a standard deviation of one).

$Foreign_{jt}$ is a 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.

We add to the model firm-specific fixed effects (f_j) and firm-specific time trends in wages ($f_j * t$) 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 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 the firm change in ownership.

As we control for individual fixed effect in our most preferred specification, δ_2 is identified from the wage change of three different worker groups: (i) incumbent workers after acquisition and who did not change occupation; (ii) incumbent 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 7 for more detailed discussion and for the number of relevant cases.

First, we estimate the model 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 quantify how much the selectivity across firms affects the returns to task after acquisition. The reason for this strategy is that previous literature on FDI showed (Earle et al., 2018), foreign firms tend to cherry-pick the best firms. Furthermore, if firms screen workers' abilities better than domestic firms then the worker composition would improve after acquisition. Thus we would overestimate the causal effect of FDI on task return without firm and worker fixed effect.

Table 3: The effect of foreign acquisition on task returns - Matched sample and Placebo test

VARIABLES	(1) coef.	(2) se	(3) coef.	(4) se	(5) coef.	(6) se	(7) coef.	(8) se
Foreign	0.136***	(0.042)	0.008	(0.008)	0.108***	(0.040)	0.006	(0.010)
Foreign * Abstract	0.047***	(0.016)	0.025***	(0.007)	0.039*	(0.021)	0.029***	(0.008)
Foreign * Face-to-face	-0.031*	(0.016)	-0.006	(0.008)	-0.015	(0.017)	0.001	(0.010)
Foreign * Routine	-0.008	(0.022)	0.001	(0.013)	-0.014	(0.024)	0.003	(0.015)
Placebo Post					0.061**	(0.025)	0.004	(0.008)
Placebo Post * Abstract					0.014	(0.023)	-0.009	(0.010)
Placebo Post * Face-tp-face					-0.032**	(0.015)	-0.013	(0.008)
Placebo Post * Routine					0.015	(0.018)	-0.003	(0.010)
Constant	7.982***	(0.054)	8.072***	(0.027)	7.946***	(0.061)	8.071***	(0.028)
Observations	675,779		675,779		675,779		675,779	
R-squared	0.451		0.715		0.452		0.716	
Year FE	Yes		Yes		Yes		Yes	
Trend in task return	Yes		Yes		Yes		Yes	
Worker Characteristics	Yes		Yes		Yes		Yes	
Industry FE	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. Year fixed effects and their interaction with task use indexes are included. We further control for 1 digit industry dummies, the gender and age of the worker, and its square. In the second and fourth columns, we add firm fixed effects to the model.

5 The effect of foreign acquisition on the task composition of the firm

5.1 Estimation Strategy

On the one hand, foreign acquisition increases firms' size and productivity, on the other hand, the company's employees, especially those whose work can easily be replaced by machines, often fear losing their jobs after a company is acquired. Subsidiaries of foreign companies have easier access to new (automation) technologies (see our later analysis), so machines can replace the work of people performing routine tasks more efficiently.

To test this hypothesis, we use the firm-level task measure introduced in Section 3.2 and estimate the following model:

$$taskuse_{jt} = \alpha * Foreign_{jt} + \beta * X_{jt} + [f_j + f_j * t] + s_j + \tau + \epsilon_{ijt}, \quad (7)$$

where $taskuse_{jt}$ denotes the firm-level task use indexes at firm j in year t. Our main independent variable is $Foreign_{jt}$ dummy that is equal to one if the firm is majority foreign-owned. We mimic

Equation 5 here as well. We control for industry fixed effects (s_j), and year dummies (τ) in the model. In the OLS estimates, we allow that the task usage is different at firms before acquisition or firms that were foreign-owned already at the beginning of the sampling period. Otherwise, we include firm fixed effects (f_j) in the model together with firm-level trends ($f_j * t$). First, we estimate the model without any time-varying firm-level control, as we did in our main specification, and then we add time-varying firm-level characteristics (such as size, number of employment, and a dummy indicating whether the firm is exporting or not). 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.

5.2 Results

Table 4 presents how the firm-level task usage differs after acquisition. Panel A presents the results for abstract tasks, B for face-to-face contacts, and C for routine tasks. In the case of the abstract tasks, we see that firms use 0.3 percentage points more of this type of task after the acquisition than before. But this small positive effect disappears as we take into account the selectivity in FDI (includes firm fixed effects). Foreign firms tend to use more face-to-face tasks as we take into account the selectivity in FDI (columns (2) and (4)). However, the estimated parameters (0.1 percentage points) are close to zero. Foreign firms tend to use less routine tasks according to Panel C in Table 4, but the estimated parameter is close to zero and insignificant in most of the specifications. 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 2 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 4: The effect of foreign ownership on task composition

VARIABLES	(1) coef	se	(2) coef	se	(3) coef	se	(4) coef	se
				Panel A: Abstract tasks				
Foreign	0.003**	(0.002)	-0.000	(0.000)	0.003*	(0.002)	0.000	(0.000)
Log Sales					0.002***	(0.000)	-0.000	(0.000)
Log Employment					-0.003***	(0.000)	-0.006***	(0.000)
Exporter					0.006***	(0.001)	0.000	(0.000)
Constant	0.324***	(0.000)	0.329***	(0.000)	0.304***	(0.003)	0.358***	(0.002)
R-squared	0.361		0.941		0.391		0.943	
				Panel B: Face-to-face				
Foreign	-0.001	(0.001)	0.001*	(0.000)	-0.000	(0.001)	0.001*	(0.000)
Log Sales					-0.000**	(0.000)	0.000	(0.000)
Log Employment					-0.000	(0.000)	-0.001***	(0.000)
Exporter					-0.005***	(0.000)	-0.000	(0.000)
Constant	0.344***	(0.000)	0.342***	(0.000)	0.350***	(0.001)	0.345***	(0.001)
R-squared	0.427		0.938		0.439		0.938	
				Panel C: Routine				
Foreign	-0.002	(0.002)	-0.000	(0.000)	-0.003	(0.002)	-0.001*	(0.000)
Log Sales					-0.002***	(0.000)	0.000	(0.000)
Log Employment					0.004***	(0.000)	0.006***	(0.000)
Exporter					-0.001	(0.001)	-0.000	(0.001)
Constant	0.332***	(0.000)	0.329***	(0.000)	0.347***	(0.003)	0.296***	(0.002)
R-squared	0.384		0.934		0.402		0.936	
Number of observation	778,441		778,441		778,441		778,441	
Year	Yes		Yes		Yes		Yes	
Industry	Yes		Yes		Yes		Yes	
Firm FE			Yes				Yes	
Firm-level trend			Yes				Yes	
Firm level controls					Yes		Yes	

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

Although it may be surprising at first glance that foreign acquisitions have no particular effect on workforce composition, but the literature also reaches a similar conclusion. The study by Crino (2009) provides a comprehensive literature summary of the effect of outsourcing in developed countries. This overview presents a rather ambiguous picture, and if anything offshoring has only little effect on employment at the domestic company. The study of Earle et al. (2018) focuses on the other side of the relationship, they show that in the case of Hungary, foreign acquisitions only slightly change the composition of the workforce. Koerner et al. (2023) argue that internal firm restructuring is the missing channel that can explain why adjustments after FDI lack substantial effects on firm aggregates. They show that firms' foreign direct investment into a low-wage country induces internal (within-firm) workforce restructuring at the parent company, by increasing the likelihood up- or downgrading workers to occupations that are more or less intensive in analytical and interactive tasks.

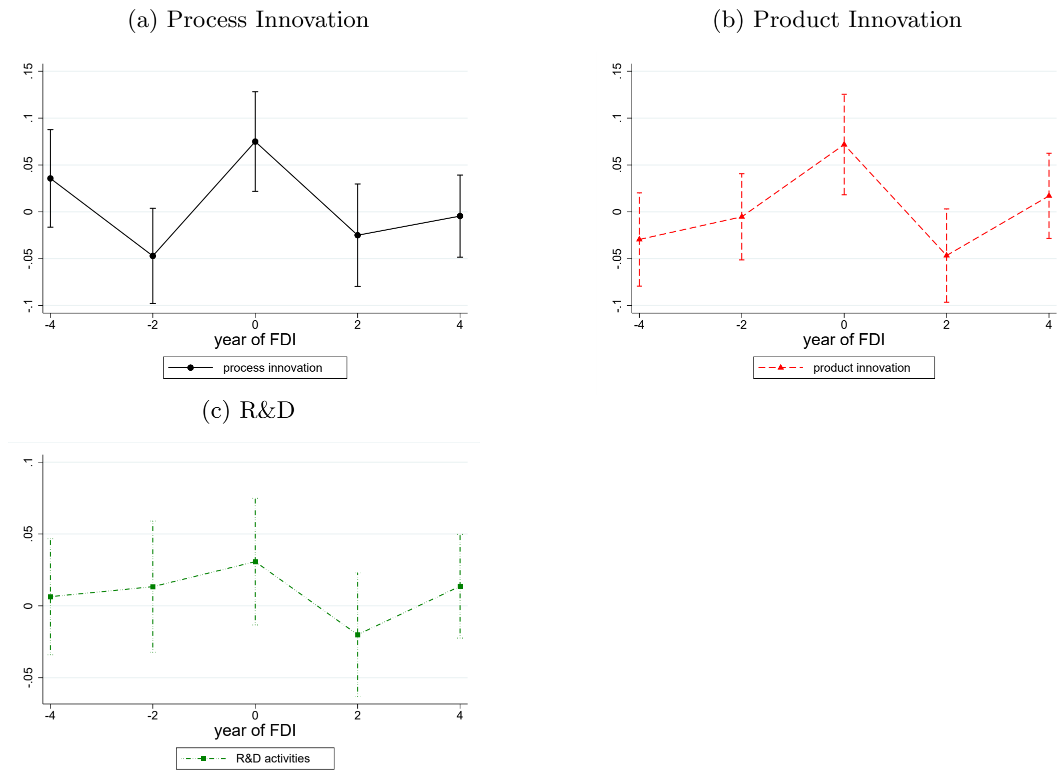
6 Underlying Mechanisms

6.1 Innovation: Technology import and product upgrading

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 by using event study approach analysis. For this purpose, we restrict attention to firms that we observe in CIS We run the following

Figure 3: Innovation



regression:

$$innov_{jt} = delta_s * Acquired_j + \gamma_1 * X_{jt} + f_j + \nu_t + \epsilon_{jt}, \tag{8}$$

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 restrict s to even numbers. s takes the value 0 in the years of acquisition and one year before. We control for size, productivity, and share of workers with college and high school diplomas, 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 by 7 percentage points in the year of FDI while 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 that firms 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. Thus in the following, we investigate in more detail these two channels (i) technology upgrading through import and (ii) product upgrading.

Technology upgrading through import As we have seen in Figure 3, firms after a foreign take-over conduct process innovation with higher probability than non-acquired firms but they do so without increased R&D expenditure. This result is consistent with the idea that after an acquisition, firms gain access to the parent company's (skill-biased) technology and adopt this technology. In this section, we explore the effect of foreign acquisition on firm's import behavior. Motivated by Koren et al. (2020) we assume that imported machines represent newer technology than the existing machine stock of the country. To learn about the firms' import behavior, we use Customs Statistics. The Customs Statistics contain the universe of trading firms, recording their exports and imports in 6-digit Harmonized System (HS) product breakdown for all years from 2004 to 2016. We translate by using the official crosswalk the HS6 codes to Broad Economic Categories (BEC) which is a three-digit classification, that groups transportable goods according to their main end-use. We focus on Capital goods (except transport equipment) (code 41), and parts and accessories thereof (code 42). The data set is matched to the Balance Sheet record of the firm based on a unique firm identifier.

We investigate the effect of FDI on capital import and we run the following regression:

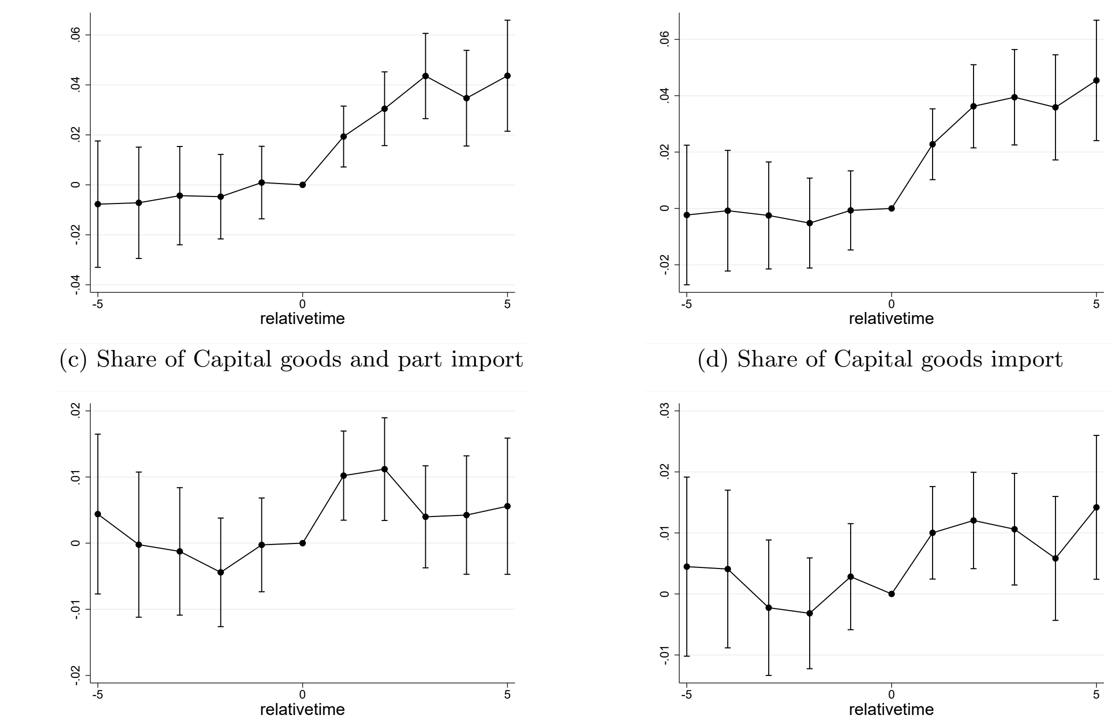
$$CapitalImport_{jt} = \delta_1 * Foreign_{jt} + s_j + f_j + \tau_t + \epsilon_{jt}, \tag{9}$$

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, for firm fixed effects f_j, and year fixed effects τ_t. We also do an event study analysis in which instead of including a foreign dummy, we include the leads and lags around the acquisition. We estimate the following regression:

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

where the dependent variable shows whether firm j imported capital goods in year t. But now instead of a single δ parameter, we have δ_s parameters. s is zero in the last year under domestic ownership thus δ_s shows the effect of the acquisition on capital import s year before or after this year. We normalize the δ_0 to zero, and negative (positive) s denotes the years before (after) our reference period. We control for industry fixed effects s_j, for 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 can have different capital import behavior than domestic firms. Table 5 shows the results. Panel A shows the probability of importing capital goods, Panel B shows the share of capital goods imported in the total import. In the case of the first three columns we define capital goods as "Capital goods (except transport equipment), and parts and accessories thereof" (BEC code 4), in columns (4)-column (6) we only consider capital goods import (BEC code 41). The probability of importing capital goods is higher at foreign firms than at domestic firms, and this is true even if used within-firm variation (column (2) and column(5)) in the identification. The results are not driven by the fact that foreign firms start to increase after the takeover in terms of revenue and employment (column (3) and column (6)). The share of capital goods in the total import is also increasing (Panel (B)). Figure 4 confirms our results. 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 remains there for about 2-3 years.

Figure 4: Technology Import



(a) Probability of importing Capital goods and part

(b) Probability of importing Capital goods

(c) Share of Capital goods and part import

(d) Share of Capital goods import

Table 5: The effect of foreign acquisition on importing capital goods

	(1)	(2)	(3)	(4)	(5)	(6)
		Capital goods, and parts			capital goods	
		Panel A: Probability				
Foreign	0.257***	0.042***	0.037***	0.241***	0.040***	0.036***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
Constant	0.089***	0.115***	-0.091***	0.074***	0.097***	-0.081***
	(0.001)	(0.000)	(0.005)	(0.001)	(0.000)	(0.005)
R-squared	0.201	0.696	0.709	0.184	0.675	0.687
		Panel B: Share of capital import value in the total import value				
Foreign	0.072***	0.011***	0.010***	0.045***	0.010***	0.009***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.027***	0.034***	-0.023***	0.028***	0.032***	-0.024***
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.003)
R-squared	0.109	0.675	0.684	0.056	0.520	0.529
Observations	719,641	706,706	637,075	719,641	706,706	637,075
Year	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES
Firm FE		YES	YES		YES	YES
Controls			YES			YES

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. In the last column, we add firm-level controls to the model: the logarithm of the number of employees, the logarithm of the sales revenue, an indicator of the firm's export activity, and an indicator that shows if the firm is under public ownership in the given year.

Product upgrading Motivated by Figure 3 Panel B, in this section, we show that firms start to produce more expensive products after they are acquired by foreign firms.

We estimate the following regression where

$$Y_{jvt} = \beta_1 * Acquired_{jt} + f_j + f_t + \chi_{jt}, \quad (11)$$

where the dependent variable is the 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_j) while χ_{jvt} denotes the error term. Then, we decompose the effect of foreign acquisition into quality and composition effects. For this purpose, we use the average quality and variety of price measures introduced in Section 3.3 as the dependent variable.

The effect of the foreign acquisition on product prices are summarized in Table 6. The first column shows that firms after acquisition have 10.6 percent (s.e 4.5 percent) higher average prices than firms that were not acquired. Columns (2)-(4) show that 5.4 percent of this increase can be contributed to the fact that firms start to export more expensive product varieties after acquisition and 5.1 percent to the increase of product quality. Finally, we do not see evidence that firms start to export to countries that buy the same product for a higher price after acquisition. See Appendix Table **??**

Table 6: The effect of foreign acquisition on product quality

	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)
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

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

FDI from high-income countries

Foreign investors are coming from heterogeneous countries. To test whether there is a heterogeneous effect of foreign investment on the return to tasks by the development of the country of origin, we re-estimate Equation 5 with a slight modification. We allow in the modified model that foreign ownership has a different effect on the return to tasks by the characteristics of the source country. We define a country to be high-income country if it was in the top 10 by GDP per capita in 2011 (We use Gravitational Data developed by CEPII, See Appendix Section A.1.1. for more details on the measurements used to compare the country of origin of the FDI.), the results are robust if we consider the top 25 percent as high-income countries.

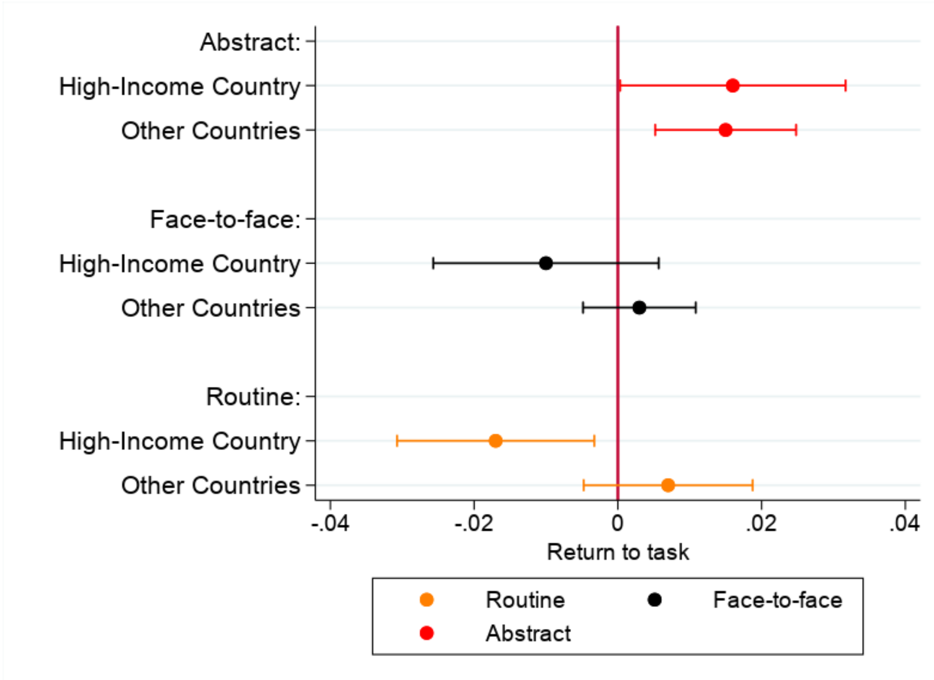
Figure 5 shows the results. The x-axis shows the return to the given tasks, while the y-axis shows the given comparison. We compare firms bought up by investors from high-income countries to the rest of the acquired firms. The return to abstract tasks increases after a foreign acquisition no matter whether the investor is coming from a high-income country or not. The return to face-to-face tasks does not change after a takeover in both types of firms. While the return to routine tasks decreases significantly in firms originating in high-income countries and does not change in other firms. This result is in line with the hypothesis that firms get access to the technology of the parent company after a take-over and in the case of the more advanced countries this would mean getting access to technologies that automatize the production process and thus substitute routine tasks.

6.2 Alternative Mechanisms

6.2.1 Change of task composition in production.

The within-firm returns of tasks can change after FDI even if the technology of firms does not change after acquisition. For the 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).

Figure 5: The effect of FDI by the income of the source country



In this setup, the rise of firm size or the Hicks-neutral technology change decreases the share of abstract tasks and has an opposite effect on the task return and the amount of task use. Thus the share of the cognitive task should decrease in production if the return to cognitive tasks increases (Lindner et al., 2022). We show in Section 5 that there is no evidence for change in the composition of tasks used at production in an economically significant magnitude.

6.2.2 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 tasks reflects only the task specialization at high-paid occupations.

We formally test this hypothesis by re-estimating Equation 7 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.

The results are shown in Table 7. In line with (Becker et al., 2019), the table shows that larger firms use more occupations. According to Column (3), the number of occupations grows by 0.95 if the size of the firm grows by 10 percent, the parameters halves as we take into account the selectivity of the FDI (column (4)). In contrast to this, we do not find evidence that the number of occupations significantly changes after FDI. Panel B highlights that the Herfindahl index of occupations remains unchanged after acquisition. The estimated parameter of the foreign dummy is close to zero (-0.001 and 0.002) and statistically not significant. We use event study style analysis to show that there is no pre-trend in the number of occupations and the Herfindahl index at acquired firms and that the acquisition has no effect on these measures, see Appendix Figure 3.

Table 7: The effect of foreign ownership on task specialization.

VARIABLES	(1) coef	se	(2) coef	se	(3) coef	se	(4) coef	se
Panel A: Number of occupations								
Foreign	11.608*	(6.594)	1.184	(1.010)	3.542	(4.071)	0.858	(0.946)
log Sales					1.148***	(0.222)	0.141	(0.104)
log Employment					9.503***	(0.493)	5.978***	(0.451)
Exporter					1.055	(1.111)	-0.360*	(0.217)
Constant	12.301***	(0.508)	25.405***	(0.152)	-41.290***	(2.880)	-7.663***	(2.508)
R-squared	0.373		0.986		0.740		0.987	
Panel B: Herfindhal index								
Foreign	-0.035*	(0.020)	-0.001	(0.004)	0.011	(0.013)	0.002	(0.004)
log Sales					-0.018***	(0.002)	0.000	(0.000)
log Employment					-0.030***	(0.003)	-0.047***	(0.003)
Exporter					-0.064***	(0.005)	-0.003	(0.003)
Constant	0.402***	(0.003)	0.326***	(0.001)	0.785***	(0.021)	0.567***	(0.018)
R-squared	0.141		0.891		0.287		0.892	
No obs.	778,441		778,441		778,441		778,441	
Year	Yes		Yes		Yes		Yes	
Industry	Yes		Yes		Yes		Yes	
Firm FE			Yes				Yes	
Firm-level trend			Yes				Yes	
Firm-level controls					Yes		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.

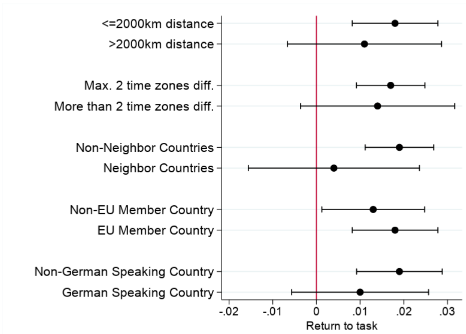
6.2.3 Efficiency wage and monitoring

Monitoring The cost of monitoring a worker is different by the tasks the worker is doing. Some tasks are well-suited to supervision, at the extreme they can be even paid on an output base, while the output of other tasks is difficult to measure ((Lazear, 2018)). On the one hand, monitoring repetitive tasks, and measuring their output is easier than monitoring abstract tasks. This difference can lead to a difference in the compensating shame of the two types of tasks. On the other hand, we can assume that geographical distance or time zone difference affects the possibility and effectiveness of monitoring a worker. The two channels can even interact: tasks that are easily monitored and results measurable output are easy to monitor even from a long distance, while others that do not produce easily measurable tasks (abstract tasks) are even more difficult to monitor from a distance. Such a pattern can lead to a change in the relative return to routine and abstract tasks observed in Figure 2. If this pattern would lead to our main results, we would expect a gap in the return to a given task by the location of the foreign firm's headquarters. To test this hypothesis, we re-estimate Equation 5 with a slight modification. We allow in the modified model that foreign ownership has a different effect on the return to tasks by the (cultural and geographical) distance between the source of the FDI and Hungary. Although we do not observe the headquarters of the parent firm, we use the firm's country of origin as a proxy for that. We measure the distance between Hungary and the source country by using several distance measures: geographical location, and time zone difference. We even see administration and legislation differences as an aggravating factor, and compare firms originating in EU member countries and firms originating in the rest of the world. In order to analyze this pattern further, we also look at FDI from countries that are historically and economically connected to Hungary in many ways (they account for 30 percent of its foreign trade), i.e. capital from German-speaking countries.

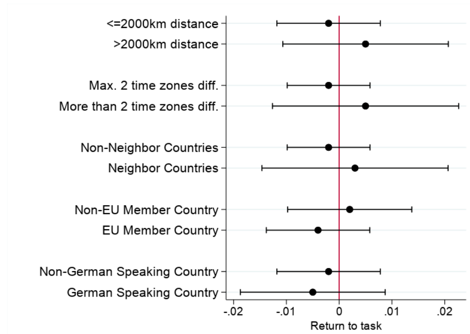
Panel (a) of Figure 6 shows the comparisons of the return to abstract task by the source country of the FDI (see Appendix Table 19-Table 23 for the parameter estimates). The parameter estimates are close to each other and they are comparable to the results in the main part of the analysis (see Table 9. Firms having their parent firms within a 2000 km distance pay almost 2 percentage points higher return

Figure 6: The effect of FDI by the source country of the FDI

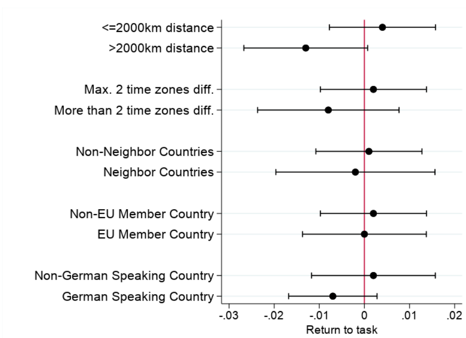
(a) Abstract tasks



(b) Face-to-face tasks



(c) Routine tasks



on abstract tasks than domestic firms, this premium is significant. Although the foreign premium of abstract tasks at firms having their parent firms in the longer distance is marginally not significant, the magnitude is comparable at the two types of firms. A similar pattern can be observed if we use time zone differences of the country of origin and Hungary to distinguish between firms. Both types of firms with FDI from EU and non-EU members pay about a 2 percentage point premium on abstract tasks compared to domestic firms. While the foreign premium at firms originating in German-speaking countries is marginally insignificant, the magnitude is comparable to the one in Non-German-speaking countries.

7 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 these 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 change the task composition of the production function or task specializations.

The most likely interpretation of these results is that firms change 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.

References

Abowd, J. M., Kramarz, F., & Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, *67*(2), 251–333. https://doi.org/10.1111/1468-0262.00020

Arnold, J. M., & Javorcik, B. S. (2009). Gifted kids or pushy parents? foreign direct investment and plant productivity in indonesia. *Journal of International Economics*, *79*(1), 42–53.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333.

Barth, E., Bratsberg, B., Hægeland, T., & Raaum, O. (2012). Performance pay, union bargaining and within-firm wage inequality. *Oxford Bulletin of Economics and Statistics*, *74*(3), 327–362.

Barth, E., Bryson, A., Davis, J. C., & Freeman, R. (2016). It's where you work: Increases in the dispersion of earnings across establishments and individuals in the united states. *Journal of Labor Economics*, *34*(S2), S67–S97.

Barth, E., Roed, M., Schøne, P., & Umblijs, J. (2020). How robots change within-firm wage inequality.

Basu, P., & Guariglia, A. (2007). Foreign direct investment, inequality, and growth. *Journal of Macroeconomics*, *29*(4), 824–839. https://doi.org/10.1016/j.jmacro.2006.02.004

Becker, S. O., Egger, H., Koch, M., & Muendler, M.-A. (2019). Tasks, occupations, and wage inequality in an open economy. *Mimeo*.

Bernard, A. B., & Jensen, J. B. (1997). Exporters, skill upgrading, and the wage gap. *Journal of international Economics*, *42*(1-2), 3–31.

Bhandari, B. (2007). Effect of inward foreign direct investment on income inequality in transition countries. *Journal of Economic Integration*, *22*(4), 888–928. https://doi.org/10.11130/jei.2007.22.4.888

Bonhomme, S., Holzheu, K., Lamadon, T., Manresa, E., Mogstad, M., & Setzler, B. (2023). How much should we trust estimates of firm effects and worker sorting? *Journal of Labor Economics*, *41*(2), 291–322.

Breau, S., & Brown, W. M. (2011). Exporting, foreign direct investment, and wages: Evidence from the canadian manufacturing sector. *Growth and Change*, *42*(3), 261–286.

Brown, J. D., Earle, J. S., & Telegdy, A. (2006). The productivity effects of privatization: Longitudinal estimates from hungary, romania, russia, and ukraine. *Journal of Political Economy*, *114*(1), 61–99.

Bruns, B. (2019). Changes in workplace heterogeneity and how they widen the gender wage gap. *American Economic Journal: Applied Economics*, *11*(2), 74–113.

Card, D., Cardoso, A. R., Heining, J., & Kline, P. (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics*, *36*(S1), S13–S70.

Card, D., Cardoso, A. R., & Kline, P. (2016). Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women. *The Quarterly journal of economics*, *131*(2), 633–686.

Card, D., Heining, J., & Kline, P. (2013). Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly journal of economics*, *128*(3), 967–1015.

Chen, Z., Ge, Y., & Lai, H. (2011). Foreign direct investment and wage inequality: Evidence from china. *World Development*, *39*(8), 1322–1332.

Conte, M., Cotterlaz, P., & Mayer, T. (2022). The cepii gravity database highlights.

Crépon, B., Duguet, E., & Mairessec, J. (1998). Research, innovation and productivi [ty: An econometric analysis at the firm level. *Economics of Innovation and new Technology*, *7*(2), 115–158.

Crescenzi, R., Di Cataldo, M., & Giua, M. (2021). Fdi inflows in europe: Does investment promotion work? *Journal of International Economics*, *132*, 103497.

Crinò, R. (2009). Offshoring, multinationals and labour market: A review of the empirical literature. *Journal of Economic Surveys*, *23*(2), 197–249.

David Brown, J., Earle, J. S., & Telegdy, Á. (2010). Employment and wage effects of privatisation: Evidence from hungary, romania, russia and ukraine. *The Economic Journal*, *120*(545), 683–708.

Deming, D., & Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, *36*(S1), S337–S369.

Earle, J. S., Telegdy, Á., & Antal, G. (2018). Foreign ownership and wages: Evidence from hungary, 1986–2008. *ILR Review*, *71*(2), 458–491.

Ebenstein, A., Harrison, A., McMillan, M., & Phillips, S. (2014). Estimating the impact of trade and offshoring on american workers using the current population surveys. *Review of Economics and Statistics*, *96*(4), 581–595.

Faber, B. (2014). Trade liberalization, the price of quality, and inequality: Evidence from mexican store prices. *UC-Berkeley Working Paper*.

Feenstra, R. C., & Hanson, G. H. (1997). Foreign direct investment and relative wages: Evidence from mexico's maquiladoras. *Journal of International Economics*, *42*(3-4), 371–393. https://doi.org/10.1016/s0022-1996(96)01475-4

Fieler, A. C., Eslava, M., & Xu, D. Y. (2018). Trade, quality upgrading, and input linkages: Theory and evidence from colombia. *American Economic Review*, *108*(1), 109–146.

Figini, P., & Görg, H. (2011). Does foreign direct investment affect wage inequality? an empirical investigation. *The World Economy*, *34*(9), 1455–1475. https://doi.org/10.1111/j.1467-9701.2011.01397.x

Firpo, S., Fortin, N. M., & Lemieux, T. (2011). Occupational tasks and changes in the wage structure. *Mimeo*.

Freeman, R. B. (1982). Union wage practices and wage dispersion within establishments. *ILR Review*, *36*(1), 3–21.

Frıas, J. A., Kaplan, D. S., Verhoogen, E., & Alfaro-Serrano, D. (2022). Exports and wage premia: Evidence from mexican employer-employee data. *The Review of Economics and Statistics*, 1–45. https://doi.org/10.1162/rest_a_01178

Goldberg, P. K., & Pavcnik, N. (2007). Distributional effects of globalization in developing countries. *Journal of Economic Literature*, *45*(1), 39–82.

Griffith, R., Huergo, E., Mairesse, J., & Peters, B. (2006). Innovation and productivity across four european countries. *Oxford review of economic policy*, *22*(4), 483–498.

Hakkala, K. N., Heyman, F., & Sjöholm, F. (2014). Multinational firms, acquisitions and job tasks. *European Economic Review*, *66*, 248–265.

Hardy, W., Keister, R., & Lewandowski, P. (2018). Educational upgrading, structural change and the task composition of jobs in europe. *Economics of Transition*, *26*(2), 201–231.

Haskel, J. E., Pereira, S. C., & Slaughter, M. J. (2007). Does inward foreign direct investment boost the productivity of domestic firms? *The review of economics and statistics*, *89*(3), 482–496.

Helpman, E., Itskhoki, O., Muendler, M.-A., & Redding, S. J. (2016). Trade and inequality: From theory to estimation. *The Review of Economic Studies*, *84*(1), 357–405. https://doi.org/10.1093/restud/rdw025

Herzer, D., Hühne, P., & Nunnenkamp, P. (2014). FDI and income inequality-evidence from latin american economies. *Review of Development Economics*, *18*(4), 778–793. https://doi.org/10.1111/rode.12118

Javorcik, B. S. (2004). Does foreign direct investment increase the productivity of domestic firms? in search of spillovers through backward linkages. *American economic review*, *94*(3), 605–627.

Koch, M., & Smolka, M. (2019). Foreign ownership and skill-biased technological change. *Journal of International Economics*, *118*, 84–104.

Koerner, K., Borrs, L., & Eppelsheimer, J. (2023). Fdi and onshore job stability: Upgrades, downgrades, and separations in multinationals. *European Economic Review*, *152*, 104332.

Lai, H., & Zhu, S. C. (2007). Technology, endowments, and the factor content of bilateral trade. *Journal of International Economics*, *71*(2), 389–409. https://doi.org/10.1016/j.jinteco.2006.07.002

Lazear, E. P. (2018). Compensation and incentives in the workplace. *Journal of Economic Perspectives*, *32*(3), 195–214.

Leamer, E. E. (1995). The heckscher-ohlin model in theory and practice.

Lemieux, T. (2006). Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill? *American Economic Review*, *96*(3), 461–498.

Lindner, A., Muraközy, B., Reizer, B., & Schreiner, R. (2022). Firm-level technological change and skill demand.

Mueller, H. M., Ouimet, P. P., & Simintzi, E. (2017). Wage inequality and firm growth. *American Economic Review*, *107*(5), 379–83.

Neumann, L. (2006). Collective agrements still decentralized with shrinking coverage. *Hungarian labor market review and analysis*. Institute of Economics IE-HAS, National Employment Service - Hungary.

OECD. (2023). *Fdi in figures - april 2023*. Retrieved February 12, 2024, from https://www.oecd.org/daf/inv/investment-policy/FDI-in-Figures-April-2023.pdf

Ottaviano, G. I. P., Peri, G., & Wright, G. C. (2013). Immigration, offshoring, and american jobs. *American Economic Review*, *103*(5), 1925–1959.

Poole, J. P. (2013). Knowledge transfers from multinational to domestic firms: Evidence from worker mobility. *Review of Economics and Statistics*, *95*(2), 393–406.

Riboud, M., Sánchez-Páramo, C., & Silva-Jáuregui, C. (2002). Does eurosclerosis matter? institutional reform and labour market performance in central and eastern european countries. *Labour, Employment and Social Policies in the EU Enlargement Process. Washington DC: World Bank*, 243–311.

Song, J., Price, D. J., Guvenen, F., Bloom, N., & Von Wachter, T. (2019). Firming up inequality. *The Quarterly journal of economics*, *134*(1), 1–50.

Stolper, W. F., & Samuelson, P. A. (1941). Protection and real wages. *The Review of Economic Studies*, *9*(1), 58–73.

Svarstad, E., & Nymoen, R. (2022). Wage inequality and union membership at the establishment level: An econometric study using norwegian data. *Oxford Economic Papers*.

Tonin, M. (2009). Employment protection legislation in central and east european countries. *SEER-South-East Europe Review for Labour and Social Affairs*, *12*(04), 477–491.

Trefler, D., & Zhu, S. C. (2010). The structure of factor content predictions. *Journal of International Economics*, *82*(2), 195–207. https://doi.org/10.1016/j.jinteco.2010.07.006

Vanek, J. (1968). The factor proportion theory: The n-factor case. *Kyklos*, *21*(4), 749–756. https://doi.org/10.1111/j.1467-6435.1968.tb00141.x

A Appendix

A.1 Data

A.1.1 Matching procedure

To construct a counterfactual for our analysis we apply propensity score matching. We match on firm characteristics, as the acquisition is a firm-level event. We run a linear probability 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. For acquired firms (treated firms), we only keep the year of the acquisition in the analysis. We exclude acquired firms for which we do not observe the last year under domestic ownership and the first year after the acquisition. We include only those acquired firms that have non-missing observations on the relevant variables one (and two years) before the event. As for the control group, we include always domestic firm years that satisfy the same requirement relative to the year when we include them in our sample. We exclude firms that were ever publicly owned from the sample.

We use a linear regression model to obtain the propensity scores on the sample including the acquisition year of acquired firms and all years satisfying the above-mentioned criteria of always domestic firms. We pool all year together to increase the sample size and control for year-fixed effects. All independent variables are taken from the year before the acquisition. Independent variables are the following: the number of job changes at the firms, number of up-, and downgrades by each task (e.g. the number of upgrades according to abstract task...), the logarithm of the number of employment, the logarithm of value added per employee, the logarithm of the wage bill, age of the firm, the share of female workers, the share of pink and blue-collar workers, the growth on the value added per employee and the growth in the number of employment from two years prior the one year before, industry, county and year.

To ensure common support, we drop acquired firms having larger propensity scores than the maximum among always domestic firms, we also drop always domestic firms having lower propensity scores than the lowest value among acquired firms. we force an exact match on industry and year, and within each industry-year cell, we match (without replacement) each acquired firm to its nearest neighbor measured by the propensity score. We use 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. This procedure ensures that we can assign the year of acquisition of the acquired firm to his always domestic pair as pseudo acquisition. To ensure that the nearest neighbor is not too far we drop the matched pairs for which the gap in the propensity score is larger than 0.1 in absolute terms.

Appendix Table 1 compares domestic and foreign firms in the full sample and in our matched sample. Not surprisingly foreign and domestic firms differ in many dimensions. Foreign firms are larger in terms of size, and wage bill, they are also more productive, and slightly younger. The share of blue-collar workers is smaller at foreign firms, while the share of female workers is larger. The number of occupation changes and within firm up and downgrades is also larger at foreign firms. All these differences disappear in our matched sample, except for the age of firms, even in our matched sample foreign firms remain slightly younger.

Table 1: Descriptive statistics for unmatched and matched sample.

	Full Sample				Matched Sample			
	Domestic	Foreign	diff	p-stat	Domestic	Foreign	diff	p-stat
log productivity	7.97	8.39	-0.42	0.000	8.38	8.37	0.010	0.768
	(0.0014)	(0.0260)	(0.023)		(0.023)	(0.026)	(0.034)	
No occup. change	0.48	1.26	-0.77	0.000	1.24	1.14	0.11	0.575
	(0.0047)	(0.159)	(0.076)		(0.13)	(0.13)	(0.19)	
No abstract upgrade	0.235	0.609	-0.37	0.000	0.636	0.569	0.068	0.502
	(0.0026)	(0.077)	(0.04)		(0.07)	(0.07)	(0.10)	
No abstract downgrade	0.22	0.57	-0.35	0.000	0.54	0.50	0.037	0.688
	(0.003)	(0.084)	(0.045)		(0.06)	(0.07)	(0.092)	
No routine upgrade	0.22	0.57	-0.35	0.000	0.59	0.54	0.022	0.808
	(0.003)	(0.069)	(0.04)		(0.06)	(0.06)	(0.09)	
No routine downgrade	0.24	0.61	-0.38	0.000	0.62	0.53	0.08	0.426
	(0.003)	(0.092)	(0.048)		(0.068)	(0.078	(0.10)	
No face-to-face upgrade	0.24	0.58	-0.338	0.000	0.58	0.55	0.0267	0.790
	(0.003)	(0.075)	(0.049)		(0.068)	(0.074)		
No face-to-face downgrade	0.218	0.603	-0.385	0.000	0.594	0.516	0.078	0.399
	(0.002)	(0.089)	(0.039)		(0.065)	(0.066)	(0.092)	
log size	2.53	3.10	-0.56	0.000	3.05	3.09	-0.042	0.342
	(0.02)	(0.03)	(0.03)		(0.03)	(0.03)	(0.044)	
log wage bill	9.95	10.81	-0.86	0.000	10.79	10.79	0.00	0.970
	(0.02)	(0.04)	(0.03)		(0.035)	(0.037)	(0.05)	
firm age	12.2	10.5	1.70	0.000	11.1	10.5	0.60	0.024
	(0.01)	(0.20)	(0.21)		(0.18)	(0.20)	(0.27)	
share of blue-collar	0.46	0.37	0.09	0.000	0.36	0.37	-0.016	0.244
	(0.00)	(0.01)	(0.01)		(0.01)	(0.01)	(0.014)	
share of female	0.35	0.40	-0.05	0.000	0.40	0.40	-0.00	0.822
	(0.00)	(0.01)	(0.01)		(0.01)	(0.01)	(0.01)	

A.1.2 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.

defining the source of origin of the foreign direct investment: A firm is considered to be foreign if the share of foreign capital is above 50 percent. We only know the country of origin for those firms that are directly owned by foreign investors. If the firm is owned by a firm that is considered to be a majority foreign-owned firm, the firm is also considered a foreign firm, but the country of origin is missing. If the investment is coming from more than one country, we consider all of the countries with equal shares as source countries. We use 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 the GDP per capita. We consider a country to be high-income country if the GDP per capita in 2011 was in the top 10 in the world according to the CEPII dataset. Our results are robust to considering the top 25 percent as high income country. Table 2 shows the high-income countries and the number of firm-year observations related to them. Investments from the Netherlands, USA, and Switzerland are the most common in our sample.

Table 2: High Income Countries.

Country	Number of firm-year	percentage
Netherlands	7,093	37.90
USA	4,484	23.96
Switzerland	4,466	23.86
Luxembourg	2,043	10.92
Norway	182	0.97
Hongkong	186	0.99
Singapore	142	0.76
United Arab Emirates	60	0.32
CAYMAN country	19	0.10
Saudi Arabia	16	0.09
Bermuda	15	0.08
State of Kuwait	6	0.03
Qatar	2	0.01
Brunei	1	0.01

We use the Education Statistics of the World Bank to measure the level of education in the source country. We define a country to be highly educated if the percentage of the population age 15+ with tertiary schooling is in the top 25 percent of the countries in 2005. To elicit the property of the foreign investors, we use the first foreign year of the firm, e.g. if the firm became foreign-owned in 2007, we use the ownership structure of the year 2007 to define the properties of the investors even if the ownership structure changes thereafter. In the case of more than one source country, we define the firm to originate in a highly educated country if at least one of the owners is coming from such country. We follow the same rule in the case of defining firms coming from high-income, German-speaking, and neighboring countries. To define the distance and time zone difference, we define a firm to originate within 2000 km distance, if the capital of the investors' source countries is on average less than 2000 km distance away from Budapest in the case of more than one main owner.

A.1.3 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[3] 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 12 summaries our method. Each task measure for occupation "o" is computed as:

$$TaskMeasure_o = \sum_{n=1}^{N} IMP_n^{2/3} * LEV_n^{1/3} + \sum_{m=1}^{M} F_k * V_k, \tag{12}$$

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 3 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 4 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 5 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.

---

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

Table 3: 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 4: 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 5: 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.1.4 Number of observations used for identification

Table 6 shows the number of acquired firms by years. 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 years.

See Table 7 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 6: Number of acquisition 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

Table 7: 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 8: Parameter estimates of Figure 1

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
(t-13) * Abstract	-0.007	(0.047)	-0.001	(0.028)	0.011	(0.021)
(t-12) * Abstract	-0.024	(0.059)	-0.026	(0.034)	-0.002	(0.028)
(t-11) * Abstract	-0.017	(0.045)	-0.017	(0.026)	0.000	(0.018)
(t-10) * Abstract	-0.009	(0.038)	-0.001	(0.023)	0.005	(0.018)
(t-9) * Abstract	0.006	(0.035)	0.009	(0.023)	0.014	(0.020)
(t-8) * Abstract	-0.011	(0.027)	-0.002	(0.019)	-0.000	(0.018)
(t-7) * Abstract	-0.011	(0.024)	-0.014	(0.017)	-0.007	(0.018)
(t-6) * Abstract	-0.017	(0.021)	-0.004	(0.016)	-0.000	(0.016)
(t-5) * Abstract	-0.004	(0.018)	0.003	(0.014)	0.004	(0.014)
(t-4) * Abstract	-0.004	(0.016)	-0.007	(0.012)	-0.002	(0.011)
(t-3) * Abstract	-0.004	(0.014)	-0.003	(0.010)	-0.001	(0.010)
(t-2) * Abstract	-0.004	(0.012)	-0.008	(0.009)	-0.008	(0.009)
(t-1) * Abstract	-0.006	(0.006)	-0.007	(0.005)	-0.007	(0.005)
(t+1) * Abstract	0.020***	(0.007)	0.008*	(0.004)	0.006	(0.004)
(t+2) * Abstract	0.025***	(0.009)	0.023***	(0.006)	0.021***	(0.005)
(t+3) * Abstract	0.037***	(0.013)	0.028***	(0.006)	0.026***	(0.006)
(t+4) * Abstract	0.035**	(0.017)	0.026***	(0.008)	0.028***	(0.008)
(t+5) * Abstract	0.059***	(0.022)	0.028**	(0.011)	0.033***	(0.011)
(t+6) * Abstract	0.054**	(0.023)	0.022	(0.014)	0.029**	(0.014)
(t+7) * Abstract	0.042**	(0.019)	0.030**	(0.014)	0.035**	(0.015)
(t+8) * Abstract	0.043*	(0.023)	0.032**	(0.016)	0.037**	(0.017)
(t+9) * Abstract	0.034	(0.027)	0.026	(0.019)	0.032	(0.020)
(t+10) * Abstract	0.026	(0.033)	0.023	(0.022)	0.030	(0.024)
(t+11) * Abstract	0.035	(0.035)	0.026	(0.025)	0.032	(0.027)
(t+12) * Abstract	0.039	(0.042)	0.040	(0.029)	0.036	(0.033)
(t+13) * Abstract	0.037	(0.043)	0.060**	(0.030)	0.073**	(0.035)
(t+14) * Abstract	0.009	(0.050)	0.067*	(0.040)	0.100**	(0.040)
(t-13) * Face-to-face	-0.033	(0.037)	-0.015	(0.022)	0.003	(0.020)
(t-12) * Face-to-face	-0.026	(0.039)	-0.023	(0.028)	-0.015	(0.029)
(t-11) * Face-to-face	-0.043	(0.031)	-0.028	(0.020)	-0.008	(0.017)
(t-10) * Face-to-face	-0.078**	(0.031)	-0.033	(0.020)	-0.003	(0.017)
(t-9) * Face-to-face	-0.057**	(0.028)	-0.027*	(0.015)	-0.010	(0.013)
(t-8) * Face-to-face	-0.036	(0.027)	-0.028	(0.019)	-0.012	(0.016)
(t-7) * Face-to-face	-0.036	(0.022)	-0.019	(0.014)	-0.008	(0.013)
(t-6) * Face-to-face	-0.017	(0.020)	0.000	(0.012)	0.005	(0.010)
(t-5) * Face-to-face	-0.015	(0.018)	-0.004	(0.013)	0.003	(0.012)
(t-4) * Face-to-face	-0.010	(0.016)	0.005	(0.009)	0.003	(0.009)
(t-3) * Face-to-face	-0.005	(0.014)	-0.006	(0.008)	-0.009	(0.007)
(t-2) * Face-to-face	0.003	(0.012)	0.001	(0.007)	0.001	(0.006)
(t-1) * Face-to-face	0.002	(0.007)	-0.007**	(0.004)	-0.005	(0.003)
(t+1) * Face-to-face	-0.021***	(0.007)	-0.008	(0.006)	-0.007	(0.006)
(t+2) * Face-to-face	-0.016*	(0.009)	-0.013*	(0.007)	-0.013*	(0.007)
(t+3) * Face-to-face	-0.022	(0.014)	-0.015*	(0.009)	-0.014	(0.009)
(t+4) * Face-to-face	-0.011	(0.015)	-0.015*	(0.009)	-0.014	(0.009)

(t+5) * Face-to-face	-0.004	(0.017)	-0.005	(0.013)	-0.002	(0.012)
(t+6) * Face-to-face	0.024	(0.021)	0.009	(0.015)	0.012	(0.015)
(t+7) * Face-to-face	0.031	(0.021)	0.010	(0.017)	0.017	(0.017)
(t+8) * Face-to-face	0.018	(0.026)	0.013	(0.021)	0.023	(0.021)
(t+9) * Face-to-face	0.035	(0.025)	0.020	(0.022)	0.030	(0.023)
(t+10) * Face-to-face	0.046	(0.029)	0.033	(0.025)	0.041	(0.026)
(t+11) * Face-to-face	0.040	(0.032)	0.037	(0.030)	0.035	(0.031)
(t+12) * Face-to-face	0.060	(0.043)	0.056	(0.037)	0.047	(0.038)
(t+13) * Face-to-face	0.031	(0.045)	0.019	(0.032)	0.017	(0.034)
(t+14) * Face-to-face	0.020	(0.046)	-0.005	(0.041)	-0.015	(0.042)
(t-13) * Routine	-0.067**	(0.034)	-0.019	(0.027)	-0.020	(0.025)
(t-12) * Routine	-0.037	(0.040)	-0.031	(0.024)	-0.050**	(0.022)
(t-11) * Routine	-0.004	(0.036)	0.004	(0.020)	-0.006	(0.017)
(t-10) * Routine	-0.034	(0.029)	0.001	(0.017)	0.001	(0.015)
(t-9) * Routine	-0.028	(0.026)	-0.009	(0.015)	-0.004	(0.014)
(t-8) * Routine	-0.034	(0.025)	-0.021	(0.018)	-0.013	(0.017)
(t-7) * Routine	-0.023	(0.023)	-0.021	(0.016)	-0.015	(0.015)
(t-6) * Routine	-0.012	(0.019)	0.000	(0.014)	0.001	(0.014)
(t-5) * Routine	-0.009	(0.022)	-0.003	(0.018)	-0.000	(0.019)
(t-4) * Routine	-0.024	(0.016)	-0.005	(0.011)	-0.002	(0.012)
(t-3) * Routine	-0.012	(0.014)	-0.008	(0.009)	-0.006	(0.010)
(t-2) * Routine	0.002	(0.010)	-0.001	(0.006)	0.003	(0.006)
(t-1) * Routine	0.003	(0.007)	-0.005	(0.004)	-0.004	(0.004)
(t+1) * Routine	0.003	(0.011)	0.002	(0.006)	0.002	(0.006)
(t+2) * Routine	-0.001	(0.010)	-0.002	(0.007)	-0.003	(0.007)
(t+3) * Routine	-0.004	(0.013)	-0.002	(0.008)	-0.003	(0.008)
(t+4) * Routine	-0.006	(0.018)	-0.004	(0.009)	-0.003	(0.010)
(t+5) * Routine	-0.010	(0.021)	0.001	(0.011)	0.005	(0.011)
(t+6) * Routine	0.005	(0.023)	0.006	(0.014)	0.007	(0.014)
(t+7) * Routine	0.004	(0.026)	0.011	(0.018)	0.013	(0.018)
(t+8) * Routine	-0.029	(0.030)	0.002	(0.020)	0.004	(0.021)
(t+9) * Routine	-0.027	(0.033)	0.001	(0.024)	0.001	(0.025)
(t+10) * Routine	-0.027	(0.035)	0.006	(0.026)	0.007	(0.028)
(t+11) * Routine	-0.039	(0.041)	0.001	(0.032)	-0.002	(0.034)
(t+12) * Routine	-0.029	(0.045)	0.029	(0.034)	0.024	(0.035)
(t+13) * Routine	-0.056	(0.054)	-0.002	(0.042)	0.012	(0.041)
(t+14) * Routine	-0.088**	(0.041)	-0.005	(0.035)	0.003	(0.040)
Age	0.027***	(0.003)	0.025***	(0.001)	0.025***	(0.001)
Age Square	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Constant	7.942***	(0.057)	8.081***	(0.032)	8.080***	(0.033)
Observations	628,331		628,331		628,331	
R-squared	0.455		0.709		0.730	
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE			YES		YES	
Firm-trend					YES	

$***p < 0.01, **p < 0.05, *p < 0.1$

A.2.2 Heterogeneity analysis and the Robustness of the results

A.2.2.1 Worker selectivity To account for the selectivity in the workforce composition together with the 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 by using OLS and a fixed effect approach in the following difference-in-difference setting:

$$lnw_{ijot} = \delta_1 * Foreign_{jt} + \delta_2 * Foreign_{jt} * TaskMeasure_o + \\ + \tau_t * TaskMeasure_o + \gamma_1 * X_{ijt} + s_j + \tau_t + [\nu_i + f_j + f_j * t] + \epsilon_{ijt},, \tag{13}$$

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 occupation-level task indexes defined above (standardized to have a mean of zero and a standard deviation of one).

$Foreign_{jt}$ is a 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.

We add to the model firm-specific fixed effects (f_j) and firm-specific time trends in wages ($f_j * t$) 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 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 the firm change in ownership.

As we control for individual fixed effect, δ_2 is identified from the wage change of three different worker groups: (i) incumbent workers who stayed at the firm around ownership change (either changed or did not not change occupation), (i) workers who arrived to the firm after the acquisition. See Appendix A3 and Table 7 for more detailed discussion and for the number of relevant cases.

First, we estimate the model 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 quantify how much the selectivity across firms affects the returns to task 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:

$$lnw_{ijot} = \delta_1 * Foreign_{jt} + \delta_s * Foreign_{jt} * TaskMeasure_o + \\ + \alpha * TaskMeasure_o * AllwaysForeign_j + \alpha_t * TaskMeasure_o + \\ + \alpha_t * TaskMeasure_o + \gamma_1 * X_{ijt} + s_j + \tau_t + [\nu_i + f_j + f_j * t] + \epsilon_{ijt}, \tag{14}$$

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. 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 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 remains the same as in the previous equation.

Table 9: The effect of foreign acquisition on task returns

VARIABLES	(1) coef	se	(2) coef	se	(3) coef	se	(4) coef	se
Other Foreign	0.433***	(0.011)						
Other Fo * Abstract	0.077***	(0.007)	0.044***	(0.006)	0.046***	(0.006)	0.022***	(0.002)
Other Fo * Face-to-face	-0.007	(0.007)	0.002	(0.006)	0.004	(0.006)	0.000	(0.002)
Other Fo * Routine	-0.055***	(0.006)	-0.046***	(0.006)	-0.044***	(0.006)	-0.020***	(0.002)
Acquired	0.192***	(0.015)						
Acquired * Abstract	0.012	(0.012)	-0.008	(0.007)	-0.005	(0.007)	0.002	(0.003)
Acquired * Face-to-face	0.002	(0.008)	0.008	(0.007)	0.006	(0.007)	-0.005	(0.005)
Acquired * Routine	-0.005	(0.008)	-0.019***	(0.006)	-0.017***	(0.005)	-0.008***	(0.003)
Acq. Foreign	0.150***	(0.033)	0.029***	(0.008)	0.009	(0.007)	0.016**	(0.007)
Acq. Fo * Abstract	0.049***	(0.012)	0.034***	(0.006)	0.031***	(0.007)	0.012***	(0.003)
Acq. Fo * Face-to-face	-0.033***	(0.013)	-0.016**	(0.007)	-0.011	(0.007)	-0.002	(0.003)
Acq. Fo * Routine	-0.026*	(0.016)	0.007	(0.009)	0.005	(0.009)	-0.000	(0.004)
Age	0.024***	(0.001)	0.022***	(0.001)	0.023***	(0.001)		
Age square	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Constant	7.799***	(0.016)	8.057***	(0.012)	8.048***	(0.013)	9.220***	(0.009)
Observations	11,957,372		11,957,372		11,957,372		11,957,372	
R-squared	0.567		0.761		0.776		0.933	
Worker charact.	YES		YES		YES		YES	
Industry-year FE	YES		YES		YES		YES	
trend in skill usage	YES		YES		YES		YES	
Firm FE			YES		YES		YES	
Firm-level trend					YES		YES	
Worker FE							YES	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year-fixed effects and their interaction with task use indexes 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 sample. We interact these dummies with the task measures. 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. We further control for firm-specific fixed effects (second column), firm-level trends (third column), and worker fixed-effects (fourth column).

Table 10: Parameter estimates of Figure 2

VARIABLES	(1) coef	se	(2) coef	se	(3) coef	se	(4) coef	se
(t-13)*Abstract	0.007	(0.041)	0.002	(0.023)	0.020	(0.017)	0.002	(0.024)
(t-13)*Abstract	-0.024	(0.054)	-0.028	(0.030)	0.004	(0.026)	-0.012	(0.018)
(t-11)*Abstract	-0.026	(0.042)	-0.023	(0.022)	0.002	(0.015)	-0.012	(0.014)
(t-10)*Abstract	-0.019	(0.036)	-0.008	(0.021)	0.005	(0.016)	-0.004	(0.011)
(t-9)*Abstract	0.001	(0.033)	0.003	(0.021)	0.015	(0.019)	-0.002	(0.010)
(t-8)*Abstract	-0.009	(0.026)	-0.006	(0.017)	-0.001	(0.017)	-0.009	(0.008)
(t-7)*Abstract	-0.008	(0.023)	-0.018	(0.016)	-0.007	(0.018)	-0.010	(0.011)
(t-6)*Abstract	-0.019	(0.022)	-0.007	(0.014)	-0.001	(0.015)	-0.009	(0.008)
(t-5)*Abstract	0.007	(0.019)	0.000	(0.012)	0.004	(0.013)	0.001	(0.007)
(t-4)*Abstract	-0.001	(0.015)	-0.009	(0.011)	-0.001	(0.011)	-0.002	(0.006)
(t-3)*Abstract	0.002	(0.014)	-0.004	(0.009)	-0.000	(0.009)	-0.005	(0.005)
(t-2)*Abstract	0.002	(0.014)	-0.008	(0.009)	-0.007	(0.009)	-0.007	(0.005)
(t-1)*Abstract	-0.007	(0.006)	-0.006	(0.005)	-0.005	(0.005)	-0.002	(0.003)

(t+1)*Abstract	0.021**	(0.008)	0.007	(0.005)	0.005	(0.004)	0.004	(0.003)
(t+2)*Abstract	0.022**	(0.009)	0.022***	(0.005)	0.020***	(0.005)	0.011**	(0.004)
(t+3)*Abstract	0.037***	(0.012)	0.028***	(0.006)	0.025***	(0.006)	0.015**	(0.006)
(t+4)*Abstract	0.036**	(0.015)	0.028***	(0.007)	0.027***	(0.007)	0.014**	(0.007)
(t+5)*Abstract	0.060***	(0.020)	0.031***	(0.009)	0.033***	(0.008)	0.014**	(0.007)
(t+6)*Abstract	0.056***	(0.021)	0.028***	(0.009)	0.029***	(0.009)	0.008	(0.007)
(t+7)*Abstract	0.054***	(0.014)	0.041***	(0.010)	0.038***	(0.009)	0.011*	(0.007)
(t+8)*Abstract	0.059***	(0.015)	0.045***	(0.011)	0.041***	(0.010)	0.015*	(0.009)
(t+9)*Abstract	0.056***	(0.016)	0.043***	(0.011)	0.038***	(0.010)	0.008	(0.008)
(t+10)*Abstract	0.053***	(0.016)	0.042***	(0.011)	0.037***	(0.012)	0.008	(0.007)
(t+11)*Abstract	0.061***	(0.017)	0.047***	(0.013)	0.038***	(0.014)	0.007	(0.008)
(t+12)*Abstract	0.079***	(0.027)	0.059***	(0.019)	0.042**	(0.020)	0.000	(0.012)
(t+13)*Abstract	0.066***	(0.023)	0.078***	(0.016)	0.076***	(0.019)	0.022	(0.014)
(t+14)*Abstract	0.058	(0.036)	0.085***	(0.029)	0.102***	(0.027)	0.029*	(0.017)
(t-13)*Face-to-face	-0.012	(0.033)	-0.004	(0.021)	0.005	(0.019)	0.001	(0.014)
(t-13)*Face-to-face	-0.006	(0.037)	-0.008	(0.026)	-0.008	(0.029)	0.001	(0.015)
(t-11)*Face-to-face	-0.014	(0.029)	-0.008	(0.019)	0.003	(0.016)	0.010	(0.012)
(t-10)*Face-to-face	-0.052*	(0.028)	-0.015	(0.019)	0.006	(0.017)	0.009	(0.012)
(t-9)*Face-to-face	-0.026	(0.026)	-0.010	(0.014)	-0.001	(0.013)	0.001	(0.008)
(t-8)*Face-to-face	-0.016	(0.023)	-0.017	(0.016)	-0.007	(0.016)	-0.009	(0.008)
(t-7)*Face-to-face	-0.020	(0.020)	-0.007	(0.012)	-0.002	(0.012)	-0.007	(0.011)
(t-6)*Face-to-face	-0.003	(0.018)	0.011	(0.010)	0.009	(0.009)	0.001	(0.008)
(t-5)*Face-to-face	0.003	(0.018)	0.004	(0.010)	0.006	(0.010)	-0.003	(0.009)
(t-4)*Face-to-face	0.003	(0.015)	0.011	(0.008)	0.005	(0.007)	-0.002	(0.006)
(t-3)*Face-to-face	0.002	(0.013)	-0.001	(0.007)	-0.007	(0.006)	-0.008	(0.005)
(t-2)*Face-to-face	0.008	(0.012)	0.003	(0.006)	0.002	(0.006)	-0.003	(0.004)
(t-1)*Face-to-face	0.007	(0.007)	-0.005	(0.003)	-0.005	(0.003)	-0.003	(0.003)
(t+1)*Face-to-face	-0.027***	(0.009)	-0.011*	(0.006)	-0.009	(0.006)	-0.003	(0.003)
(t+2)*Face-to-face	-0.027***	(0.010)	-0.018**	(0.008)	-0.017**	(0.008)	-0.003	(0.004)
(t+3)*Face-to-face	-0.038***	(0.012)	-0.024***	(0.009)	-0.021**	(0.009)	-0.011**	(0.004)
(t+4)*Face-to-face	-0.035***	(0.013)	-0.028***	(0.008)	-0.024***	(0.008)	-0.013**	(0.005)
(t+5)*Face-to-face	-0.032**	(0.013)	-0.021**	(0.010)	-0.015	(0.009)	-0.007	(0.006)
(t+6)*Face-to-face	-0.012	(0.015)	-0.011	(0.011)	-0.004	(0.010)	-0.004	(0.006)
(t+7)*Face-to-face	-0.012	(0.014)	-0.014	(0.011)	-0.001	(0.010)	0.001	(0.006)
(t+8)*Face-to-face	-0.028	(0.017)	-0.014	(0.014)	0.002	(0.013)	-0.001	(0.007)
(t+9)*Face-to-face	-0.013	(0.015)	-0.007	(0.015)	0.009	(0.014)	0.007	(0.008)
(t+10)*Face-to-face	-0.002	(0.016)	0.003	(0.015)	0.020	(0.015)	0.017**	(0.007)
(t+11)*Face-to-face	-0.006	(0.018)	0.005	(0.018)	0.012	(0.018)	0.009	(0.011)
(t+12)*Face-to-face	0.013	(0.030)	0.021	(0.028)	0.026	(0.028)	0.022	(0.015)
(t+13)*Face-to-face	-0.010	(0.030)	-0.011	(0.020)	0.001	(0.019)	0.013	(0.013)
(t+14)*Face-to-face	-0.016	(0.035)	-0.033	(0.028)	-0.028	(0.028)	-0.007	(0.015)
(t-13)*Routine	-0.061**	(0.029)	-0.023	(0.025)	-0.030	(0.023)	0.009	(0.015)
(t-13)*Routine	-0.036	(0.037)	-0.032	(0.023)	-0.055***	(0.021)	-0.010	(0.015)
(t-11)*Routine	0.001	(0.034)	0.006	(0.019)	-0.008	(0.016)	0.018	(0.014)
(t-10)*Routine	-0.032	(0.028)	0.004	(0.016)	-0.001	(0.014)	0.015	(0.010)
(t-9)*Routine	-0.026	(0.026)	-0.006	(0.015)	-0.005	(0.014)	0.006	(0.008)
(t-8)*Routine	-0.041*	(0.024)	-0.021	(0.017)	-0.017	(0.017)	-0.007	(0.009)
(t-7)*Routine	-0.034	(0.024)	-0.021	(0.016)	-0.019	(0.016)	-0.008	(0.010)
(t-6)*Routine	-0.021	(0.020)	0.001	(0.014)	-0.002	(0.014)	0.005	(0.009)
(t-5)*Routine	-0.007	(0.025)	-0.003	(0.019)	-0.003	(0.021)	0.001	(0.014)
(t-4)*Routine	-0.027	(0.017)	-0.005	(0.012)	-0.004	(0.012)	-0.005	(0.007)
(t-3)*Routine	-0.014	(0.015)	-0.009	(0.010)	-0.008	(0.010)	-0.006	(0.006)
(t-2)*Routine	-0.004	(0.012)	-0.001	(0.006)	0.002	(0.006)	-0.000	(0.004)
(t-1)*Routine	0.004	(0.007)	-0.006*	(0.004)	-0.006*	(0.003)	-0.004	(0.003)
(t+1)*Routine	-0.010	(0.012)	0.002	(0.006)	0.003	(0.007)	0.000	(0.003)
(t+2)*Routine	-0.016	(0.011)	-0.001	(0.007)	-0.002	(0.007)	-0.001	(0.003)

(t+3)*Routine	-0.020*	(0.011)	-0.000	(0.008)	-0.002	(0.008)	0.000	(0.005)
(t+4)*Routine	-0.024*	(0.014)	-0.004	(0.008)	-0.003	(0.008)	-0.000	(0.006)
(t+5)*Routine	-0.020	(0.016)	-0.001	(0.007)	0.005	(0.007)	0.002	(0.005)
(t+6)*Routine	-0.004	(0.016)	0.003	(0.008)	0.009	(0.008)	0.000	(0.005)
(t+7)*Routine	0.001	(0.018)	0.011	(0.010)	0.018*	(0.010)	0.002	(0.006)
(t+8)*Routine	-0.027	(0.020)	0.001	(0.010)	0.010	(0.009)	-0.009	(0.007)
(t+9)*Routine	-0.023	(0.021)	-0.001	(0.011)	0.008	(0.010)	-0.011	(0.008)
(t+10)*Routine	-0.015	(0.021)	0.005	(0.012)	0.017	(0.011)	-0.004	(0.006)
(t+11)*Routine	-0.021	(0.024)	-0.002	(0.015)	0.008	(0.016)	-0.013	(0.009)
(t+12)*Routine	0.002	(0.028)	0.026	(0.022)	0.037**	(0.019)	0.008	(0.010)
(t+13)*Routine	-0.026	(0.035)	-0.005	(0.025)	0.024	(0.021)	0.002	(0.010)
(t+14)*Routine	-0.047*	(0.026)	-0.006	(0.021)	0.015	(0.022)	0.017	(0.016)
Other Foreign	0.433***	(0.011)						
Other Fo * Abstract	0.077***	(0.007)	0.045***	(0.006)	0.046***	(0.006)	0.022***	(0.002)
Other Fo * Face-to-face	-0.007	(0.007)	0.002	(0.006)	0.004	(0.006)	0.000	(0.002)
Other Fo * Routine	-0.055***	(0.006)	-0.046***	(0.006)	-0.044***	(0.006)	-0.020***	(0.002)
Acquired	0.217***	(0.024)						
Acq * Abstract	0.012	(0.014)	-0.009	(0.011)	-0.006	(0.010)	0.003	(0.006)
Acq * Face-to-face	-0.002	(0.011)	0.009	(0.008)	0.005	(0.008)	-0.003	(0.005)
Acq * Routine	-0.006	(0.012)	-0.015**	(0.007)	-0.016**	(0.007)	-0.006*	(0.003)
Age	0.024***	(0.001)	0.022***	(0.001)	0.023***	(0.001)		
Age square	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Constant	7.799***	(0.016)	8.059***	(0.012)	8.048***	(0.013)	9.220***	(0.009)
Obs	11,957,372		11,957,372		11,957,372		11,957,372	
R-squared	0.567		0.761		0.776		0.933	
Worker charact.	YES		YES		YES		YES	
Industry-year FE	YES		YES		YES		YES	
trend in skill usage	YES		YES		YES		YES	
Firm FE			YES		YES		YES	
Firm-level trend					YES		YES	
Worker FE							YES	

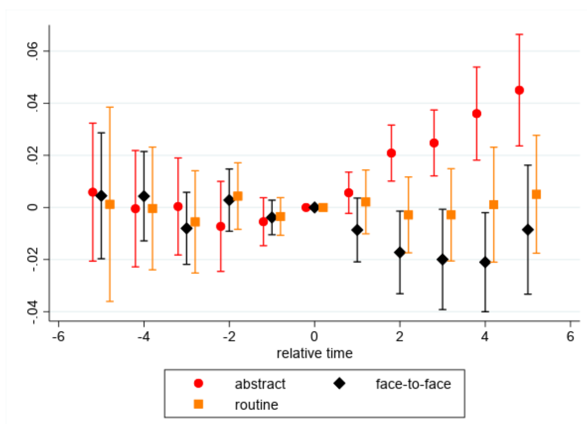
*** $p < 0.01, ** p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year-fixed effects and their interaction with task use indexes are included. We include a dummy indicating that the firm was acquired during our sampling period and a dummy showing that the firm was foreign-owned at the beginning of the sample. We interact these dummies with the task measures. 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. We further control for firm-specific fixed effects (second column), firm-level trends (third column), and worker fixed-effects (fourth column).

Table 11: Re-estimation of Table 2 by excluding post-divestment years

VARIABLES	(1) coef	se	(2) coef	se	(3) coef	se
Foreign	0.172***	(0.038)	0.032***	(0.010)	0.011	(0.010)
Foreign * Abstract	0.045***	(0.014)	0.027***	(0.007)	0.023***	(0.008)
Foreign * Face-to-face	-0.016	(0.015)	-0.009	(0.008)	-0.008	(0.008)
Foreign * Routine	-0.005	(0.017)	0.003	(0.009)	0.003	(0.009)
Age	0.029***	(0.003)	0.024***	(0.001)	0.024***	(0.002)
Age Square	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Constant	7.847***	(0.071)	8.047***	(0.032)	8.063***	(0.033)
Observations	540,017		540,017		540,017	
R-squared	0.464		0.719		0.739	
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE			YES		YES	
Firm-trend					YES	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. We exclude post-divestment years from the sample. Year-fixed effects and their interaction with task use indexes are included. 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. We further control for firm-specific fixed effects in the second, for firm-level trends in the third column.

Figure 1: Reestimation if Figure 1 by excluding post-divestment years.



$***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. We exclude post-divestment years from the sample. Year-fixed effects and their interaction with task use indexes are included. 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. We further control for firm-specific fixed effects and firm-level trends in the third column.

Table 12: Parameter estimates of Figure 1

	(1)	(2)	(3)	(4)	(5)	(6)

VARIABLES	coef	se	coef	se	coef	se
(t-13)*Abstract	-0.011	(0.046)	-0.005	(0.026)	0.008	(0.021)
(t-13)*Abstract	-0.025	(0.059)	-0.027	(0.033)	-0.004	(0.028)
(t-11)*Abstract	-0.018	(0.045)	-0.018	(0.024)	-0.001	(0.018)
(t-10)*Abstract	-0.010	(0.038)	-0.002	(0.022)	0.004	(0.017)
(t-9)*Abstract	0.006	(0.035)	0.008	(0.022)	0.015	(0.020)
(t-8)*Abstract	-0.011	(0.027)	-0.002	(0.018)	0.001	(0.018)
(t-7)*Abstract	-0.012	(0.023)	-0.015	(0.016)	-0.005	(0.018)
(t-6)*Abstract	-0.018	(0.021)	-0.004	(0.015)	0.001	(0.015)
(t-5)*Abstract	-0.004	(0.018)	0.003	(0.013)	0.006	(0.014)
(t-4)*Abstract	-0.004	(0.015)	-0.006	(0.011)	-0.000	(0.011)
(t-3)*Abstract	-0.005	(0.013)	-0.002	(0.009)	0.000	(0.010)
(t-2)*Abstract	-0.004	(0.012)	-0.008	(0.009)	-0.007	(0.009)
(t-1)*Abstract	-0.006	(0.006)	-0.007	(0.004)	-0.005	(0.005)
(t+1)*Abstract	0.021***	(0.006)	0.008*	(0.004)	0.006	(0.004)
(t+2)*Abstract	0.025**	(0.010)	0.025***	(0.005)	0.021***	(0.005)
(t+3)*Abstract	0.036**	(0.015)	0.031***	(0.007)	0.025***	(0.006)
(t+4)*Abstract	0.048**	(0.019)	0.038***	(0.008)	0.036***	(0.009)
(t+5)*Abstract	0.059***	(0.017)	0.039***	(0.011)	0.045***	(0.011)
(t+6)*Abstract	0.063***	(0.019)	0.042***	(0.014)	0.047***	(0.014)
(t+7)*Abstract	0.070***	(0.020)	0.045***	(0.016)	0.047***	(0.016)
(t+8)*Abstract	0.075***	(0.024)	0.048***	(0.018)	0.050***	(0.019)
(t+9)*Abstract	0.062**	(0.025)	0.042**	(0.020)	0.044**	(0.021)
(t+10)*Abstract	0.076***	(0.028)	0.042*	(0.025)	0.052**	(0.025)
(t+11)*Abstract	0.052*	(0.030)	0.042	(0.028)	0.059**	(0.029)
(t+12)*Abstract	0.058*	(0.034)	0.045	(0.032)	0.053	(0.033)
(t+13)*Abstract	0.069**	(0.032)	0.062*	(0.032)	0.081**	(0.032)
(t+14)*Abstract	0.088**	(0.037)	0.069	(0.044)	0.100**	(0.045)
(t-13)*Face-to-face	-0.032	(0.037)	-0.011	(0.022)	0.004	(0.021)
(t-13)*Face-to-face	-0.028	(0.039)	-0.019	(0.028)	-0.014	(0.029)
(t-11)*Face-to-face	-0.044	(0.031)	-0.024	(0.020)	-0.008	(0.017)
(t-10)*Face-to-face	-0.078**	(0.031)	-0.028	(0.020)	-0.002	(0.017)
(t-9)*Face-to-face	-0.058**	(0.028)	-0.024	(0.015)	-0.009	(0.013)
(t-8)*Face-to-face	-0.037	(0.027)	-0.025	(0.019)	-0.012	(0.016)
(t-7)*Face-to-face	-0.036*	(0.022)	-0.016	(0.014)	-0.008	(0.013)
(t-6)*Face-to-face	-0.018	(0.019)	0.003	(0.011)	0.005	(0.010)
(t-5)*Face-to-face	-0.016	(0.018)	-0.002	(0.013)	0.004	(0.012)
(t-4)*Face-to-face	-0.011	(0.016)	0.005	(0.009)	0.004	(0.009)
(t-3)*Face-to-face	-0.006	(0.014)	-0.006	(0.007)	-0.008	(0.007)
(t-2)*Face-to-face	0.003	(0.012)	0.002	(0.006)	0.003	(0.006)
(t-1)*Face-to-face	0.003	(0.007)	-0.007*	(0.003)	-0.004	(0.003)
(t+1)*Face-to-face	-0.021***	(0.007)	-0.009	(0.006)	-0.009	(0.006)
(t+2)*Face-to-face	-0.025**	(0.010)	-0.016**	(0.008)	-0.017**	(0.008)
(t+3)*Face-to-face	-0.033**	(0.015)	-0.019*	(0.010)	-0.020**	(0.010)
(t+4)*Face-to-face	-0.022	(0.017)	-0.019*	(0.010)	-0.021**	(0.010)
(t+5)*Face-to-face	-0.016	(0.018)	-0.011	(0.014)	-0.009	(0.013)
(t+6)*Face-to-face	0.016	(0.023)	0.002	(0.017)	0.005	(0.016)
(t+7)*Face-to-face	0.026	(0.025)	0.010	(0.019)	0.018	(0.019)
(t+8)*Face-to-face	0.002	(0.031)	0.008	(0.024)	0.021	(0.024)
(t+9)*Face-to-face	0.026	(0.029)	0.018	(0.026)	0.034	(0.026)
(t+10)*Face-to-face	0.047	(0.033)	0.043	(0.030)	0.057*	(0.030)
(t+11)*Face-to-face	0.047	(0.040)	0.053	(0.037)	0.055	(0.037)
(t+12)*Face-to-face	0.046	(0.055)	0.066	(0.043)	0.054	(0.043)
(t+13)*Face-to-face	-0.015	(0.046)	0.020	(0.036)	0.007	(0.036)
(t+14)*Face-to-face	-0.058	(0.036)	-0.040	(0.048)	-0.047	(0.047)
(t-13)*Routine	-0.068**	(0.033)	-0.019	(0.025)	-0.020	(0.025)

(t-13)*Routine	-0.038	(0.040)	-0.025	(0.024)	-0.048**	(0.022)
(t-11)*Routine	-0.005	(0.036)	0.009	(0.020)	-0.004	(0.017)
(t-10)*Routine	-0.034	(0.029)	0.006	(0.017)	0.002	(0.015)
(t-9)*Routine	-0.029	(0.026)	-0.006	(0.015)	-0.004	(0.014)
(t-8)*Routine	-0.035	(0.025)	-0.017	(0.018)	-0.013	(0.017)
(t-7)*Routine	-0.023	(0.023)	-0.017	(0.016)	-0.016	(0.016)
(t-6)*Routine	-0.012	(0.019)	0.004	(0.014)	0.001	(0.013)
(t-5)*Routine	-0.011	(0.022)	-0.001	(0.018)	0.001	(0.019)
(t-4)*Routine	-0.026	(0.016)	-0.004	(0.011)	-0.000	(0.012)
(t-3)*Routine	-0.013	(0.014)	-0.007	(0.009)	-0.006	(0.010)
(t-2)*Routine	0.002	(0.010)	0.001	(0.006)	0.004	(0.007)
(t-1)*Routine	0.003	(0.007)	-0.004	(0.004)	-0.003	(0.004)
(t+1)*Routine	0.003	(0.011)	0.002	(0.006)	0.002	(0.006)
(t+2)*Routine	-0.007	(0.011)	-0.003	(0.007)	-0.003	(0.007)
(t+3)*Routine	-0.008	(0.015)	-0.001	(0.009)	-0.003	(0.009)
(t+4)*Routine	-0.007	(0.020)	-0.000	(0.011)	0.001	(0.011)
(t+5)*Routine	-0.028	(0.024)	-0.000	(0.012)	0.005	(0.012)
(t+6)*Routine	0.002	(0.027)	0.013	(0.015)	0.013	(0.015)
(t+7)*Routine	0.006	(0.032)	0.018	(0.019)	0.016	(0.020)
(t+8)*Routine	-0.029	(0.034)	0.009	(0.021)	0.007	(0.023)
(t+9)*Routine	-0.023	(0.039)	0.009	(0.026)	0.003	(0.029)
(t+10)*Routine	-0.004	(0.041)	0.023	(0.029)	0.020	(0.032)
(t+11)*Routine	-0.030	(0.050)	0.020	(0.036)	0.018	(0.039)
(t+12)*Routine	-0.019	(0.053)	0.046	(0.037)	0.034	(0.041)
(t+13)*Routine	-0.036	(0.061)	0.026	(0.042)	0.017	(0.047)
(t+14)*Routine	-0.104**	(0.044)	-0.021	(0.038)	-0.024	(0.041)
Age	0.028***	(0.003)	0.024***	(0.001)	0.024***	(0.001)
Age Square	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Constant	7.907***	(0.056)	8.071***	(0.031)	8.109***	(0.033)
Observations	540,017		540,017		540,017	
R-squared	0.475		0.721		0.740	
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE			YES		YES	
Firm-trend					YES	

A.2.2.2 Divestment

$***p < 0.01, **p < 0.05, *p < 0.1$

Table 13: Re-estimation of Table 2 by including additional controls in the model.

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign	0.006	(0.006)	0.006	(0.006)	0.005	(0.006)
Fo * Abstract	0.028***	(0.007)	0.029***	(0.007)	0.029***	(0.007)
Fo * Face-to-face	-0.006	(0.006)	-0.006	(0.006)	-0.005	(0.006)
Fo * Routine	0.002	(0.009)	0.003	(0.009)	0.003	(0.009)
Age	0.024***	(0.001)	0.024***	(0.001)	0.024***	(0.001)
Age square	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Constant	8.078***	(0.048)	8.079***	(0.048)	8.084***	(0.048)
Observations	625,725		625,725		625,725	
R-squared	0.733		0.734		0.740	
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE	YES		YES		YES	
Firm-trend	YES		YES		YES	
Firm Charact.	YES		YES		YES	
County-Year	YES		YES			
Industry-Year			YES			
Ind-County-Year					YES	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. We re-estimate Column (3) of Table 2 by including additional control variables. The original model included year-fixed effects and their interaction with task use indexes, the gender and age of the worker, whether the firm is a public firm, 1-digit industry fixed effects, and firm-specific fixed effects and trends. We extend the list of control variables by time-varying firm-specific control (logarithm of sales and employment, dummy indicating that the firm participates in export activities) and county-year fixed effects in the first column, we further add industry-year fixed effects in the second column, and industry-county-year fixed effects in the last column.

A.2.2.3 Additional control variables

Table 14: Re-estimation of Table 2 on specific subsamples.

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Panel A: Large Firms						
Foreign	0.142***	(0.039)	0.031**	(0.014)	0.002	(0.010)
Fo * Abstract	0.042**	(0.017)	0.032***	(0.008)	0.034***	(0.008)
Fo * Face-to-face	-0.014	(0.016)	-0.006	(0.009)	-0.008	(0.009)
Fo * Routine	-0.003	(0.019)	0.017	(0.011)	0.010	(0.012)
Constant	7.943***	(0.073)	8.090***	(0.040)	8.099***	(0.042)
Observations	465,293		465,293		465,293	
R-squared	0.490		0.686		0.701	
Panel B: Excluding managers						
Foreign	0.154***	(0.033)	0.029***	(0.011)	0.006	(0.007)
Fo * Abstract	0.047***	(0.013)	0.026***	(0.006)	0.025***	(0.006)
Fo * Face-to-face	-0.032*	(0.017)	-0.018***	(0.006)	-0.016***	(0.006)
Fo * Routine	-0.018	(0.017)	0.005	(0.008)	-0.000	(0.008)
Constant	7.928***	(0.060)	8.081***	(0.026)	8.094***	(0.028)
Observations	581,272		581,272		581,272	
R-squared	0.455		0.730		0.753	
Panel C: Incumbent workers only						
Foreign	0.160***	(0.037)	0.035***	(0.011)	0.013**	(0.006)
Fo * Abstract	0.049***	(0.012)	0.025***	(0.007)	0.022***	(0.007)
Fo * Face-to-face	-0.006	(0.014)	0.000	(0.007)	0.004	(0.006)
Fo * Routine	-0.008	(0.018)	0.008	(0.009)	0.004	(0.010)
Constant	8.011***	(0.090)	8.191***	(0.053)	8.223***	(0.049)
Observations	219,702		219,702		219,702	
R-squared	0.424		0.701		0.726	
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE			YES		YES	
Firm-specific trend					YES	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. We re-estimate Column (3) of Table 2 on specific subsamples. We include year-fixed effects and their interaction with task use indexes, the gender and age of the worker, whether the firm is a public firm, 1-digit industry fixed effects. In the second column, we add firm-specific fixed effects to the model, and in the last column, we further add firm-specific trends.

A.2.2.4 Specific sub-samples

Table 15: Re-estimation of Table 2 by controlling for exporting activity.

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign	0.133***	(0.032)	0.030***	(0.011)	0.007	(0.007)
Fo * Abstract	0.044***	(0.012)	0.028***	(0.006)	0.028***	(0.006)
Fo * Face-to-face	-0.022*	(0.013)	-0.009	(0.007)	-0.006	(0.006)
Fo * Routine	-0.012	(0.015)	0.009	(0.009)	0.004	(0.009)
Export status	0.223***	(0.022)	0.009	(0.008)	-0.009	(0.008)
Export * Abstract	0.009	(0.016)	0.009	(0.009)	0.010	(0.009)
Export * Face-to-face	-0.026**	(0.012)	-0.010	(0.007)	-0.012*	(0.007)
Export * Routine	-0.029**	(0.013)	-0.018**	(0.008)	-0.017**	(0.009)
Age	0.028***	(0.003)	0.025***	(0.001)	0.025***	(0.001)
Age square	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Constant	7.784***	(0.064)	8.053***	(0.031)	8.078***	(0.033)
Observations	628,331		628,331		628,331	
R-squared	0.474		0.708		0.730	
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE			YES		YES	
Firm-trend					YES	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. We re-estimate Table 2 by controlling for export activity. We include year-fixed effects and their interaction with task use indexes, the gender and age of the worker, whether the firm is a public firm, 1-digit industry fixed effects. In the second column, we add firm-specific fixed effects to the model, and in the last column, we further add firm-specific trends.

A.2.2.5 Export activity

Table 16: Re-estimation of Table 2 by comparing Service and Manufactoring sectors.

VARIABLES	(1) coef	se	(2) coef	se	(3) coef	se
Service	-0.096*	(0.055)				
Service * Abstract	0.020	(0.022)	-0.012	(0.012)	-0.015	(0.011)
Service * Face-to-face	0.004	(0.015)	0.013	(0.009)	0.008	(0.009)
Service * Routine	-0.022*	(0.013)	0.006	(0.010)	-0.001	(0.008)
Foreign	0.174***	(0.059)	0.036**	(0.016)	0.007	(0.009)
Foreign * Service	-0.035	(0.057)	-0.008	(0.016)	-0.001	(0.013)
Fo * Abstract	0.048***	(0.017)	0.033***	(0.009)	0.034***	(0.008)
Fo * Face-to-face	-0.003	(0.013)	-0.004	(0.008)	-0.011	(0.009)
Fo * Routine	0.005	(0.020)	0.012	(0.014)	0.005	(0.014)
Fo * Service * Abstract	0.002	(0.023)	-0.006	(0.012)	-0.009	(0.012)
Fo * Service * Face-to-face	-0.024	(0.019)	-0.009	(0.014)	0.005	(0.014)
Fo * Service * Routine	-0.046*	(0.025)	-0.010	(0.017)	-0.006	(0.018)
Age	0.027***	(0.003)	0.025***	(0.001)	0.025***	(0.001)
Age square	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Constant	7.972***	(0.068)	8.060***	(0.031)	8.074***	(0.032)
Observations	628,331		628,331		628,331	
R-squared	0.454		0.708		0.730	
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE			YES		YES	
Firm-trend					YES	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. We re-estimate Table 2 by including an additional sectoral dummy and interact it with the foreign dummy and the task measures. We include year-fixed effects and their interaction with task use indexes, the gender and age of the worker, whether the firm is a public firm, 1-digit industry fixed effects. In the second column, we add firm-specific fixed effects to the model, and in the last column, we further add firm-specific trends.

A.2.2.6 Sectoral comparison

Table 17: Replication of Table 2 by using alternative task measures

VARIABLES	(1) coef	se	(2) coef	se	(3) coef	se
Foreign	0.161***	(0.034)	0.030***	(0.010)	0.007	(0.007)
Fo * Abstract	0.053***	(0.013)	0.024***	(0.009)	0.027***	(0.007)
Fo * Face-to-face	-0.018	(0.012)	-0.007	(0.006)	-0.004	(0.006)
Fo * Routine	-0.023	(0.015)	-0.005	(0.007)	-0.003	(0.007)
Age	0.028***	(0.003)	0.025***	(0.001)	0.025***	(0.001)
Age Square	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Constant	7.912***	(0.064)	8.060***	(0.030)	8.074***	(0.031)
Observations	628,487		628,487		628,487	
R-squared	0.439		0.702		0.724	
Worker Charact.	YES		YES		YES	
Industry	YES		YES		YES	
Year	YES		YES		YES	
Trend in task usage	YES		YES		YES	
Firm FE			YES		YES	
Firm-trend					YES	

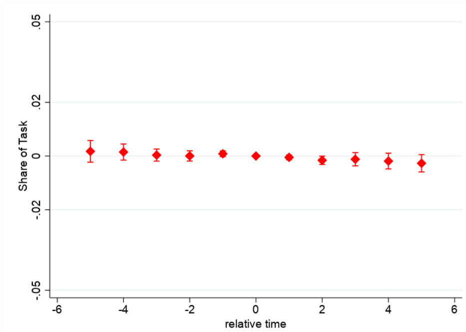
*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year-fixed effects and their interaction with task use indexes are included. We further control for the gender and age of the worker, and whether the firm is a public firm, and 1-digit industry fixed effects. We further control for firm-specific fixed effects in the second, for firm-level trends in the third column.

A.2.2.7 Alternative task measure

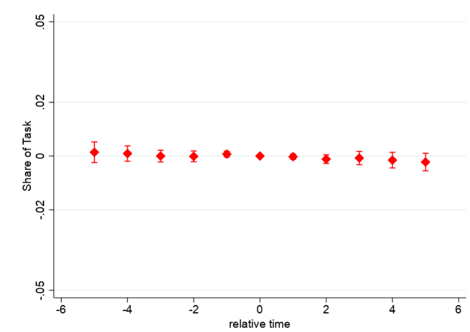
A.2.3 Change of task composition in production

Figure 2: Change of task composition in production

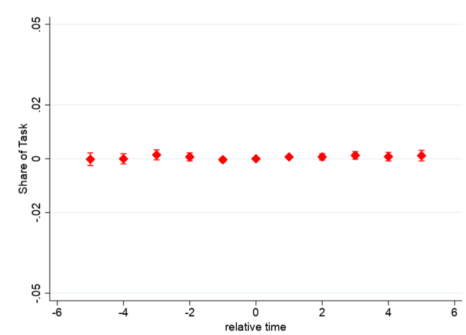
(a) Abstract task - no control



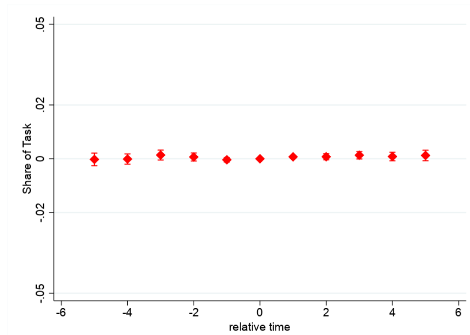
(b) Abstract task - firm level control



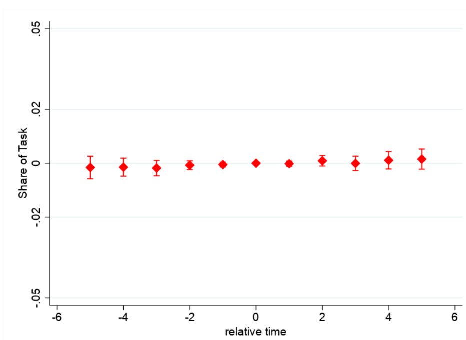
(c) Face-to-face task - no control



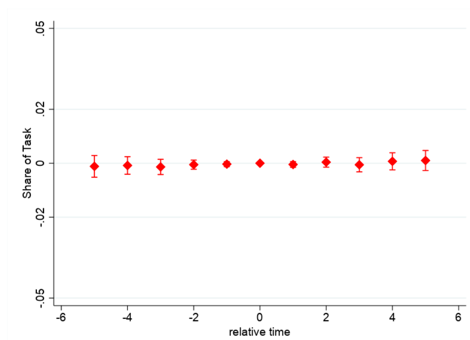
(d) Face-to-face task - firm level control



(e) Routine task - no control



(f) Routine task - firm level control

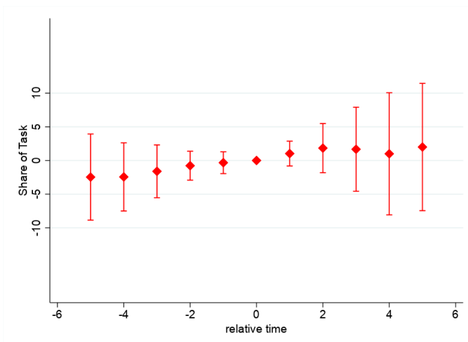


A.2.4 Change in firm size and task specialization

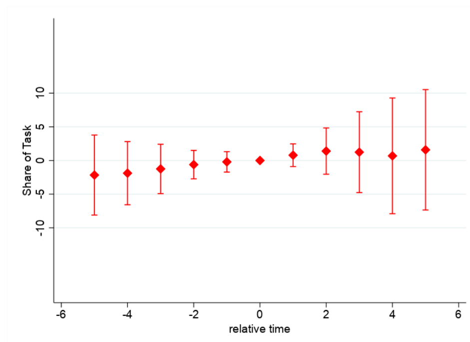
The event study analysis confirms our finding, that foreign acquisition does not have an effect on task specialization (see Figure 3)

Figure 3: Number of occupation codes and Herfindahl index around the acquisition

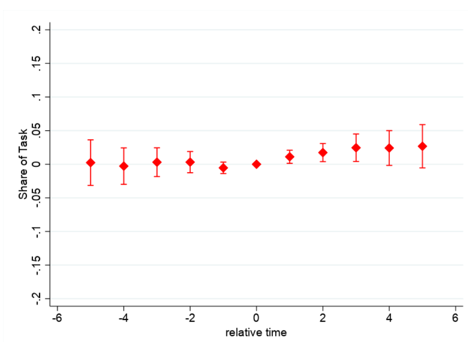
(a) Number of Occupations - no control



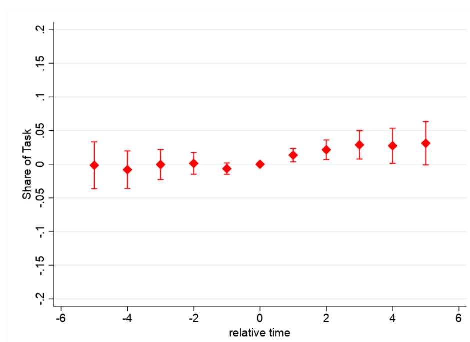
(b) Number of Occupations - firm-level control



(c) Herfindahl index - no control



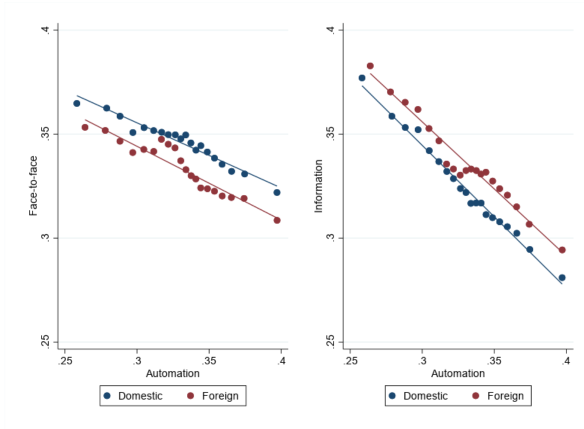
(d) Herfindahl index - firm level control



A.2.5 Composition effect - additional details

Figure 4 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 tasks and more abstract tasks. As soon as we control for firm fixed effects the differences by ownership types disappear, see Figure 5. These figures also suggest that firms do not change the share of routine cognitive tasks after acquisition.

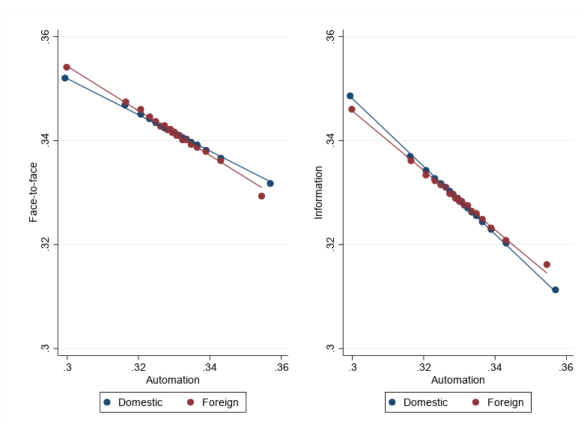
Figure 4: Variance in firm-level task usage (share)



[hbt!]

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

Figure 5: Variance in firm-level task usage (share)



[hbt!]

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

A.2.6 Heterogeneous effect by the source country of the FDI

This section contains the point estimates shown in the Figure 5.

Table 18: The effect of the foreign acquisition on task returns by the income of the source country of the FDI

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign Hign-Income	0.172***	(0.031)	-0.013	(0.022)	-0.007	(0.009)
Foreign Non-High-Income	0.178***	(0.043)	0.021**	(0.010)	0.026**	(0.010)
Abstract * High-Income	0.084***	(0.025)	0.050***	(0.016)	0.016**	(0.008)
Abstract * Non-High-Income	0.046***	(0.013)	0.032***	(0.010)	0.015***	(0.005)
Face-to-face * High-Income	-0.064**	(0.029)	-0.020	(0.020)	-0.010	(0.008)
Face-to-face * Non-High-Income	-0.011	(0.012)	-0.002	(0.006)	0.003	(0.004)
Routine * High-Income	-0.093***	(0.023)	-0.029*	(0.017)	-0.017**	(0.007)
Routine * Non-High-Income	-0.001	(0.017)	0.017	(0.012)	0.007	(0.006)
Constant	7.801***	(0.016)	8.043***	(0.013)	9.239***	(0.009)
Observations	11,743,369		11,743,369		11,743,369	
R-squared	0.557		0.762		0.922	
Year FE	YES		YES		YES	
Worker charact.	YES		YES		YES	
Industry FE	YES		YES		YES	
trend in task return	YES		YES		YES	
Firm FE			YES		YES	
Firm-level trend			YES		YES	
Worker FE					YES	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year-fixed effects and their interaction with task 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, and whether the firm is a public firm, and 1 digit industry fixed effects. We further control for firm-level trends in the second column, and worker fixed-effects in the third column.

Table 19: The effect of the foreign acquisition on task returns by the time zone difference between Hungary and the source country of the FDI

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign > 2hours	0.116***	(0.042)	0.014	(0.009)	0.014	(0.008)
Foreign <= 2hours	0.178***	(0.036)	0.010	(0.011)	0.017*	(0.010)
Abstract * Foreign > 2hours	0.102***	(0.032)	0.027	(0.018)	0.014	(0.009)
Abstract * Foreign <= 2hours	0.052***	(0.013)	0.040***	(0.009)	0.017***	(0.004)
Face-to-face * Foreign > 2hours	-0.051**	(0.020)	0.027***	(0.009)	0.005	(0.009)
Face-to-face * Foreign <= 2hours	-0.026*	(0.014)	-0.014*	(0.008)	-0.002	(0.004)
Routine * Foreign > 2hours	-0.087***	(0.034)	-0.005	(0.017)	-0.008	(0.008)
Routine * Foreign <= 2hours	-0.018	(0.017)	0.007	(0.014)	0.002	(0.006)
Constant	7.802***	(0.016)	8.043***	(0.013)	9.239***	(0.009)
Observations	11,743,369		11,743,369		11,743,369	
R-squared	0.557		0.762		0.922	
Year FE	YES		YES		YES	
Worker charact.	YES		YES		YES	
Industry FE	YES		YES		YES	
trend in task return	YES		YES		YES	
Firm FE			YES		YES	
Firm-level trend			YES		YES	
Worker FE					YES	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year-fixed effects and their interaction with task 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, and whether the firm is a public firm, and 1 digit industry fixed effects. We further control for firm-level trends in the second column, and worker fixed-effects in the third column.

Table 20: The effect of the foreign acquisition on task returns by the geographical distance between Hungary and the source country of the FDI

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign $> 2000km$	0.124***	(0.037)	0.014	(0.009)	0.013	(0.008)
Foreign $<= 2000km$	0.177***	(0.036)	0.009	(0.012)	0.017	(0.011)
Abstract * Foreign $> 2000km$	0.103***	(0.029)	0.028*	(0.016)	0.011	(0.009)
Abstract * Foreign $<= 2000km$	0.051***	(0.014)	0.040***	(0.009)	0.018***	(0.005)
Face-to-face * Foreign $> 2000km$	-0.047**	(0.019)	0.027***	(0.009)	0.005	(0.008)
Face-to-face * Foreign $<= 2000km$	-0.027*	(0.014)	-0.015*	(0.009)	-0.002	(0.005)
Routine * Foreign $> 2000km$	-0.087***	(0.031)	-0.016	(0.018)	-0.013*	(0.007)
Routine * Foreign $<= 2000km$	-0.016	(0.017)	0.010	(0.014)	0.004	(0.006)
Constant	7.801***	(0.016)	8.043***	(0.013)	9.239***	(0.009)
Observations	11,743,369		11,743,369		11,743,369	
R-squared	0.557		0.762		0.922	
Year FE	YES		YES		YES	
Worker charact.	YES		YES		YES	
Industry FE	YES		YES		YES	
trend in task return	YES		YES		YES	
Firm FE			YES		YES	
Firm-level trend			YES		YES	
Worker FE					YES	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year-fixed effects and their interaction with task 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, and whether the firm is a public firm, and 1 digit industry fixed effects. We further control for firm-level trends in the second column, and worker fixed-effects in the third column.

Table 21: The effect of the foreign acquisition on task returns by the EU membership of the source country of the FDI

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign EU	0.121***	(0.021)	-0.001	(0.011)	0.007	(0.008)
Foreign Non-EU	0.287***	(0.072)	0.036***	(0.013)	0.037**	(0.017)
Abstract * Foreign EU	0.054***	(0.015)	0.038***	(0.011)	0.018***	(0.005)
Abstract * Foreign Non-EU	0.072***	(0.024)	0.036***	(0.011)	0.013**	(0.006)
Face-to-face * Foreign EU	-0.006	(0.015)	-0.016	(0.011)	-0.004	(0.005)
Face-to-face * Foreign Non-EU	-0.071***	(0.025)	0.006	(0.007)	0.002	(0.006)
Routine * Foreign EU	-0.024	(0.017)	-0.003	(0.015)	-0.000	(0.007)
Routine * Foreign Non-EU	-0.030	(0.026)	0.016	(0.013)	0.002	(0.006)
Constant	7.802***	(0.016)	8.043***	(0.013)	9.239***	(0.009)
Observations	11,743,369		11,743,369		11,743,369	
R-squared	0.557		0.762		0.922	
Year FE	YES		YES		YES	
Worker charact.	YES		YES		YES	
Industry FE	YES		YES		YES	
trend in task return	YES		YES		YES	
Firm FE			YES		YES	
Firm-level trend			YES		YES	
Worker FE					YES	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year-fixed effects and their interaction with task 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, and whether the firm is a public firm, and 1 digit industry fixed effects. We further control for firm-level trends in the second column, and worker fixed-effects in the third column.

Table 22: The effect of the foreign acquisition on task returns for by neighboring and non-neighboring countries to Hungary

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign Neighbor	0.263***	(0.034)	0.005	(0.014)	0.016	(0.018)
Foreign Non-Neighbor	0.153***	(0.044)	0.012	(0.011)	0.017*	(0.010)
Abstract * Foreign Neighbor	0.020	(0.020)	0.014	(0.021)	0.004	(0.010)
Abstract * Foreign Non-Neighbor	0.070***	(0.014)	0.044***	(0.008)	0.019***	(0.004)
Face-to-face * Foreign Neighbor	0.001	(0.020)	-0.012	(0.019)	0.003	(0.009)
Face-to-face * Foreign Non-Neighbor	-0.030**	(0.014)	-0.007	(0.008)	-0.002	(0.004)
Routine * Foreign Neighbor	-0.036*	(0.018)	-0.018	(0.016)	-0.002	(0.009)
Routine * Foreign Non-Neighbor	-0.017	(0.021)	0.012	(0.014)	0.001	(0.006)
Constant	7.801***	(0.016)	8.043***	(0.013)	9.239***	(0.009)
Observations	11,743,369		11,743,369		11,743,369	
R-squared	0.557		0.762		0.922	
Year FE	YES		YES		YES	
Worker charact.	YES		YES		YES	
Industry FE	YES		YES		YES	
trend in task return	YES		YES		YES	
Firm FE			YES		YES	
Firm-level trend			YES		YES	
Worker FE					YES	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year-fixed effects and their interaction with task 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, and whether the firm is a public firm, and 1 digit industry fixed effects. We further control for firm-level trends in the second column, and worker fixed-effects in the third column.

Table 23: The effect of the foreign acquisition on task returns for by German and non-German speaking countries

	(1)		(2)		(3)	
VARIABLES	coef	se	coef	se	coef	se
Foreign German	0.142***	(0.039)	-0.005	(0.011)	-0.003	(0.010)
Foreign Non-German	0.186***	(0.046)	0.014	(0.012)	0.023**	(0.011)
Abstract * Foreign German	0.040*	(0.021)	0.015	(0.018)	0.010	(0.008)
Abstract * Foreign Non-German	0.061***	(0.014)	0.045***	(0.009)	0.019***	(0.005)
Face-to-face * Foreign German	-0.030	(0.021)	-0.023	(0.016)	-0.005	(0.007)
Face-to-face * Foreign Non-German	-0.030**	(0.015)	-0.004	(0.008)	-0.002	(0.005)
Routine * Foreign German	-0.043**	(0.018)	-0.022**	(0.011)	-0.007	(0.005)
Routine * Foreign Non-German	-0.021	(0.019)	0.017	(0.015)	0.002	(0.007)
Constant	7.802***	(0.016)	8.043***	(0.013)	9.240***	(0.009)
Observations	11,743,369		11,743,369		11,743,369	
R-squared	0.557		0.762		0.922	
Year FE	YES		YES		YES	
Worker charact.	YES		YES		YES	
Industry FE	YES		YES		YES	
trend in task return	YES		YES		YES	
Firm FE			YES		YES	
Firm-level trend			YES		YES	
Worker FE					YES	

*** $p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at the firm level. Year-fixed effects and their interaction with task 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, and whether the firm is a public firm, and 1 digit industry fixed effects. We further control for firm-level trends in the second column, and worker fixed-effects in the third column.

Processing Firms*

Boris Georgiev
McKinsey & Company

Marcel Smolka§
University of Flensburg
and CESifo

March 26, 2024

Abstract

In this paper, we explore a novel and detailed firm-product-level trade and production data set from Bulgaria over the period 2008-2015. Our focus is on firm heterogeneity in relation to two radically different production regimes: (i) production on the firm's own account; and (ii) production on behalf of another firm (processing trade). Our data allow us to study the selection of firms and products into processing trade by focusing on transitions between production regimes over time. We find strong evidence for positive selection in Bulgaria. Firms sorting into processing trade are bigger and more productive than firms producing on their own account. They are also much more specialized in actual production tasks, and they choose their most important (core) product for processing trade. We then study within-firm changes following processing trade with respect to a variety of outcome variables. We find total firm sales to be flat, because processing trade crowds out own-manufacturing production. However, we find that both the level and the composition of the workforce change: processing firms hire more production workers, which raises the labor and wage share of production workers as well as the total employment and labor intensity of the firm. This points to substantial restructuring and reorganization efforts within the firm when taking up processing trade.

JEL codes: F14, F23, F61, F66, L23, L25
Keywords: Processing trade; offshoring; firm-level data; labor shares; productivity; Bulgaria.

*Marcel Smolka gratefully acknowledges funding from the European Union's H2020 research and innovation programme GI-NI under the grant agreement number 101004494. The contents of this publication are the sole responsibility of the GI-NI project consortium and do not necessarily reflect the opinion of the European Union. I would like to thank Linnéa Kremer and Kira Kristin Schliephake for proofreading the manuscript.
§Email: marcel.smolka@uni-flensburg.de

1 Introduction

The economic effects of offshoring—relocating parts of a fragmented production process abroad—are a matter of considerable public and academic concern. A rich theoretical literature, starting in the 1990s, highlights the gains from specialization through offshoring, but also identifies conditions under which offshoring implies distributional conflict.[1] Over the years, economists have produced an impressive body of evidence on the effects of offshoring in countries at risk of losing production. Indeed, most studies on the effects of offshoring focus on *source* countries, i.e., countries moving production abroad in search of cost advantages or market opportunities, like Germany or the United States.

Our study focuses on a *host* country of offshoring—Bulgaria. This country acts as a major offshore destination for Western Europe due to its geographical proximity, low labor costs, and status as an EU member state since 2007.[2] We explore a novel and detailed Bulgarian firm-product level data set over the period 2008-2015. Our focus is on differences between firms in two radically different production regimes: (i) production on the firm's own account ("own-manufacturing"); and (ii) production on behalf of another firm ("processing trade"). Processing trade, in our view, is the flip side of offshoring. Over the last several decades, many firms in the U.S. and Western Europe have become increasingly involved in offshoring. To do so, firms need to form linkages with local suppliers abroad. Our knowledge of these suppliers is limited, however. Evidence about them is scarce and derives mainly from China.

To gain a better understanding of these issues, we merge several micro-level data sets with panel information on firms, products, and trade transactions. Importantly, our data allow us to draw a sharp line at the firm-product level between "ordinary" manufacturing firms, and firms conducting narrow processing activities for foreign headquarters. These processing firms do not hold property rights in the production process, the input materials used, and the final good produced. Nor are they responsible for the sourcing of inputs, the R&D activities, or the activities related to marketing, distribution, and sales. Instead, they carry out well-defined production tasks against payment of a manufacturing service fee from the headquarter.[3] Processing firms in Bulgaria, thus, play a fundamental role in enabling firms in Western Europe to move production offshore.

The nature and detail of our data, in particular the long-enough panel structure, allow us to study the selection of firms (and products) into processing trade in a convincing way by focusing

[1] See e.g. Jones and Kierzkowski (1990, 2001); Arndt (1997); Kohler (2004a,b); and Grossmann and Rossi-Hansberg (2008).

[2] In 2022, Bulgaria had the lowest labor costs of all EU member states (a mere 21% of the labor costs in Germany, which is a major source country of offshoring); see Eurostata data at https://ec.europa.eu/eurostat/databrowser/view/lc_lci_lev/default/table?lang=en.

[3] Yu (2015) defines processing trade in China as follows: "Processing trade is the process by which a domestic firm initially obtains raw materials or intermediate inputs from abroad and, after local processing, exports the value-added final goods." Eurostat (2014) defines processing trade in a similarly way: "Under this type of production arrangement, the resident firm owns the input materials as well as the intellectual property associated with the production process and is simply purchasing manufacturing services from abroad to transform the inputs into another product." Source: https://ec.europa.eu/eurostat/web/economic-globalisation/globalisation-macroeconomic-statistics/global-production-arrangements/goods-for-processing.

on transitions between production regimes. Differently from the literature, we can also distinguish between processing trade on behalf of a foreign headquarter, and processing trade for a domestic (Bulgarian) headquarter. Finally, we can study within-firm changes following processing trade with respect to a variety of outcome variables, including sales, product scope, employment, occupational and wage shares, and exports.

We generate two sets of results. First, and differently from China, we find strong evidence for positive selection in Bulgaria. Firms sorting into processing trade are bigger and more productive than firms producing on their own account. They are also much more specialized in actual production tasks (which is reflected in higher labor and wage bill shares of blue-collar workers compared with the average firm), and they choose their most important (core) product rather than a peripheral product for processing trade. Importantly, these observations are true before firms take up processing trade, that is, they are not a result of processing trade. This implies that processing trade might play an even more important role for the Bulgarian economy than perhaps previously believed, as it concerns some of the biggest and best-performing firms in the manufacturing sector with arguably high levels of human capital.

Our second set of results concerns the effects of processing trade on various firm outcomes. We obtain three main results. First, we find a substitutive relationship between own manufacturing and processing trade, at least in the short run. In particular, we see that, while total firm sales do not change following processing trade, the composition of sales change, away from the firm's own goods, and towards processing trade. Secondly, we find that both the level and the composition of the workforce change: processing firms hire more production workers, which raises the labor and wage share of production workers as well as total employment of the firm. In other words, labor demand, and especially demand for production workers, rises among processing firms, with a non-negative effect on production wages. And finally, we find that firms exporting a certain good under a processing trade regime are more likely to start exporting their own goods to the same destination. This is evidence for positive spill-over effects of processing trade into the firm's own activities.

Our paper is related to two important strands of the literature. The first is the literature on processing trade (Fernandes and Tang, 2012, 2015; Yu, 2015; Dai et al., 2016; Manova and Zhihong, 2016; Brandt and Morrow, 2017; Defever and Riaño, 2017; Brandt et al., 2021; Li et al., 2023). One focal point of this literature are significant productivity differences between own-manufacturing firms and processing firms. However, this literature is focused on China, while we provide evidence from an offshore destination that has received little attention so far. One important difference between China and Bulgaria is the role of policy. In China, imported inputs used in processing trade for exports are exempt from any import tariffs. For Bulgaria, which has been a member of the EU's single market since 2007, this does not play any role for intra-EU importing, processing, and exporting. The second strand of the literature we contribute to is related to global value chains (GVCs) and how firms, especially firms in less developed countries, can benefit from joining GVCs. An important recent contribution in this literature is Alfaro-Ureña et al. (2022) who provide detailed evidence on this question using firm-to-firm linkages in Costa Rica. Other papers using firm-level data and with a focus on foreign ownership and multinational enterprises include Almeida (2007); Javorcik and Spatareanu (2009); Guadalupe et al. (2012); Koch and Smolka (2019) and others.

The remainder of this paper is organized as follows. In the next section we introduce the data we use in our analysis. In Section 3 we conduct a selection analysis and identify important ex ante differences in firms and products that help in explaining ex post selection into processing trade. In Section 4 we investigate some of the consequences of processing trade, in particular with respect to sales, employment, and exports. Section 5 concludes.

2 Data

Data sources. The data we use come from the National Statistical Institute (NSI) in Bulgaria. Specifically, we combine three data sets across the years 2008 to 2015 for the purposes of our analysis[4]:

1. A data set on *production statistics* covering all manufacturing firms. For a firm to be included in the data set, it must generate a total revenue of more than 60,000 EUR per year. These data include the sales value and quantity at the 8-digit European Prodcom (PC8) firm-product level. A rare feature of the data is that firms report sales and quantities for products sold domestically and abroad (FOB). In total, the data include 2,100 unique products.

2. A data set on *trade statistics* from customs records covering the universe of Bulgarian import and export transactions. These data are available at the country-firm-product-year level and follow the European 8-digit Combined Nomenclature (or CN8). They include the sales value, quantity, and weight for each trade transaction.[5] In total, the data include 6,715 unique products.

3. A data set on *business statistics* with typical firm-level variables from balance sheet data, income data, information on employment, assets, subsidies etc. The variables include, for example, the wage bill, total sales, materials expenditure, the number of employees, the capital stock etc. This will be important for estimating the firm's level of productivity (among other things).

Prevalence of PT by industry. The key feature of our data set that we exploit is the information about the production regime operated by the firm. More precisely, the production statistics allow us to make an explicit distinction at the firm-product level between production on the firm's own account (OM) and production on behalf of another firm (PT). Moreover, in the case

[4] See chapter 2 in Georgiev (2018) for a study investigating firm-level markup differences across markets based on the Bulgarian data.

[5] The first six digits of the CN8 products correspond to (international) 6-digit Harmonized System (HS6) products. The CN8 classification is more detailed than the PC8 classification. Aggregating up to PC6 (CPA product classification of the EU) allows for an $m:1$ mapping of CN8 to PC6 where it is not necessary to concord product changes over time as the PC6 classification remains constant between 2008 and 2015.

of PT we know the location (at home or abroad) of the firm that "owns" the production process, so that we can distinguish, not just between OM and PT, but also between *domestic* and *foreign* PT. For all OM products, we know both revenues and quantities from the production statistics. For domestic PT we know the revenues (manufacturing service fee). For foreign PT we know both revenues and quantities from the trade statistics.

Table 1: Share of firms in processing trade—Full sample

NACE	OM	OM & PT	PT	Firm-year Obs.
Textiles, apparel, leather	25.98	23.87	50.15	11446
Pharmaceuticals, medicinal	80.07	19.93	.	286
Computer, electronic, optical	84.52	7.99	7.48	1176
Manufactured transport equipment	84.63	6.02	9.35	631
Food, beverages	86.50	12.60	0.90	12351
Electrical equipment	87.85	6.27	5.88	1753
Basic and fabricated metals	89.12	8.22	2.67	8581
Coke, refined petroleum	91.30	8.70	.	23
Chemicals	92.06	7.30	0.64	2027
Wood, paper	93.82	5.16	1.02	6781
Other manufacturing	95.44	3.14	1.41	5090
Manufactured machinery	95.76	3.55	0.68	3376
Rubber, plastic	95.96	3.40	0.63	8203
Overall	79.08	10.29	10.63	61724

Note: The table reports shares of firm-year observations classified into OM, OM & PT or PT by 2-digit NACE rev. 2. The data are sorted by the share of OM activities. *Source*: National Statistical Institute of Bulgaria. Years 2008-2015.

Table 1 reports the prevalence of PT in the full sample of firms at the industry level (aggregated from 2-digit NACE rev. 2 classification). In the table, we pool the data across all years from 2008 to 2015. There are a couple of noteworthy points. First, most firms in Bulgaria can be found in food, textiles & apparel, and metals production. Together, these three sectors account for more than 50% of all firms active in the manufacturing sector. Secondly, OM is by far the most prevalent type of production regime in all industries, with typical shares of firms doing only OM around 90%. However, there is one important exception: the textiles & wearing apparel industry, where 84% of firms are involved in PT. Finally, in firms where PT prevails, it is often done *in parallel* to OM, that is, typical PT firms are not just "pure" PT firms, but hybrid firms involved in both OM and PT at the same time.[6]

Our full sample includes roughly 7,000 firms per year and 13,838 unique firms between 2008 and 2015. In the next section we drop those firms that enter our sample as PT firms (either pure PT or hybrid PT). These are 2,776 firms, so that we are left with 11,062 firms. We do this because we are interested in the selection decision of firms, and thus the *switch* into PT. We observe 784 firms that switch—at some point in time over our sample period—from OM to PT (either pure PT or

[6] We note very similar observations when looking, not just at the share of firms, but also at the share of total sector sales attributable to the different firm types (not reported).

hybrid PT).[7] When we further exclude those firms that enter our sample as foreign-owned firms, we are left with 692 firms that switch.[8] Out of these, 97 firms switch into foreign PT, the rest into domestic PT. Table A.1 in the Appendix reports the distribution of firms in our thus restricted sample across industries.

Productivity by production regime. To get a first impression of potential performance differences between OM and PT firms, we illustrate in Figure 1 the productivity distributions of firms by production regime. We distinguish between OM and PT firms, and restrict the sample to pure OM and pure PT firms for convenience, but otherwise retain the full sample, that is, we pool the data across all years and simply sort firm-year observations into one of the two different production regimes (discarding hybrid OM & PT firms). In terms of the productivity measure, we use estimation techniques familiar from the literature. Specifically, in Figure 1a we use (revenue-based) total factor productivity (TFP) estimated from Levinsohn and Petrin (2003) as the underlying performance measure of the firm. Figure 1b uses instead the estimation routine proposed by Ackerberg et al. (2015) to estimate TFP (likewise revenue-based). This estimation routine overcomes issues related to multicollinearity and measurement error. However, the results that we find are similar regardless of the TFP measure that we use. In particular, we find that the productivity distribution of PT firms dominates the corresponding productivity distribution of OM firms. This holds true for the entire range of productivity levels, except for the very top productivity levels, where we observe a slightly higher density of OM than PT firms.[9]

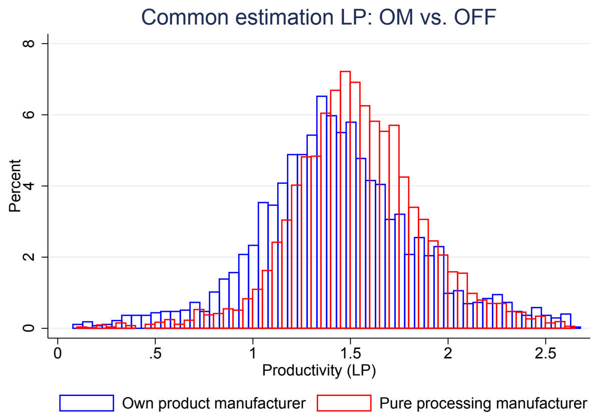
The observation that, by and large, PT firms tend to be more productive than OM firms indicates a major difference to the findings on processing trade firms from China in relation to their performance (Dai et al., 2016). However, the evidence in Figure 1 is entirely silent on the direction of causality. Are PT firms more productive ex ante than OM firms, and subsequently select into PT activities? Or are both types of firms equally productive to start with, and productivity differences emerge afterwards? In the next section, we conduct a careful analysis into the first possibility, namely that PT firms are already more productive *before* they sort themselves into a PT production regime.

[7] We observe 846 switching events in total, but some of them are due to switches back and forth.

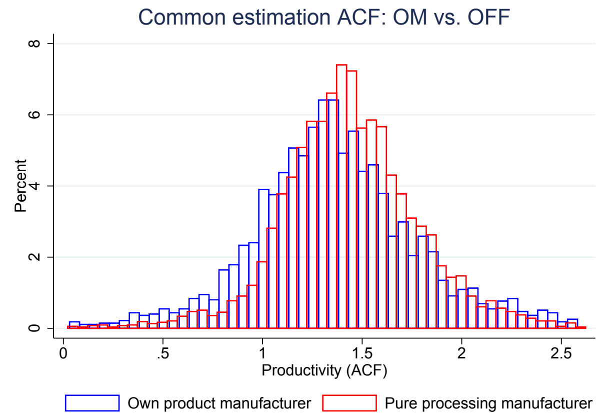
[8] We should like to stress that processing firms and foreign-owned firms are two very different groups of firms. The large majority of firms doing PT on behalf of a foreign client—70%—are domestically owned. The same number for PT on behalf of a domestic client is 93%.

[9] The TFP estimates underlying Figure 1 assume common production function coefficients by industry. We have also estimated different production function coefficients by industry for the two types of firms, to allow for different production technologies depending on production regime. However, doing so does very little to our productivity distributions as shown in Figure 1 (results not reported).

Figure 1: Productivity distributions by production regime (2008-2015).



(a) TFP from Levinsohn and Petrin (2003).



(b) TFP from Ackerberg et al. (2015).

3 Selection into processing trade

3.1 Selection of firms

In this section, we address the selection of Bulgarian firms into PT activities. While PT seems to play an important role, not just in Bulgaria, but also in other major offshore destinations, especially China, we have a very limited understanding of this selection process. Dai et al. (2016) show significant productivity differences between firms in China that export under an ordinary trade regime and those that export through a PT regime. However, their focus is on average performance differences between the two types of firms. They do not investigate the actual selection decisions of firms (the switch from one trade regime to another).

The nature of our data, in particular the long-enough panel structure, allows us to address the issue of selection in a convincing way. We focus on two central channels of selection: the firm's productivity and its share of labor in production.

Productivity. We begin to investigate the possibility of productivity-based selection by estimating an equation of the following form:

$$PT_i = \alpha + \beta\phi_{i0} + d_s + \varepsilon_i, \tag{1}$$

where PT_i is a 0/1 indicator variable for whether firm i selects into PT during the sample period, ϕ_{i0} is the firm's productivity in the year of sample entry, α and β are parameters to be estimated, d_s is an industry fixed effect, and ε_i is the error term. We thus collapse the time-series information available for each firm in our sample into one observation referenced by subscript i. For simplicity, we do not distinguish between a full and a partial switch of the firm's production activities into PT here, that is, we sort hybrid OM & PT firms and pure PT firms into the same category ($PT_i = 1$). We also do not, in a first step, distinguish between domestic and foreign PT, but we will do so later. As we said before, we only keep firms in the estimation that produce all of their products on their own account when they first appear in the sample. The null hypothesis we test is that there is no selection on productivity, i.e., $\beta = 0$. Under positive (negative) selection on productivity, the parameter β would be positive (negative).

Table 2 reports the first set of results using a linear probability model (LPM) to estimate Equation (1).[10] In these regressions we use three different measures of productivity: sales, value added, and TFP based on Ackerberg et al. (2015). Odd-numbered columns give estimates of β as given in Equation (1). Even-numbered columns give estimates of a slightly modified version of the equation, namely of the effect of falling into a certain quartile of the productivity distribution, relative to falling into the bottom quartile, on the probability of doing PT. Table 2 reports positive and significant estimates of β for all three productivity measures. The estimates range from 0.015 for value added to 0.018 for TFP. This implies that a unit-increase in productivity raises the likelihood of PT by at least 1.5%-points. The table also reports positive and significant effects of falling into higher quartiles of the productivity distribution. We find that firms in the top quartile of the sales and value added distribution have the highest probability of sorting themselves into PT activities over the sample period. For example, moving from the bottom to the top quartile of the sales distribution raises the likelihood of doing PT by 5%-points. We also find that firms in the bottom quartile of the TFP distribution have the lowest probability of doing so. Overall, we find clear evidence of positive selection. That is, firms that sort themselves into PT activities are significantly larger and display higher levels of value added and TFP than other firms that remain pure OM firms throughout.[11]

To gain further insights into the selection on productivity, we next distinguish between PT on behalf of a domestic vs. a foreign client. We use an estimation framework similar to Equation (1), but we now sort firms that do OM when they enter the sample into three rather than just two categories: those that never select into PT ($PT_i^* = 0$); those that switch into domestic PT ($PT_i^* = 1$); and those that switch into foreign PT ($PT_i^* = 2$). In this sample, more than 90% belong to the first group, 7% to the second group, and just 2% to the last group. To evaluate the effects of (initial) productivity on the relative probabilities of falling into any one of these three categories, we estimate a multinomial logit (MNL) model with PT_i^* as the outcome variable (where $PT_i^* = 0$ is the baseline outcome). Table 3 reports estimates of relative risk ratios (RRR) obtained from the MNL model. These estimates indicate how a unit-increase in productivity affects the probability of falling into any one of the PT outcomes (say, $PT_i^* = 1$) relative to the probability

[10] Results based on a non-linear Probit model (not reported) are qualitatively very similar.

[11] In another set of regressions we exploit the panel dimension of our data set more directly by estimating the following equation:

$$PT_{it} = \alpha + \beta\phi_{i,t-1} + d_{st} + \varepsilon_{it}, \tag{2}$$

where PT_{it} is a 0/1 indicator for whether firm i engages in PT in year t, $\phi_{i,t-1}$ is the firm's productivity (lagged by one year), and d_{st} is an industry-year fixed effect. In these regressions we exclude observations from the estimation after a firm takes up PT for the first time in the sample period, as we are interested in firms that do OM in the initial period and then switch (fully or partially) to PT in a later period. The results reported in Table A.2 in the Appendix suggest significant positive selection in terms of value added and TFP, but not in terms of total sales.

Table 2: Selection based on productivity

	Sales		Value added		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Initial productivity$_i$	0.016***		0.015***		0.018*	
	(0.003)		(0.002)		(0.010)	
Q2 - Initial productivity$_i$		0.007		0.009		0.020**
		(0.009)		(0.009)		(0.009)
Q3 - Initial productivity$_i$		0.022**		0.037***		0.024***
		(0.009)		(0.010)		(0.009)
Q4 - Initial productivity$_i$		0.050***		0.059***		0.021**
		(0.010)		(0.010)		(0.009)
Industry FE	✓	✓	✓	✓	✓	✓
Observations	7456	7456	6496	6496	7451	7451
R^2	0.05	0.05	0.06	0.06	0.05	0.05

Note: The table reports estimates of variants of Equation (1). The dependent variable in all regressions is an indicator variable for PT that equals one if the firm starts doing PT over the sample period, and zero otherwise. The sample includes all domestically owned firms that are OM producers in the first year they enter the sample. Initial productivity is the natural logarithm of one of the firm's productivity variables relative to the industry mean, in the first year the firm appears in the sample. We use real sales, real value added, and TFP as productivity variables. TFP is estimated following Ackerberg et al. (2015). Q2, Q3, and Q4 are dummy variables for whether the firm falls into the second, third, or fourth quartile of the industry's productivity distribution, with Q1 being the baseline category. Robust standard errors in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

of falling into the baseline outcome $PT_i^* = 0$. Hence, RRR estimates that exceed one, as found across all productivity measures in the case of domestic PT, indicate that firms with higher initial levels of productivity are more likely to select into domestic PT afterwards; see odd-numbered columns in Table 3. Moreover, we find consistently higher RRR point estimates for foreign PT than for domestic PT, regardless of the productivity measure that we use. This demonstrates a clear performance hierarchy, in the sense that the largest and most productive firms within an industry tend to sort themselves into foreign PT, followed by firms that sit within an intermediate segment of the firm sales and productivity distribution and which choose domestic PT. The firms that remain pure OM firms tend to perform worse (in terms of sales and productivity). The regressions in the even-numbered columns use dummy variables for the productivity quartiles rather than the levels of productivity as such. The results from these regressions unambiguously support this hierarchy.

Share of labor in production. We now consider the share of labor allocated to different activities as further selection variables. We assume that firms will specialize in those activities in which they have a comparative advantage (with correspondingly higher labor shares). The activities we consider follow the 1-digit International Standard Classification of Occupations (ISCO-08), as this information is readily available in our data. In a first step, we simply differentiate between production (blue-collar) workers and non-production (white-collar) workers, and lump the following ISCO-08 1-digit occupations together into the group of production workers: (7) Craft and related trades workers; (8) Plant and machine operators and assemblers; and (9) Elementary occupations.[12] We then augment Equation (1) by the thus constructed firm's initial share of production workers. We also estimate a panel version of the same model by similarly augmenting Equation (2) in Footnote 11. Moreover, we run separate regressions for each ISCO-08 occupational group to provide a more fine-grained picture of the role of occupational shares in the selection of firms into PT.[13]

Table 4 reports the estimation results. Panels A and B show the cross-sectional and the panel results, respectively. In all columns we use TFP as the productivity variable, and we always include industry fixed effects (or industry-year fixed effects). In column (1) we use the share of production workers as an explanatory variable, while in the other columns we include, separately, the corresponding shares for the specific ISCO-08 occupational groups. We find, consistently across Panels A and B, that firms are significantly more likely to select into PT when they produce with a larger share of production workers (conditional on TFP). Looking into the results for the different occupational groups, we find consistently positive effects for plant & machine operators, and consistently negative effects for service & sales occupations. We do not find robustly significant results for any of the other occupational groups.[14]

To take a slightly deeper look into the selection effects stemming from the share of plant &

[12] Note that the line we draw between production and non-production workers in this way is not perfect, because ISCO group (9) Elementary occupations also includes elementary sales and service occupations.

[13] We find the estimation results to be very similar to the ones reported below when we consider the wage bill of each occupation instead of the labor share.

[14] We have not found any material differences between selection into domestic vs. foreign PT based on the labor shares, which is why we do not report separate results for the two types of PT.

Table 3: Selection into domestic vs. foreign PT—Multinomial logit (MNL)

	Sales		Value added		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic PT						
Initial productivity$_i$	1.191***		1.163***		1.212	
	(0.037)		(0.037)		(0.145)	
Q2 - Initial productivity$_i$		1.189		1.197		1.237*
		(0.187)		(0.200)		(0.160)
Q3 - Initial productivity$_i$		1.456**		1.628***		1.281*
		(0.216)		(0.255)		(0.165)
Q4 - Initial productivity$_i$		1.838***		1.940***		1.249*
		(0.264)		(0.294)		(0.166)
Foreign PT						
Initial productivity$_i$	1.541***		1.553***		1.376	
	(0.105)		(0.131)		(0.329)	
Q2 - Initial productivity$_i$		2.560*		0.506		1.612
		(1.315)		(0.261)		(0.517)
Q3 - Initial productivity$_i$		3.386**		1.588		1.819*
		(1.661)		(0.620)		(0.569)
Q4 - Initial productivity$_i$		6.209***		3.552***		1.860*
		(2.942)		(1.244)		(0.598)
Pseudo-R squared	0.08	0.08	0.09	0.09	0.07	0.07
LR Chi squared	23,219.1	22,274.4	18,266.3	17,253.4	22,638.6	25,068.3
Industry FE	✓	✓	✓	✓	✓	✓
Log pseudolikelihood	-2,301.2	-2,306.7	-1,935.3	-1,930.9	-2,328.6	-2,325.8
Observations	7,430	7,430	6,472	6,472	7,428	7,428

Note: The table reports relative risk ratios corresponding to a multinomial logit model where OM (baseline), domestic PT, and foreign PT are the three choice categories. The sample includes all domestically owned firms that are OM producers in the first year they enter the sample. Those firms that remain pure OM producers throughout fall into the baseline category. Those choosing PT for a domestic (foreign) client over the sample period are classified as domestic (foreign) PT. Initial productivity is the natural logarithm of one of the firm's productivity variables relative to the industry mean, in the first year the firm appears in the sample. We use real sales, real value added, and TFP as productivity variables. TFP is estimated following Ackerberg et al. (2015). Q2, Q3, and Q4 are dummy variables for whether the firm falls into the second, third, or fourth quartile of the industry's productivity distribution, with Q1 being the baseline category. Robust standard errors in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

machine operators, we run a number of additional regressions. Specifically, we exclude foreign-owned firms; we test whether the results depend on the productivity measure that we use as a control variable (sales; value added; TFP); and we include a set of dummy variables separating the quartiles of the labor share variable, rather than the initial labor share variable as such. The results in Table 5 clearly confirm the type of selection into PT based on the firm's share of plant & machine operators discussed above, irrespective of the precise specification that we use. We conclude from our exercise that firms with a comparative advantage in production-related activities tend to choose PT, while firms with a comparative advantage in service- and sales-related activities (headquarter functions) tend to remain pure OM firms.

Table 4: Selection based on occupational shares—Cross-section and panel analysis

Panel A Cross-section analysis	Production workers (1)	Managers (2)	Professionals (3)	Technicians (4)	Clerical support (5)	Service & sales (6)	Craft & related trades (7)	Plant & machine operators (8)	Elementary occupations (9)
Initial occupation intensity$_i$	0.033***	0.024	0.015	0.005	-0.023	-0.077***	0.001	0.048***	-0.020**
	(0.012)	(0.033)	(0.034)	(0.023)	(0.025)	(0.017)	(0.011)	(0.012)	(0.010)
Initial TFP$_i$	0.021**	0.017*	0.018*	0.018*	0.019*	0.019*	0.018*	0.019**	0.017*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
R^2	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	8,141	8,141	8,141	8,141	8,141	8,141	8,141	8,141	8,141

Panel B Panel analysis	Production workers (1)	Managers (2)	Professionals (3)	Technicians (4)	Clerical support (5)	Service & sales (6)	Craft & related trades (7)	Plant & machine operators (8)	Elementary occupations (9)
Occupation intensity$_{i,t-1}$	0.011***	0.013	0.003	-0.000	-0.014*	-0.023***	0.002	0.009**	-0.003
	(0.004)	(0.011)	(0.010)	(0.007)	(0.008)	(0.005)	(0.003)	(0.004)	(0.003)
TFP$_{i,t-1}$	0.012***	0.010***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Industry-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	33,238	33,237	33,237	33,237	33,237	33,237	33,237	33,237	33,237

Note: The table reports estimates of variants of Equations (1) and (2) augmented by occupational labor shares as an additional right-hand side variable. The sample includes all domestically owned firms that are OM producers in the first year they enter the sample. In Panel A, the dependent variable in all regressions is an indicator variable for PT that equals one if the firm starts doing PT over the sample period, and zero otherwise. Initial occupation intensity is the labor share in a given occupation in the first year the firm appears in the sample. Initial TFP is the natural logarithm of the firm's TFP relative to the industry mean, in the first year the firm appears in the sample. TFP is estimated following Ackerberg et al. (2015). In Panel B we run a similar regression for a panel analysis. Robust standard errors in parentheses. In Panel B, these are clustered by firm. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table 5: Selection based on the share of plant & machine operators

	(1)	(2)	(3)	(4)	(5)	(6)
Initial share$_i$	0.036***		0.046***		0.040***	
	(0.012)		(0.013)		(0.012)	
Q2 - Initial share$_i$		-0.011		-0.014		-0.008
		(0.009)		(0.009)		(0.009)
Q3 - Initial share$_i$		0.019**		0.025**		0.029***
		(0.009)		(0.010)		(0.009)
Q4 - Initial share$_i$		0.020**		0.024**		0.026***
		(0.009)		(0.010)		(0.009)
Proxy for productivity	sales	sales	value added	value added	TFP	TFP
Industry FE	✓	✓	✓	✓	✓	✓
Observations	7456	7456	6496	6496	7451	7451
R^2	0.05	0.05	0.06	0.07	0.05	0.05

Note: The table reports estimates of variants of Equation (1) augmented by the labor share of plant and machine operators as an additional right-hand side variable. The sample includes all domestically owned firms that are OM producers in the first year they enter the sample. The dependent variable in all regressions is an indicator variable for PT that equals one if the firm starts doing PT over the sample period, and zero otherwise. Initial share is the share of plant and machine operators in total employment in the first year the firm appears in the sample. Q2, Q3, and Q4 are dummy variables for whether the firm falls into the second, third, or fourth quartile of the industry's labor share distribution, with Q1 being the baseline category. Robust standard errors in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

3.2 Selection of products

In the final step of our selection analysis, we ask which products firms choose to produce under a processing trade regime when they transition from OM to PT. To answer this question, we index products by j and estimate equations of the following form via OLS:

$$PT_{ij} = \alpha + \beta_1 \sigma_{ij0} + \beta_2 age_{ij} + d_i + d_j + \varepsilon_{ij}, \tag{3}$$

where PT_{ij} is a dummy variable equal to one if firm i switches from pure OM to PT over the sample period and selects product j for PT, and zero otherwise, and σ_{ij0} measures the initial (period 0) importance of product j of firm i in terms of its rank (by their sales), sales, and price.[15] The variable age_{ij} measures the tenure of the product (in years), and d_i and d_j are firm fixed effects and product fixed effects, respectively. These fixed effects make sure that our estimates of β_1 are not influenced by firm- or product-specific parameters (such as the firm's industry, productivity, number of products etc., or product-specific retooling costs when transitioning to PT). We should

[15]For simplicity, we do not distinguish here between partial PT and full PT for a given product and firm. Partial PT means that the firm entertains both production regimes, OM and PT, at the same time and for the exact same product, while full PT means that the firm does not produce the product on its own account.

also like to emphasize again that all right-hand side variables in these estimations come from pure OM observations, that is, before any processing trade has been taken up by the firm.

The estimation results in Table 6 suggest that firms tend to select their most important products for processing trade. Column (1) reports a negative and highly significant coefficient of the rank of the product within the firm. This means that products become increasingly unlikely to be chosen for PT the further we move away from the firm's core competence. This idea is also supported by the estimates in column (3), which looks at the product's level of sales (in logs) directly, rather than its rank within the firm. We find a positive and highly significant coefficient there, which means that products generating more revenue are more likely to be chosen for PT. A unit-increase in sales raises the likelihood of PT by 0.8 percentage points.[16]

In columns (2) and (4) we alternatively measure the importance of product j in terms of rank and sales within products across firms (rather than within firms across products, as we do in columns (1) and (3)). We find similar coefficients as before. This suggests that products likely to be chosen for PT are not just important for the individual firm, but also in the sector as a whole. When exploiting variation in the (initial) price of a given product across firms, we find a negative and marginally significant coefficient estimate; see column (5). If we abstract from quality and demand-side differences, then this implies that the firms that are most efficient at producing a given good are more likely to transition from pure OM to processing trade.

Table 6: Selection of products

	(1) Rank w-i/b-j	(2) Rank w-j/b-i	(3) Sales w-i/b-j	(4) Sales w-j/b-i	(5) Prices w-j/b-i
σ_{ij0}	-0.004***	-0.004***	0.008***	0.006***	-0.004*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
age$_{ij}$	0.012***	0.013***	0.010***	0.011***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Firm FE	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓
Observations	13906	13906	13690	13690	11692
R^2	0.55	0.55	0.56	0.56	0.58

Note: The table reports estimates of variants of Equation (3). The sample includes all domestically owned firms that are OM producers in the first year they enter the sample. The dependent variable is an indicator variable for PT that equals one if firm i starts doing PT for product j over the sample period, and zero otherwise. The key independent variable, σ_{ij0}, measures the importance of product j in firm i by its rank (in terms of sales, within i or j), sales (within i or j), and price (within j). The variable age measures the tenure of product j in firm i (in years). Robust standard errors in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

[16] We also find that products with longer tenure are more likely to be chosen for PT.

4 Some consequences of processing trade

In the previous section we have documented a consistent picture that suggests that the most efficient firms with a comparative advantage in production activities select their best products for PT. In this section we turn to some of the consequences of processing trade. Specifically, we estimate the effects on sales and products, occupations and wages, and exports.

4.1 Sales and products

When firms take up PT activities, they can do this in addition to their own-manufacturing activities, or they could replace some of their own production, and use the freed up resources for doing PT. This boils down to the question of whether OM and PT activities are complements or substitutes. To answer this question empirically, we estimate the effect of processing trade on the total sales of the firm exploiting the panel structure of our data set and including a rich set of fixed effects as follows:

$$Y_{it} = \alpha + \beta PT_{it} + \delta_i + \delta_{srt} + \epsilon_{it}, \tag{4}$$

where Y_{it} is the outcome variable (here: log total sales), PT_{it} is a dummy variable for processing trade (the variable of interest)[17], and δ_i is a firm fixed effect that absorbs the direct effects of the initial level of productivity and the share of production workers (which, as we have seen, both correlate positively with PT), along with any other time-constant unobserved firm characteristics. Including firm fixed effects implies that the estimated parameter $\hat{\beta}$ measures the change in sales after firms take up PT, controlling for the fact that PT is chosen among the best-performing firms to start with. Equation (4) also includes fixed effects for the industry-region-year triplet, δ_{srt}, to account for location×industry-specific shocks to sales, e.g. due to the business cycle or policies.[18] We always estimate robust standard errors clustered at the firm level.

Column (1) in Table 7 reports the estimation results for the effect of PT on total sales as specified in Equation (4). Importantly, the total sales variable includes sales stemming from both types of activities: OM *and* PT. We find that the estimated coefficient of the PT dummy is positive and equal to 0.016, but insignificant. Column (2) augments the estimation by the one-year lag of PT, to get a better impression of the timing of a potential effect. The estimated coefficients of PT and its lag are both insignificant. Hence, we cannot reject the null hypothesis that PT has a zero effect on total sales. This would support the idea of a substitutive relationship between the activities from own-manufacturing and those from processing trade. To explore this possibility, we run the

[17] We keep the analysis simple here and do not distinguish between (i) domestic and foreign PT; (ii) different *levels* of PT; and (iii) permanent vs. temporary PT. Hence, PT_{it} is equal to one if the firm reports *some* PT (whether domestic or foreign) for any of its products in year t, and zero otherwise.

[18] Our fixed effects specification controls for selection based on time-invariant firm characteristics (such as initial productivity and the initial allocation of labor inside the firm), as well as for selection driven by industry shocks specific to the location of the firm. However, it could be that firm productivity (along with other firm characteristics) develops differently over time and affect the decision to take up PT differentially. The results reported in this section should therefore not be interpreted in a strictly causal sense.

Table 7: Effects on sales and products

	Log Sales		Log OM-sales		# OM Products	
	(1)	(2)	(3)	(4)	(5)	(6)
PT	0.016	-0.005	-0.188***	-0.177***	-0.045	-0.023
	(0.022)	(0.024)	(0.027)	(0.029)	(0.039)	(0.043)
Lagged PT		0.018		-0.015		0.055
		(0.022)		(0.025)		(0.041)
Firm FE	✓	✓	✓	✓	✓	✓
Industry-Region-Year FE	✓	✓	✓	✓	✓	✓
Observations	38395	29240	38222	29096	38395	29240
R^2	0.92	0.94	0.92	0.93	0.91	0.93

Note: The table reports estimates of variants of Equation (4). The dependent variables in the different regressions are written at the top of the respective columns. PT is a dummy variable equal to one if the firm does at least some PT on behalf of a domestic or foreign client. The sample includes all domestically owned firms that are OM producers in the first year they enter the sample. Robust standard errors (clustered by firm) in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

same regressions as before, but restrict the sales variable to include only the sales generated from the firm's OM activities; see columns (3) and (4). We find a quantitatively important and quite precisely estimated drop in OM sales by around 18% occurring in the same year as the firm takes up PT for the first time. When we look at the number of different own-manufacturing products of the firm, we find a negative but insignificant estimate for the coefficient of the PT dummy; see columns (5) and (6). We thus conclude from these regressions that firms taking up PT tend to produce the same number of products as before on their own account. Yet, they reduce their OM sales to the same extent as they raise their PT sales, leaving total sales unchanged.

4.2 Workers and occupations

We next turn to the labor market effects of processing trade at the firm level. We address several questions. The first is whether and how processing trade affects total employment. The second question is how the composition of the workforce changes. And finally, we ask how wages develop following processing trade.

In our view, one plausible scenario in this context is that through processing trade firms are able to focus more narrowly on where their comparative advantage lies, and thus become more efficient. This would imply that actual production activities will expand following PT, while other activities, in particular headquarter activities like input sourcing, R&D, and marketing, will contract (relative to production activities). Under this scenario, the composition of the workforce would consequently change towards production workers. At least for large enough efficiency gains we would also expect the firm's overall labor demand to rise.

A further possibility, compatible with the above-described scenario, is that there are spill-over effects in production from PT to OM, in the sense that firms become more efficient in their own-manufacturing production once they take up PT, for example by learning through the productionsupplier relationship with the firm for which they do PT. Positive spill-over effects of this kind would further contribute to an increase in the firm's labor demand following PT. However, testing for such spill-over effects directly in a production function framework is difficult, because we do not see in our data how the firm allocates its resources across OM production vs. PT production (e.g. what share of production workers is employed in OM vs. PT).[19]

Empirically, we estimate the same fixed effects specification as before in Equation (4), with Y_{it} now being the following firm-level outcome variables: (i) log employment (measured by the number of workers); (ii) share of labor in production activities; and (iii) share of production wages.[20] Table 8 reports the estimation results. We find positive and significant effects of PT on firm-level employment. The point estimate in column (1) implies that the number of jobs increases by 6.4% following PT. This is a sizable effect. Moreover, we find that the share of production workers in total employment increases by 1.5%-points due to PT (columns (3) and (4)), and similarly for the share of production wages (columns (5) and (6)).

To summarize, processing trade creates a significant number of jobs within PT firms. It also raises the overall labor intensity of the firm (measured by the employment-to-sales ratio), and in particular the intensity in raw labor. Average wages of production workers also rise following PT.[21]

Table 8: Effects on labor

	Log Emp.		Emp.-share prod.		Wage-share prod.	
	(1)	(2)	(3)	(4)	(5)	(6)
PT	0.064***	0.044***	0.015***	0.013**	0.014**	0.009
	(0.015)	(0.016)	(0.005)	(0.006)	(0.006)	(0.007)
Lagged PT		0.012		0.001		0.011
		(0.015)		(0.006)		(0.007)
Firm FE	✓	✓	✓	✓	✓	✓
Industry-Region-Year FE	✓	✓	✓	✓	✓	✓
Observations	38395	29240	38395	29240	38394	29239
R^2	0.94	0.95	0.80	0.82	0.78	0.81

Note: The table reports estimates of variants of Equation (4). The dependent variables in the different regressions are written at the top of the respective columns. PT is a dummy variable equal to one if the firm does at least some PT on behalf of a domestic or foreign client. The sample includes all domestically owned firms that are OM producers in the first year they enter the sample. Robust standard errors (clustered by firm) in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

[19] We similarly do not see in our data the use of material inputs in PT production, because the firm receives the material inputs "for free" from the PT client and has no property rights in them. TFP estimates in the context of processing trade, therefore, have to be interpreted with caution.

[20] Production workers include the same three ISCO-08 groups as in the previous section: craft and related trades workers; plant and machine operators; and elementary occupations.

[21] This is so because the share of production wages is significantly smaller than the share of production workers in total employment, but PT lifts the two shares equally (in absolute terms).

4.3 Exports

In the final step of our analysis we provide a somewhat more explicit look into potential spill-over effects from PT to OM, but we focus on exports. More precisely, we ask whether PT on behalf of a foreign client prompts firms to start exporting their own-manufactured products into the same location as the PT product. This could happen, for instance, through a reduction in the market-specific fixed costs of exporting due to information gained about the destination market.[22]

Table 9: Effects on exports

	(1) OM-Export
Lagged PT	0.110**
	(0.044)
Firm FE	✓
Industry-Destination-Year FE	✓
Observations	2236480
R^2	0.05

Note: The table reports estimates of Equation (**??**). The dependent variable is a dummy variable equal to one if the firm exports its own-manufacturing goods to a certain destination d at time t, and zero otherwise. PT is a dummy variable equal to one if the firm exported its PT goods to the same destination d in the previous year $t-1$. The sample includes all domestically owned firms that are OM producers in the first year they enter the sample and that did not export to destination d. Robust standard errors (clustered by firm) in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

For this analysis, we take advantage of the comprehensive (merged) data set including the trade statistics. We estimate the following equation using OLS:

$$Exp^{OM}_{idt} = \alpha + \beta_1 PT_{idt-1} + \delta_i + \delta_{sdt} + \epsilon_{idt}, \tag{5}$$

where Exp^{OM}_{idt} is an export dummy equal to one if firm i exports its own goods to destination d in year t, and zero otherwise, PT_{idt-1} is a PT export dummy equal to one if the firm exported its PT goods to the same destination in the previous year, and δ_i and δ_{sdt} are fixed effects for firms and industry-destination-year triplets, respectively. Importantly, we include in the sample only firms that did not export to destination d when they entered the sample, in order to mitigate reverse causality concerns. The estimation results in Table 9 suggest that the probability of exporting to a certain destination d rises by more than 10%-points in the year after a firm ships its PT products to that destination for the first time. This indicates very strong spill-over effects across PT and OM activities in foreign markets.

[22] If processing trade makes the firm's OM production more efficient, then this would also make exporting more likely, but the effect would not be specific to the PT market.

5 Conclusion

We exploit a novel Bulgarian firm-product-level trade and production data set to investigate firm heterogeneity in relation to processing trade. We summarize our paper in two sets of results. The first set includes strong positive selection effects by which firms taking up PT are bigger (in terms of total sales and value added) and more productive (in terms of total factor productivity) than firms producing on their own account. In addition, we find that, relative to OM firms, PT firms were already specialized in raw production activities ex ante, that is, before sorting into PT. They had significantly higher labor and wage shares of production workers relative to the industry mean. Finally, we also find that firms tend to select their most important rather than some peripheral product (in terms of rank and sales) for PT. Overall, our first set of results demonstrates the important role PT plays in the manufacturing sector in Bulgaria. It is the top-performing firms that sort into PT, and they do this for their most important products. Interestingly, our results on ex-ante performance inequality between firms go against some of the findings in the literature on processing trade in China (Dai et al., 2016).

Our second set of results concerns the effects of PT on various firm and worker outcomes. We obtain three main results. First, we find a substitution effect between OM and PT: while total firm sales do not change, the composition of sales changes, away from OM and towards PT. Secondly, we find that both the level and the composition of the workforce change: PT firms hire more production workers, raising the labor and wage share of production workers as well as total employment of the firm. And finally, we find that firms exporting a certain good under a PT regime are more likely to start exporting an OM good to the same destination. This is evidence for an important positive spill-over effect of PT activities into OM activities.

References

Ackerberg, D. A., K. Caves, and G. Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

Alfaro-Ureña, A., I. Manelici, and J. P. Vasquez, "The Effects of Joining Multinational Supply Chain: New Evidence from Firm-to-Firm Linkages," *The Quarterly Journal of Economics*, August 2022, *137* (3), 1495–1552.

Almeida, R., "The labor market effects of foreign owned firms," *Journal of International Economics*, 2007, *72* (1), 75–96.

Arndt, S. W., "Globalization and the Open Economy," *The North American Journal of Economics and Finance*, 1997, *8* (1), 71–79.

Brandt, L. and P. M. Morrow, "Tariffs and the Organization of Trade in China," *Journal of International Economics*, January 2017, *104.*

_ , L. Bingjing, and P. M. Morrow, "Processing trade and costs of incomplete liberalization: The case of China," *Journal of International Economics*, July 2021, *131.*

Dai, M., M. Maitra, and M. Yu, "Unexceptional exporter performance in China? The role of processing trade," *Journal of Development Economics*, July 2016, *121*, 177–189.

Defever, F. and A. Riaño, "Subsidies with export share requirements in China," *Journal of Development Economics*, 2017, *126*, 33–51.

Fernandes, A. P. and H. Tang, "Determinants of Vertical Integration in Export Processing: Theory and Evidence from China," *Journal of Development Economics*, 2012, *99* (2), 396–414.

_ and _ , "Scale, Scope and Trade Dynamics of Export Processing Plants," *Economics Letters*, August 2015, *133*, 68–72.

Georgiev, B., "Essays on Firms in International Trade." PhD dissertation, Aarhus University 2018.

Grossmann, G. M. and E. Rossi-Hansberg, "Trading Tasks: A Simple Theory of Offshoring," *American Economic Review*, December 2008, *98* (5), 1978–1997.

Guadalupe, M., O. Kuzmina, and C. Thomas, "Innovation and Foreign Ownership," *American Economic Review*, December 2012, *102* (7), 3594–3627.

Javorcik, B. S. and M. Spatareanu, "Tough Love: Do Czech Suppliers Learn from their Relationships with Multinationals?," *The Scandinavian Journal of Economics*, December 2009, *111* (4), 811–833.

Jones, R. W. and H. Kierzkowski, "The Role Of Services In Production And International Trade: A Theoretical Framework," *The Political Economy of International Trade*, 1990, pp. 31–48.

_ **and** _ , "Horizontal Aspects of Vertical Fragmentation," in L. K. Cheng and H. Kierzkowski, eds., *Global Production and Trade in East Asia*, 1 ed., Springer New York, NY, 2001, chapter 3, pp. 33–51.

Koch, M. and M. Smolka, "Foreign ownership and skill-biased technological change," *Journal of International Economics*, 2019, *118*, 84–104.

Kohler, W., "Aspects of International Fragmentation," *Review of International Economics*, 2004, *12* (5), 793–816.

_ , "International Outsourcing and Factor Prices with Multistage Production," *2004*, 2004, *114* (494), 166–185.

Levinsohn, J. and A. Petrin, "Estimating Production Functions Using Inputs to Control for Unobservables," *The Review of Economic Studies*, 2003, *70* (2), 317–341.

Li, J., Z. Ouyang, and N. Zhang, "Processing trade and credit constraints," *Journal of Corporate Finance*, 2023, *83*, 102483.

Manova, K. and Y. Zhihong, "How Firms Export: Processing vs. Ordinary Trade with Financial Frictions," *Journal of International Economics*, May 2016, *100*, 120–137.

Yu, M., "Processing Trade, Tariff Reductions and Firm Productivity: Evidence from Chinese Firms," *The Economic Journal*, 2015, *125* (585), 943–988.

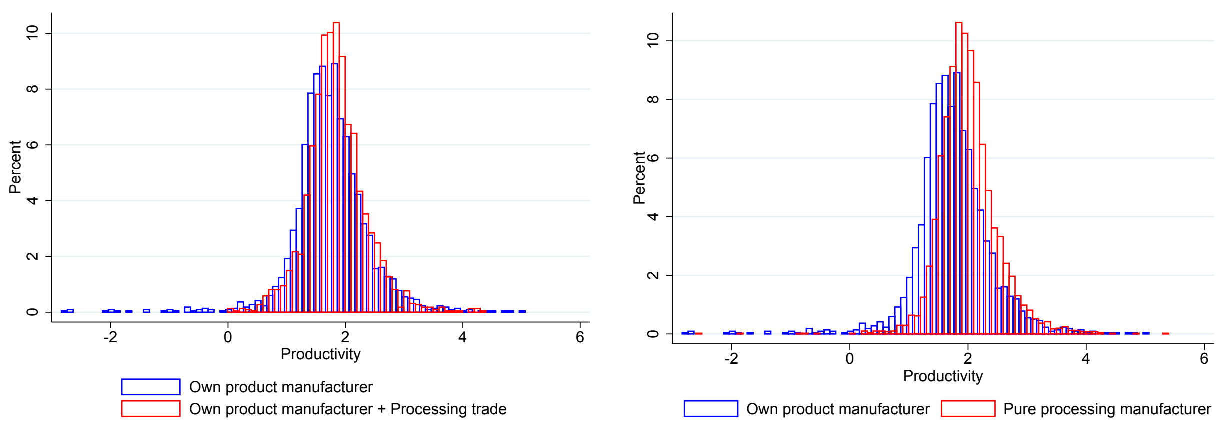
A Appendix

Table A.1: Share of firms in processing trade—Restricted sample

NACE	OM	OM & PT	PT	Firm-year Obs.
Textiles, apparel, leather	83.29	14.53	2.17	2532
Basic and fabricated metals	95.22	3.93	0.85	6813
Chemicals	95.23	4.77	.	1551
Computer, electronic, optical	95.79	3.71	0.50	808
Food, beverages	96.07	3.80	0.14	9378
Pharmaceuticals, medicinal	96.73	3.27	.	214
Electrical equipment	96.82	3.18	.	1290
Manufactured transport equipment	96.86	2.90	0.24	414
Wood, paper	97.35	2.51	0.15	5501
Manufactured machinery	97.59	2.23	0.18	2823
Other manufacturing	98.49	1.27	0.24	4171
Rubber, plastic	98.59	1.34	0.08	6504
Overall	96.06	3.56	0.38	41999

Note: The sample includes all domestically owned firms that are OM producers in the first year they enter the sample. The table reports shares of firm-year observations classified into OM, OM & PT or PT by 2-digit NACE rev. 2. The data are sorted by the share of OM activities. *Source*: National Statistical Institute of Bulgaria. Years 2008-2015.

Figure A.1: Productivity distributions by production regime (2008-2015).



(a) OM versus OM+PT firms.

(b) OM versus PT firms.

Table A.2: Selection based on productivity—Panel

	Sales		Value added		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Productivity$_{i,t-1}$	0.000		0.001*		0.011***	
	(0.001)		(0.001)		(0.003)	
Q2 - Productivity$_{i,t-1}$		-0.003		-0.002		0.001
		(0.003)		(0.003)		(0.002)
Q3 - Productivity$_{i,t-1}$		0.000		0.003		0.005**
		(0.003)		(0.003)		(0.002)
Q4 - Productivity$_{i,t-1}$		0.001		0.004		0.009***
		(0.003)		(0.003)		(0.003)
Industry-year FE	✓	✓	✓	✓	✓	✓
Observations	30217	30217	27151	27151	30217	30217
R^2	0.03	0.03	0.04	0.04	0.03	0.03

Note: The table reports estimates of variants of Equation (2). The dependent variable in all regressions is an indicator variable for PT that equals one if the firm starts doing PT for the first time in year t, and zero otherwise. The sample includes all domestically owned firms that are OM producers in the first year they enter the sample. The sample excludes PT firms in the year after they have sorted themselves into PT for the first time. Productivity is the natural logarithm of one of the firm's productivity variables relative to the industry mean. We use real sales, real value added, and TFP as productivity variables. TFP is estimated following Ackerberg et al. (2015). Q2, Q3, and Q4 are dummy variables for whether the firm falls into the second, third, or fourth quartile of the industry's productivity distribution, with Q1 being the baseline category. Robust standard errors (clustered by firm) in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

GI-NI PROJECT IDENTITY

Project name

Growing Inequality: a novel integration of transformations research — GI-NI

Coordinator

Nederlandse Organisatie Voor Toegepast Natuurwetenschappelijk Onderzoek TNO, Netherlands

Consortium

CNAM – CEET, Centre d`études de l´emploi et du travail (France)
University of Groningen (Netherlands)
Centre for European Policy Studies (Belgium)
University of Adger (Norway)
Centre for Economic and Regional Studies (Hungary)
Utrecht University (Netherlands)
Europa-Universität Flensburg (Germany)
University of the Basque Country (Spain)

Duration

2021 – 2025

Funding Scheme

Grant Agreement no 101004494 — GI-NI — H2020-programme

Website

https://www.gini-research.org

Growing Inequality:
A novel integration of
transformations research

www.gini-research.org