DISCUSSION PAPER SERIES

DP20026

INTEGRATORS AND ROBOT ADOPTION: FACTS FROM HUNGARY

Gábor Békés, Alessandra Bonfiglioli, Rosario Crinò and Gino Gancia

INTERNATIONAL TRADE AND REGIONAL ECONOMICS AND MACROECONOMICS AND GROWTH

CEPR

ISSN 0265-8003

INTEGRATORS AND ROBOT ADOPTION: FACTS FROM HUNGARY

Gábor Békés, Alessandra Bonfiglioli, Rosario Crinò and Gino Gancia

Discussion Paper DP20026
Published 07 March 2025
Submitted 27 February 2025

Centre for Economic Policy Research
187 boulevard Saint-Germain, 75007 Paris, France
2 Coldbath Square, London EC1R 5HL
Tel: +44 (0)20 7183 8801
www.cepr.org

INTEGRATORS AND ROBOT ADOPTION: FACTS FROM HUNGARY

Abstract

This paper explores the role of intermediaries in facilitating the adoption of industrial robots. Using administrative data and firm-to-firm transactions in Hungary, we identify robot integrators, quantify their role, and develop a precise measure of robot adoption at the firm level. We find that most Hungarian firms adopting robots do so through integrators, and these firms tend to be smaller and less capital-intensive than those that import robots directly. Furthermore, we use our data to examine the import networks of integrators, the lumpiness of robot investments, and the geographic concentration of both adopters and integrators. Our findings underscore the critical role of intermediaries in expanding access to automation technologies, particularly for small and medium-sized firms.

JEL Classification: D22, O33

Keywords: Automation, Firms

Gábor Békés - bekesg@ceu.edu
Central European University and HUN-REN KRTK and CEPR

Alessandra Bonfiglioli - alessandra.bonfiglioli@unibg.it
University of Bergamo and QMUL and CEPR

Rosario Crinò - rosario.crino@unibg.it
University of Bergamo and CESifo and CEPR

Gino Gancia - gino.gancia@gmail.com
University of Milano Bicocca and CEPR

Integrators and Robot Adoption: Facts from Hungary*

Gábor Békés[†] Alessandra Bonfiglioli[‡] Rosario Crinò[§] Gino Gancia[¶]

This draft: February, 2025

Abstract

This paper explores the role of intermediaries in facilitating the adoption of industrial robots. Using administrative data and firm-to-firm transactions in Hungary, we identify robot integrators, quantify their role, and develop a precise measure of robot adoption at the firm level. We find that most Hungarian firms adopting robots do so through integrators, and these firms tend to be smaller and less capital-intensive than those that import robots directly. Furthermore, we use our data to examine the import networks of integrators, the lumpiness of robot investments, and the geographic concentration of both adopters and integrators. Our findings underscore the critical role of intermediaries in expanding access to automation technologies, particularly for small and medium-sized firms.

JEL Classification: O33, D22

Keywords: Automation, Robot Integrators, Firms, Robot Adoption

*We thank Dániel Barabás, Matyas Molnar and Martin Neubrandt for excellent research assistance, and seminar participants in the European Workshop: The Economics of AI and Automation (Milan) for useful comments. Gábor Békés thanks NKFI for financial support from "The diffusion of robotics in Hungary: A firm-level view" (OTKA #147121). Rosario Crinò gratefully acknowledges financial support from the Italian Ministry for University and Research under the project "AUTOmation, PROductivity and Wage INequality (AUTOPROWIN): Firms and Workers in Times of Economic Turmoil" - PRIN 2022, financed by the European Union - Next Generation EU, Mission 4, Component 2, Investment 1.1, D.D. MUR 104, February 2, 2022, project number:

[†]Central European University, HUN-REN KRTK and CEPR. E-mail: bekesg@ceu.edu

[‡]University of Bergamo, Dept. of Economics, Queen Mary University of London and CEPR. E-mail: alessandra.bonfiglioli@unibg.it

[§]University of Bergamo, Dept. of Economics, CEPR and CESifo. E-mail: rosario.crino@unibg.it.

[¶]University of Milan-Bicocca, Queen Mary University of London and CEPR. E-mail: ginoalessandro.gancia@unimib.it

1 Introduction

Robotics is widely regarded as a general-purpose technology with the potential to drastically alter the fabric of production. Compared to manual workers, industrial robots are stronger, faster, more accurate and capable of operating continuously. Yet, their adoption remains limited to a small number of firms in a few sectors. Although global robot installations are increasing at a staggering rate, fewer than 2% of manufacturing firms use robotics technologies, with even lower adoption rates in other sectors (e.g., Acemoglu et al., 2021). One of the key barriers to widespread robotics adoption is that industrial robots are complex machines requiring significant investment and specialized skills, often making them cost-ineffective outside of mass production. While the role of scale in adopting new technologies has been widely studied, other factors that facilitate automation have received far less attention. In this paper, we examine the role of robot integrators.

Robot integrators help identify automation needs, provide engineering services, and customize robots to meet the specific requirements of end users. Robot manufacturers typically do not perform these tasks, as they lack the staff and resources to accommodate all end users' needs. Integrators bridge this gap by offering specialized design, engineering, and programming expertise. Although these firms play a crucial role in the robotics industry, their quantitative significance is largely unexplored due to lack of data.

In this paper, we document some new facts about robot integrators using administrative data from Hungary. We show how to combine different data sources, including firm-to-firm transactions, to identify robot integrators. We quantify the importance of these firms, and use this information to develop a new measure of robot adoption at the firm level.

To organize the empirical analysis, we develop a simple model in which heterogeneous firms choose whether to adopt robots by importing them directly or to use the services of integrators. Robots substitute labor with cheaper capital. We assume that installing robots entails a fixed cost but saves on production costs. We also assume that integrators lower the fixed cost of adoption but imply an additional (variable) intermediation cost. The model predicts direct imports to be chosen more likely by firms that are more productive, enjoy stronger demand, are more capital intensive and have a greater scope for automation. However, it also shows that these results are mediated by size, suggesting that the scale of production is a crucial factor not just in the decision to automate but also in the choice to use integrators.

We then move to the evidence. We leverage administrative data on the universe of Hungarian firms from 2015 to 2021. First, we identify robot integrators using directories from major robotics industry associations and by linking robot importers and manufacturers to firms providing installation services. Next, we identify firms purchasing from these integrators using firm-to-firm transactions data. Given the high specialization of integrators, this approach allows us to trace robot purchases to their final users.

With this data, we document a number of facts about robot integrators. We identify 352 integrators with sales to 6809 unique buyers, rising from 1766 in 2015 to 3216 in 2021. We study the characteristics of robot integrators and document that they are systematically larger, more produtive and more capital intensity than the average firms operating in their industries. Since robotics largely depends on technologies produced outside Hungary, we also examine the import networks of integrators. We find that approximately 80% of integrators source at least 50% of their imports from a single country. Additionally, integrators sourcing from different countries are exposed to different foreign productivity shocks.

Next, we turn to examining robot adopters. We show that the vast majority of firms adopting robots (95%) acquire them through integrators. While most adopters are manufacturing firms, about a third of them operates in sectors other than manufacturing. In line with integrators offering highly specialized products and services, we find that, on average, adopters purchase from at most two integrators in manufacturing and from a single integrator in other sectors. We also document that firms using integrators differ from both other adopters and non-adopters. Consistently with the model, firms relying on integrators are smaller, less productive, and less capital-intensive than other adopters. However, these differences largely disappear when controlling for size, highlighting the crucial role of integrators in the diffusion of robots, particularly among small and medium-sized firms. Finally, we use our robot adoption measure to revisit some stylized facts about the lumpiness of automation investments and the geographical concentration of robot adopters and integrators.

This paper contributes to the literature on the causes and consequences of the adoption of industrial robots. While the presence of integrators in the robotics industry is generally acknowledged (see, for example, Humlum, 2019, and Brynjolfsson et al., 2023), this is, to our knowledge, the first study to quantify their activities. This endeavor also enables us to precisely document robot adoption at the firm level. Since firm-level data on robot usage are not systematically collected, how to measure adoption is a key challenge in the literature. To address this, various authors have proposed different strategies.

Import data have been used to examine the role of robots in firms across Canada (Dixen, Hong and Wu, 2020), France (Acemoglu, Lelarge and Restrepo, 2020; Bonfiglioli et al., 2024, Aghion et al. 2021), and Denmark (Humlum, 2019). However, as we demonstrate in this paper, import data significantly underestimate robot adoption. Furthermore, because firms that adopt robots through alternative channels have distinct characteristics, relying solely on import data may introduce bias.

The main alternative consists of firm-level surveys. While questions on robot usage have been recently introduced in some countries, the data are often limited in size, coverage, and time span. In the United States, the Annual Survey of Manufacturers (ASM) included questions on robots from 2018 to 2020 for a sample of approximately 50000 establishments (Brynjolfsson et al., 2023). Earlier versions of the Survey of Manufacturing Technology, conducted in 1988, 1991, and 1993, collected robot data for a subset of five 2-digit SIC manufacturing industries (Doms, Dunne and Troske, 1997; Dinlersoz and Wolf, 2018). The technology module of the Annual Business Survey from the US Census covers around 300000 firms, but automation-related questions are available only in 2019 (Acemoglu et al., 2021).

In Germany, the 2019 IAB Establishment Panel covers approximately 15000 establishments and provides data on robot usage between 2014 and 2018 (Benmelech and Zator, 2022; Findeisen, Dauth and Schlenker, 2024). However, the count of industrial robots is available only for 2019. In Spain, the Encuesta Sobre Estrategias Empresariales (ESEE), an annual survey of around 1900 manufacturing firms from 1990 to 2016, includes a qualitative question on robot use (Koch, Manulov and Smolka, 2021). A similar question appeared in the 2018 survey of nearly 4000 Danish firms conducted by Statistics Denmark (Humlum, 2019). In China, the China Employer-Employee Survey (CEES) includes questions about the use of robotics for a sample of 1115 manufacturing firms (Cheng et al. 2019). Finally, Bessen et al. (2024) analyze a sample of approximately 35000 non-financial Dutch firms with at least three years of data on expenditures for third-party automation services, collected by Statistics Netherlands.

None of these datasets provide quantitative information on robot integrators. We fill this gap by identifying these firms, analyzing their characteristics and quantifying their significance. Leveraging administrative data and firm-to-firm transactions, we also construct a comprehensive measure of robot adoption across all firms over an extended period. This novel approach allows us to examine robot adoption in Hungary, a country where firm-level automation data are otherwise unavailable. We believe that our methodology can complement existing measures of robot adoption in other countries as well.[1]

[1]Bilgin, Faia and Ottaviano (2024) examine how the benefits of technology adoption diffuse along the supply chain by combining robot import data with firm-to-firm transactions in Turkey. However, they do not study robot integrators.

The rest of the paper is organized as follows. Section 2 introduces a simple model used to interpret the data. Section 3 describes the Hungarian firm-level data used for the empirical analysis. Section 4 presents some stylized facts about robot integrators and their import network. Section 5 focuses on firms adopting robots, comparing those that use integrators to those that import robots directly. It then uses our data to document the lumpiness and geographical concentration of robot adoption. Section 6 concludes.

2 Theoretical Framework

To guide the empirical analysis, we start by building a simple partial equilibrium model in which heterogeneous firms choose whether to adopt robots and whether to use the services of integrators.[2] Consider a firm i that faces a demand function with a constant price-elasticity, $y_i = A_i p_i^{-\sigma}$. Production requires a unit measure of symmetric tasks. Workers can perform all tasks while capital can only perform a subset $[0, \alpha_i]$ of tasks. Let (k_i, l_i) denote the quantity of capital and workers, respectively, used by firm i. Denote with r the rental rate of capital and with w the wage of workers. We assume $r < w$, which implies that tasks $z \in [0, \alpha_i]$ are performed by capital only. Due to symmetry, production of task z is:

$$x_i(z) = \begin{cases} k_i(z) = k_i/\alpha_i & \text{for } z \in [0, \alpha_i] \\ l_i(z) = l_i/(1-\alpha_i) & \text{for } z \in (\alpha_i, 1] \end{cases} . \tag{1}$$

The production function of a firm with productivity φ_i is:

$$y_i = \varphi_i \exp\left(\int_0^1 \ln x_i(z) \mathrm{d}z\right) = \varphi_i \left(\frac{k_i}{\alpha_i}\right)^{\alpha_i} \left(\frac{l_i}{1-\alpha_i}\right)^{1-\alpha_i}, \tag{2}$$

which shows that α_i is the capital intensity of the firm.

Firms are monopolistically competitive and choose capital, k_i, and labor, l_i, so as to maximize profits:

$$\pi_i = \max_{k_i, l_i} \{p_i y_i - r k_i - w l_i\}.$$

The first-order conditions for capital and labor are:

$$k_i = \left(1 - \frac{1}{\sigma}\right) \frac{\alpha_i p_i y_i}{r} \tag{3}$$

$$l_i = \left(1 - \frac{1}{\sigma}\right) \frac{(1-\alpha_i) p_i y_i}{w}. \tag{4}$$

[2] The model is built along the lines of Bonfiglioli et al. (2024).

Using (3)-(4) into (2) yields:

$$y_i = A_i \varphi_i^{\sigma} \left(1 - \frac{1}{\sigma}\right)^{\sigma} \left(\frac{1}{w}\right)^{(1-\alpha_i)\sigma} \left(\frac{1}{r}\right)^{\alpha_i \sigma}$$

and:

$$\pi_i = \frac{p_i y_i}{\sigma} = \frac{1}{\sigma} A_i^{\frac{1}{\sigma}} y_i^{\frac{\sigma-1}{\sigma}}.$$

Consider now the automation choice. To simplify the notation, normalize the wage to one, $w = 1$. We model automation as a discrete choice problem. The firm can replace workers with capital in an additional measure κ_i of tasks after paying a fixed cost. If the firm automates directly, it has to pay a fixed cost f_i^d. If the firm chooses to buy the services of an integrator, the fixed cost is $f_i^b < f_i^d$. For instance, by using integrators firms may save on non-production workers specialized on installation and maintenance of robots. However, due to intermediation and transaction costs, the price of capital increases to λr, with $\lambda \in (1, r^{-\kappa_i/(\alpha_i+\kappa_i)})$.

Hence, the profits of the firm in the cases of no automation (π_i^n), adoption through integrators (π_i^b) and direct adoption (π_i^d) become:

$$\begin{aligned}
\pi_i^n &= \xi A_i \left(\varphi_i r^{-\alpha_i}\right)^{\sigma-1} \\
\pi_i^b &= \xi A_i \left[\varphi_i (\lambda r)^{-(\alpha_i+\kappa_i)}\right]^{\sigma-1} - f_i^b \\
\pi_i^d &= \xi A_i \left[\varphi_i r^{-(\alpha_i+\kappa_i)}\right]^{\sigma-1} - f_i^d,
\end{aligned}$$

where $\xi = \frac{1}{\sigma}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}$.

As depicted in Appendix Figure A1, profits are proportional to revenue in case of no automation, which summarizes the role of scale:

$$p_i^n y_i^n = A_i \left[\varphi_i \left(1 - \frac{1}{\sigma}\right) r^{-\alpha_i}\right]^{\sigma-1}. \tag{5}$$

Due to the fixed costs, profits in case of automation start from a lower level; due to the lower variable costs, however, they increase more steeply with scale.

The firm will choose the technology that yields the highest profit. A firm will prefer direct adoption to no automation ($\pi_i^d > \pi_i^n$) when:

$$p_i^n y_i^n \left(r^{-\kappa_i(\sigma-1)} - 1\right) > \sigma f_i^d. \tag{6}$$

That is, direct automation will be chosen by larger firms and those with a greater scope for automation. In turn, from (5), larger firms are those that enjoy stronger demand (A_i), are more productive (φ_i) and, since capital is cheaper than labor, are more capital intensive (α_i).

Since integrators entail a lower fixed cost but also a smaller saving of production costs, size matters in the decision of how to automate too. A firm will prefer direct adoption to adoption through integrators ($\pi_i^d > \pi_i^b$) if and only if:

$$p_i^n y_i^n r^{-\kappa_i(\sigma-1)} \left(1 - \lambda^{-(\alpha_i+\kappa_i)(\sigma-1)}\right) > \sigma(f_i^d - f_i^b). \tag{7}$$

That is, direct adoption is more likely among firms that are larger (i.e., high φ_i, A_i and α_i). Conditional on size, direct adoption is also preferred by firms that are more capital intensive (α_i) and have a greater scope for automation (κ_i). Appendix A reports conditions (6)-(7) in terms of exogenous parameters.[3]

3 Data

For our analysis, we combine multiple Hungarian administrative firm-level datasets. Hungary provides an ideal setting to study the diffusion of robotics at the firm level. Although its robot density remains lower than that of other advanced countries, the average number of automated units per 10000 employees surged from 18 to 84 between 2010 and 2018 (IFR, 2022). Additionally, Hungary's extensive manufacturing sector, employing roughly 25% of the total workforce, presents substantial potential for robot adoption. This is especially true given the importance of the automotive industry, a highly automated sector that accounts for roughly 30–40% of total manufacturing output.[4] At the same time, Hungary is not a major producer of automation technologies, so robots are almost exclusively purchased from foreign firms.[5]

We use value added tax (VAT) data on all domestic firm-to-firm transactions to track purchases from robot integrators and precisely measure robot adoption at the firm level.[6]

[3] We assume that automation must be integrated with the existing capital stock and hence the intermediation cost of integrators, λ, is proportional to the capital share. If the intermediation cost was applied to the automated tasks only, the parameter α_i would disappear from condition (7).

[4] Major automotive companies, including Audi, Mercedes-Benz, Suzuki, and BMW, along with Tier 1 suppliers such as Bosch, Valeo, and Continental, have manufacturing plants in Hungary. Another key manufacturing sector is electronics, with companies like Flextronics, Samsung, and Siemens operating in the country.

[5] Koren, Csillag and Köllo (2020) study the effect of imported machinery on wage inequality in Hungary.

[6] The VAT data includes all domestic transactions but for very small ones below a 3000 Euros threshold.

We combine these data with customs records at the product-country level to measure robot imports by each Hungarian firm and account for their participation in international trade. Additionally, we use balance sheet and income statement data, which cover all corporations in Hungary, to construct some of the main firm-level outcomes such as sales, employment, labor productivity, and capital stock per worker. The balance sheet and customs data span 2000–2021, while the VAT data cover 2015–2021. Further details on data sources, variable definitions, and sample composition are provided in Appendix B.

4 Robot Integrators

4.1 Identifying Robot Integrators

We identify robot integrators through multiple sources. First, we compile the list of integrators operating in Hungary in 2021 from the online platform HowToRobot and the IFR members directory. HowToRobot is a global online platform designed to help businesses automate their operations by connecting them with robot suppliers, integrators, and consultants. The platform provides a comprehensive directory of robot suppliers, system integrators, and consultants by country. The IFR is a global industry association that serves as the primary voice and representative body for the robotics industry. We include IFR members with affiliates or partners in Hungary. After removing duplicates, the list from these two sources comprises 200 companies.

We supplement this list with information on robot imports from custom data. Specifically, we classify as integrators also those firms that import significant amounts of robots and operate in industries primarily engaged in selling machinery equipment or technical services to other businesses.[7] More specifically, we classify as integrators firms in the top quartile of robot import shares within the following industries: "Installation of Industrial Machinery and Equipment", "Wholesale on a Fee or Contract Basis", "Wholesale of Other Machinery, Equipment, and Supplies", "Computer Programming, Consultancy, and Related Activities" and "Architectural and Engineering Activities and Related Technical Consultancy". This approach identifies 10 additional integrators.

Finally, leveraging the firm-to-firm transaction data, we also include firms in these industries having significant purchases, in top quartile of the industry distribution, from robot

[7]Hungarian customs data follow the Combined Nomenclature (CN) classification, where industrial robot trade is recorded under two 8-digit product codes: CN 84795000 and CN 84798950. Our main results remain robust under a broader definition of robot imports, which includes CN product codes for machines designed to perform tasks aligned with the IFR's robot application categories.

manufacturers or distributors identified from the HowToRobot-IFR list. After excluding overlaps, the final sample comprises 352 robot integrators. Their size varies from a few employees to several hundred, with some firms reaching up to several thousand employees. Integrators comprise domestic engineering-focused firms, domestic distributor-focused firms and affiliates of multinationals. The number of integrators has grown from 234 in 2015 to 309 in 2021, reflecting a 32% increase.

4.2 The Characteristics of Robot Integrators

We start by comparing the economic characteristics of integrators with other firms within the same industry. To this end, we run OLS regressions of the following form:

$$Y_{it} = \alpha_{jt} + \beta \cdot Integrator_i + \mathbf{X}'_{it} \cdot \boldsymbol{\gamma} + \varepsilon_{it}, \tag{8}$$

where i denotes a firm; j indicates the 3-digit NACE industry in which the firm operates; and t stands for time. Y_{it} is an outcome and $Integrator_i$ is a dummy that takes value 1 if the firm is classified as an integrator and is equal to 0 otherwise. We estimate (8) on industries comprising at least one integrator and for five major outcomes that can be directly constructed from the data: (i) log employment, (ii) log sales, (iii) log sales per worker, (iv) log value added per worker and (v) log capital stock (tangible assets) per worker. We always control for 3-digit industry×year fixed effects (α_{jt}) to account for differences in the industry of operation and for industry-specific shocks. For each outcome, we report results from two specifications: one without additional controls; and one with controls for firm characteristics—log sales and dummies for firms that export or import goods or for foreign-owned firms—measured in the first year and interacted with a full set of year dummies, $\mathbf{X}_{it}$. In this way, we flexibly control for common trends among firms with similar characteristics.[8]

The results are in Table 1. Standard errors are corrected for clustering at the firm level. Compared to other firms in the same industry, integrators are, on average, significantly larger in both employment and sales (+0.314 and +0.374 log points, respectively, in the specifications with controls). They also exhibit higher labor productivity, measured by value added per worker (+0.139 log points), and greater capital intensity (+0.162 log points). These findings suggest that robot integrators are key players in their respective industries. In Appendix Tables C1 and C2, we show that these results are robust when controlling for 4-digit NACE industry×year fixed effects or when excluding large integrators, which may

[8] Foreign-owned firms are those with foreign ownership share above 50%.

Table 1: Characteristics of Robot Integrators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log Employment	Log Employment	Log Sales	Log Sales	Log Sales per Worker	Log Sales per Worker	Log VA per Worker	Log VA per Worker	Log Capital per Worker	Log Capital per Worker
Integrator	1.121***	0.314***	2.221***	0.374***	0.841***	0.048	0.706***	0.139***	0.663***	0.162**
	[0.071]	[0.045]	[0.097]	[0.037]	[0.045]	[0.043]	[0.042]	[0.040]	[0.076]	[0.076]
Observations	757,941	715,222	764,816	764,816	635,314	635,314	576,041	575,858	511,201	507,498
R-squared	0.119	0.506	0.103	0.757	0.077	0.502	0.059	0.289	0.110	0.180
Ind x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

The dependent variables are indicated in the columns' headings. *Integrator* is a dummy equal to 1 for robot integrators and equal to 0 for other firms. *Controls* are interations between a full set of year dummies and the initial values of the following firm characteristics: log sales, a dummy for exporting firms, a dummy for importing firms and a dummy for multinational firms. All specifications control for 3-digit NACE industry x year fixed effects; industries without robot integrators are excluded. Standard errors, reported in square brackets, are corrected for clustering at the firm level. ***, **, *: denote significance at the 1%, 5% and 10% level, respectively.

also operate outside the automation business.[9]

4.3 The Import Network of Integrators

Robotics depends on technologies and equipment primarily produced outside Hungary. It is therefore instructive to look at the import activities of robot integrators. Unlike other firms, all integrators in our sample report some level of imports, highlighting the industry's reliance on foreign suppliers. Imports are highly concentrated: on average, 80% of integrators source at least 50% of their imports from a single country. The top source countries for all imported products are Germany, the US, Austria, Switzerland, and China. When focusing specifically on industrial robots, the leading suppliers are Germany, Austria, Sweden, Japan, and the Netherlands. These countries are either geographically close to Hungary or major global suppliers of parts and high-tech machinery. More details are available in Appendix Table C3.

The observation that integrators rely on very few suppliers, combined with the heterogeneity in their locations, suggests that integrators may be subject to different supply shocks. We now explore this possibility. To do so, we follow Hummels et al. (2014) and construct a variable, ESS_{it}, which combines export supply shocks in foreign countries with the pre-existing import structure of each integrator. This variable is designed to detect productivity shocks affecting foreign countries from changes in their exports to economies similar to Hungary. These exports, which are plausibly exogenous to the strategies of Hungarian integrators, are likely to have differential effects across them, depending on their initial reliance on different suppliers.

[9] We define large integrators as those with more that 500 employees in all sample years. Including 4-digit NACE industry×year fixed effects allows us to compare integrators to other firms even within the same narrow industry. However, many 4-digit industries have no integrators.

To identify foreign productivity shocks, we use exports by origin country o, 6-digit HS product p and year t to countries similar to Hungary. Given the size and composition of Hungary's industrial sector, we focus on middle-income economies as comparable destination markets. For each origin country-product pair, we calculate the log of exports to middle-income countries in each year t, $\ln EXP_{opt}$, using data from the BACI dataset. We then use the pre-existing import structure of each integrator to identify those that are more exposed to these shocks. For each integrator, we assume exposure to be proportional to the initial import share of each origin country and product. Thus, for integrator i, its exposure to export supply shocks is given by:

$$ESS_{it} = \sum_{o \in O} \sum_{p \in P} \omega_{iop} \cdot \ln EXP_{opt}, \tag{9}$$

where ω_{iop} is integrator i's import share of product p from origin country o in the first sample year.

We test if firms exposed to positive supply shocks expand their size, as measured by sales and employment, running OLS regressions on the panel of integrators. We report results with and without the firm-level controls, $\mathbf{X}_{it}$, used in specification (8). We always include firm and 3-digit industry$\times$year fixed effects. The coefficient on ESS_{it} is therefore identified from within-firm variation over time, while controlling for common shocks to the industry. The identifying assumption is that, conditional on these fixed effects and controls, integrators that import from suppliers whose exports are growing are not subject to other unobservable shocks affecting their size. The results are reported in Table 2. In all cases, we find that firms exposed to positive productivity shocks experience an increse in sales and expand employment.[10]

The results in this section highlight the importance of imports in the industry of robot integrators. First, they show that integrators rely on foreign suppliers, more than other firms. Second, consistent with the view that integrators use highly specialized technologies, we have found that their import network is very concentrated, with a few dominant source countries. Third, not only do integrators rely on foreign suppliers, but positive shocks to these suppliers translate into higher sales of integrators. This is consistent with the view that technological improvements embedded in imports affect the operating cost of integrators and thereby increase the demand for their services. That is, foreign supply shocks foster robot adoption in Hungary.

[10]In Appendix Table C4, we show that these results are robust to excluding large integrators.

Table 2: Export Supply Shocks and Integrators Size

	(1)	(2)	(3)	(4)
	Log Employment	Log Employment	Log Sales	Log Sales
ESS	0.126*	0.117*	0.109*	0.100*
	[0.064]	[0.065]	[0.057]	[0.058]
Observations	1364	1364	1240	1240
R-squared	0.96	0.96	0.97	0.97
Firm FE	Yes	Yes	Yes	Yes
Ind x Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

The dependent variables are indicated in the columns' headings. *ESS* is constructed as in eq. (9) using data on countries' exports of individual HS 6-digit products to middle-income destinations and the shares of each HS 6-digit product and origin country in the total imports of each integrator in the initial year. *Controls* are interations between a full set of year dummies and the initial values of the following firm characteristics: log sales, a dummy for exporting firms, a dummy for importing firms and a dummy for multinational firms. All specifications control for firm and 3-digit NACE industry x year fixed effects. The sample consists of robot integrators only. Standard errors, reported in square brackets, are corrected for clustering at the firm level. ***, **, *: denote significance at the 1%, 5% and 10% level, respectively.

5 Integrators and Robot Adoption

We now examine firms that purchase robots from integrators. To avoid the results being driven by very small transactions, we define buyers as firms that purchase a minimum of 15000 Euros from a given integrator in a given year. Over the sample period, we identify 6809 unique buyers, excluding integrators. Annually, the number of unique buyers has increased from 1766 in 2015 to 3216 in 2021 (see Appendix Table C5). This represents an 82% increase over seven years.[11]

Table 3 provides information about the sectors served by integrators. Among all robot purchases, 53% come from manufacturing firms, followed by wholesale and retail (19%), services (14%), construction and utilities (11%), and transport, postal, and warehousing firms (less than 3%). In terms of purchase value, the manufacturing sector accounts for 65%

[11] One challenge in identifying integrators is that some robotics firms are large, diversified multinationals like ABB or Panasonic. As a robustness test, we exclude firms with 500+ employees (5 firms) from the list. This leads to only a 2% decline in unique buyers, a proportional response.

Table 3: Robot Purchases from Integrators by Sector

Buyers' Sector	Purchases		Value of Purchases		Integrators per Buyer
	(1)	(2)	(3)	(4)	(5)
	Number	% of Total	Mln €	% of Total	Mean Count
Construction-utilities	1652	0.11	45	0.05	1.37
Manufacturing	8219	0.53	588	0.65	2.57
Primary	108	0.01	2	0.00	1.11
Services	2232	0.14	66	0.07	1.27
Transport-post	399	0.03	19	0.02	1.20
Wholesale-retail	3016	0.19	181	0.20	1.29
Total	15626	1.00	900	1.00	

Columns (1) and (2) report the number and the share of robot purchases from robot integrators over the sample period in each sector. Columns (3) and (4) report the total value of purchases (averaged over time) from robot integrators in each sector and the corresponding sector share. Column (5) reports the average number of integrators per buyer in each sector. Buyers exclude firms who are robot integrators.

of the total, followed by wholesale and retail (20%), services (7%), construction and utilities (5%), and transport, postal, and warehousing (around 2%).

The sectoral distribution of robot purchases confirms that automation is most prevalent in manufacturing, though service industries are also making significant investments in robotization. For example, retailers have increasingly invested in warehouse automation in recent years. These numbers also reflect the quantitative importance of the wholesale sector, whose activities are critical in supporting other industries, including manufacturing.

Finally, it is also instructive to look at the number of integrators per buyer. On average, manufacturing firms purchase from 2.5 distinct integrators, while firms in other industries typically buy from only one. This is consistent with the view that integrators offer highly specialized services and equipment tailored to the needs of the final user. At the same time, the complex operations of manufacturing firms may require the expertise of more than one provider of automation solutions.

5.1 Robot Adopters

We classify adopters as firms that either directly import industrial robots (and are not classified as integrators) or purchase from an integrator in any sample year. To avoid noise from very small transactions, we apply the same minimum threshold: a firm is classified as an adopter if the sum of its imports and purchases from integrators exceeds 15000 Euros in at least one year. To ensure results are not affected by changes in sample composition over time, we restrict the analysis in this section to a balanced sample of firms active throughout the 2015–2021 period (see Appendix B for details). This leaves us with 3762 adopters, representing 0.7% of all firms in the full (unbalanced) sample and 12.3% of firms in the balanced sample.

The number of adopters in our sample aligns with evidence from other countries. For example, Acemoglu et al. (2021) report that 2% of U.S. firms use robotics for automation, based on U.S. Census survey data. Similarly, Brynjolfsson et al. (2023) find that 11.1% of U.S. manufacturing plants reported having at least one robot in 2019, using data from the Annual Survey of Manufacturers. The difference between the balanced and unbalanced samples reflects the fact that firms that remain in the sample across all years tend to be larger, and larger firms are more likely to adopt robots. Importantly, out of all adopters, only 177 firms (4.7%) import robots directly, while the remaining 3585 firms (95.3%) purchase from integrators. These figures underscore the quantitative importance of integrators for correctly measuring robot adoption: focusing solely on importers would miss 95% of adopters.

5.2 Comparing Robot Adopters

We now compare the economic characteristics of adopters that procure robots from integrators with those of firms that import robots directly and of firms that do not use robots. To this end, we define three distinct groups of firms: (1) adopter-importers, which are adopters whose robot imports exceed 15000 Euros in at least one year, regardless of whether they also buy from domestic integrators or not; (2) adopter-buyers, which are all other adopters and thus predominantly, or exclusively, purchase from integrators; and (3) non-adopters, which are firms that do not engage in substantial robot procurement from any source. Our analysis revolves around estimating equation (8) with distinct dummy variables for the first two groups, while controlling for 4-digit industry×year fixed effects.[12] As before, in some specifications, we also control for time dummies interacted separately with the import, export and multinational dummies, as well as with the initial level of sales. The results are in Table 4, which also reports the differences between the coefficients on the adopter-importer and adopter-buyer dummies, along with the corresponding standard errors.

Compared to other firms in the same industry with similar initial size and globalization status, robot adopter-importers and adopter-buyers are significantly larger, both in terms of employment (+0.555 and +0.320 log points, respectively) and sales (+0.372 and +0.211 log points, respectively). Without controlling for size, they also exhibit higher productivity, as

[12] We now use 4-digit industries to compare adopters to the most similar non-adopting firms. However, as shown in Appendix Table C6, the results are similar when using 3-digit industries.

Table 4: Characteristics of Robot Adopters

	(1) Log Employment	(2) Log Employment	(3) Log Sales	(4) Log Sales	(5) Log Sales per Worker	(6) Log Sales per Worker	(7) Log VA per Worker	(8) Log VA per Worker	(9) Log Capital per Worker	(10) Log Capital per Worker
Adopter-importer	1.883***	0.555***	2.609***	0.372***	0.728***	-0.179***	0.581***	-0.046	0.941***	0.392***
	[0.102]	[0.056]	[0.122]	[0.036]	[0.055]	[0.051]	[0.042]	[0.044]	[0.074]	[0.080]
Adopter-buyer	1.156***	0.320***	1.652***	0.211***	0.473***	-0.110***	0.380***	0.007	0.673***	0.233***
	[0.022]	[0.014]	[0.027]	[0.010]	[0.014]	[0.014]	[0.012]	[0.012]	[0.023]	[0.025]
Observations	214481	214481	195840	195840	195840	195840	191277	191277	184711	184711
R-squared	0.31	0.67	0.33	0.87	0.34	0.56	0.20	0.30	0.20	0.25
Diff(importer-buyer)	0.727***	0.235***	0.956***	0.161***	0.255***	-0.069	0.201***	-0.053	0.268***	0.159**
	[0.103]	[0.055]	[0.123]	[0.035]	[0.055]	[0.050]	[0.042]	[0.044]	[0.074]	[0.078]
Ind x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

The dependent variables are indicated in the columns' headings. *Adopter-importer* is a dummy equal to 1 for firms with a value of robot imports above 15000 Euros in at least one year over the sample period (2015-2021). *Adopter-buyer* is dummy equal to 1 for all other firms who have purchased robots in at least one year over the sample period. The excluded category consists of firms whose robot purchases never exceed 15000 Euros over the sample period (non adopters). *Controls* are interations between a full set of year dummies and the initial values of the following firm characteristics: log sales, a dummy for exporting firms, a dummy for importing firms and a dummy for multinational firms. All specifications control for 4-digit NACE industry x year fixed effects. The sample consists of firms who are active in all years, have more than five employees and sales above 250 thousand Euros. Standard errors, reported in square brackets, are corrected for clustering at the firm level. ***, **, *: denote significance at the 1%, 5% and 10% level, respectively.

measured by sales per worker (+0.728 and +0.473 log points, respectively) or value-added per employee (+0.581 and +0.380 log points, respectively). However, these productivity differeces disappear when controlling for size. Finally, adopters also have higher capital intensity, as measured by capital per worker (+0.392 and +0.233 log points, respectively).

It is also useful to compare different types of adopters. Without controls, adopter-buyers are on average smaller, less productive and less capital intensive than adopter-importers. However, when adding firm-level controls including the initial level of sales, these differences become much less pronounced. In particular, the gap in labor productivity becomes statistically insignificant. These findings are consistent with the model predictions that direct adoption is preferred by larger and more capital intensive firms, and that the effect of productivity is mediated by size (see equation 7). Hence, they underscore the importance of scale for both the decision to automate and the mode of adoption. Moreover, they highlight that integrators are especially important for smaller firms, which may lack the scale to justify setting up the expertise required to import and install robots directly.

5.3 The Lumpiness of Robot Adoption

Automation requires a significant investment, often accompanied by organizational changes. Moreover, robots are indivisible, and the cost of a single unit is substantial. In our balanced sample, the average robot purchase accounts for a considerable 3.8% of total sales. Consequently, investments of this magnitude may occur unevenly over time. While the literature has highlighted the lumpiness of robot adoption (e.g., Bessen et al., 2024), accurately capturing this pattern requires a precise measure of adoption. Cross-sectional data or surveys

Table 5: Distribution of Robot Adopters by Spikiness

Spikiness	(1) Adopters (Number)	(2) Adopters (Share)	(3) Importers (Number)	(4) Importers (Share)	(5) Buyers (Number)	(6) Buyers (Share)
[1-2)	345	0.092	34	0.192	311	0.087
[2-3)	655	0.174	56	0.316	599	0.167
[3-4)	645	0.171	33	0.186	612	0.171
[4-5)	474	0.126	16	0.090	458	0.128
[5-6)	217	0.058	5	0.028	212	0.059
[6-7]	1426	0.379	33	0.186	1393	0.389
All	3762	1.000	177	1.000	3585	1.000

The table shows the distribution of robot adopters, importers and buyers across bins of the ratio between the maximum and the average purchase of robots over the sample period (*spikiness*).

are often inadequate for this purpose, while import data may be too sparse. By leveraging transactions data, we can analyze the distribution of robot purchases over time in much greater detail.

To identify a "spike" in robot adoption, we calculate the ratio between a firm's largest robot purchase (among transactions exceeding 15000 Euros) and its average purchase over the seven-year period, including years with zero purchases:

$$S_i = \frac{\text{max robot purchase}_i}{\text{mean robot purchase}_i}.$$

If a firm's robot purchases are evenly distributed over time, this ratio equals 1. Conversely, if a firm purchases robots only once, the ratio equals 7—the total number of years in the sample. We classify a firm as a "spiky adopter" if this ratio exceeds 3.5. This corresponds to a distribution of purchases more skewed than two equal purchases over the sample period. We find 2495 spiky adopters, representing two-thirds of all adopters. Among them, 1355 firms (54.3%) made only one robot purchase during the entire period.

Table 5 presents the distribution of our "spikiness" measure, S_i, for all adopters, adopter-importers, and adopter-buyers. As previously discussed, firms with S_i between 1 and 2 (first bin in the table) purchase robots relatively continuously. Only 8.7% of adopter-buyers and 19.2% of adopter-importers fall into this category. More broadly, adopter-importers tend to follow a less lumpy purchasing pattern compared to adopter-buyers. Specifically, the majority of adopter-importers are not classified as "spiky adopters", whereas the opposite is true for adopter-buyers. Moreover, 39% of adopter-buyers have $S_i \geq 6$, compared to just 18.6% of adopter-importers.

These findings confirm that robot adoption is generally lumpy, but they also reveal that a significant number of firms invest in robots more consistently over time. Notably, these non-spiky adopters tend to be adopter-importers, which are typically larger than adopter-buyers. This suggests that the scale of operations plays a crucial role not only in the decision to automate but also in determining the frequency of robot investments.

5.4 The Geography of Adopters and Integrators

Brynjolfsson et al. (2023) show that the geographical distribution of robots is highly skewed in the US and that locations where automation technologies are particularly concentrated also tend to host integrators. We revisit this evidence using our data. In Appendix Figure C1, we present maps illustrating the share of adopters and integrators across 20 NUTS3 regions. These maps reveal a high degree of geographic concentration, with most robot-using firms located near Budapest and other industrial regions. Furthermore, the location of integrators closely mirrors that of adopting firms, which strongly correlates with the distribution of manufacturing firms. To compare the degree of concentration of integrators, adopters and manufacturing firms, we compute the Herfindahl-Hirschman index across regions for each type of firm in 2019. We find that integrators have the highest level of concentration (0.19), followed by robot adopters (0.13) and then all manufaturing firms (0.11). The significantly higher concentration of integrators compared to manufacturing firms suggests that geographical clusters play a crucial role in the automation industry.

6 Conclusions

This paper presents new facts on the role of robot integrators in Hungary and their impact on the diffusion of automation technologies, particularly industrial robots, in firms. We now summarize six main takeaways.

First, most firms adopting robots in Hungary do so through integrators rather than directly importing them. This suggests that most firms lack the expertise to install industrial robots independently, making integrators a critical part of the automation supply chain. Second, integrators significantly benefit small and medium-sized firms, which may not have the scale to adopt robots independently. This underscores the importance of intermediaries in expanding access to advanced technologies beyond larger, more capital-intensive businesses. Third, robot integrators tend to be larger, more productive and more capital intensive than other firms in their industries. This aligns with their role in facilitating technological upgrades for client firms. Fourth, import data can be used to identify foreign supply shocks to integrators. Fifth, given the difficulty of tracking robot adoption using traditional data sources, firm-to-firm transaction data can provide a more accurate measure of robot adoption at the firm level. This methodology can be applied in other countries to enhance our understanding of automation trends. Sixth, our measure of robot adoption allows us to revisit some findings on the lumpiness and geographical concentration of automation investments, shedding new light on these patterns.

A natural application of our data would be to examine the effects of automation on adopting firms. However, since this question is fundamentally different from the role of intermediaries in facilitating adoption, we leave it for future research. Our central message is that robot integrators are essential for understanding industrial automation and, yet, they are often neglected in the literature due to lack of data. This study provides novel quantitative evidence on their importance and suggests that their presence helps overcome barriers to technology adoption.

References

[1] Acemoglu, D., Anderson, G., Beede, D., Buffington, C., Dinlersoz, E., Foster, L., Goldschlag, N., Haltiwanger, J., Krof, Z., Restrepo, P. and Zolas, N. (2021). "Technology and the size and composition of workforce in U.S. firms: First evidence from the 2019 Annual Business Survey," ASSA Meetings – January 5, 2021.

[2] Acemoglu, D., Lelarge C. and Restrepo, P. (2020). "Competing with robots: Firm-level evidence from France," *AEA Papers and Proceedings*, vol. 110(May), pp. 383–88.

[3] Aghion, P., Antonin, C., Bunel, S. and Jaravel, X. (2021). "What are the labor and product market effects of automation? New evidence from France," CEPR Discussion Paper 14443.

[4] Benmelech E. and Zator M. (2022). "Robots and Firm Investment," NBER Working Papers 29676.

[5] Bessen, J., Goos, M., Salomons, A. and van den Berge, W. (2024). "What happens to workers at firms that automate?" *Review of Economics and Statistics*, forthcoming.

[6] Bilgin, N., Faia, E. and Ottaviano G. (2024), "Technology Spillovers, Diffusion and Rivalry in Firm Networks," CEPR Discussion Paper No. 19804.

[7] Bonfiglioli, A., Crinò, R., Fadinger, H. and Gancia, G. (2024), "Robot imports and firm-level outcomes," *Economic Journal*, vol. 134(664), pp. 3428–3444.

[8] Brynjolfsson, E., Buffington, C., Goldschlag, N., Frank Li, J., Miranda, J. and Seamans, R. (2023). "The Characteristics and Geographic Distribution of Robot Hubs in U.S. Manufacturing Establishments" NBER Working Paper 31062.

[9] Cheng, H., Jia, R., Li, D. and Li, H. (2019). "The rise of robots in China," *Journal of Economic Perspectives*, vol. 33(2), pp. 71–88.

[10] Dinlersoz, E. and Wolf, Z. (2018). "Automation, labor share, and productivity: Plant-level evidence from U.S. manufacturing," CES Working Paper 18-39.

[11] Dixen, J., Hong, B. and Wu, L. (2020). "The employment consequences of robots: Firm-level evidence," Statistics, Canada, Analytical Studies Branch Research Paper Series 454.

[12] Doms, M., Dunne, T. and Troske, K. (1997). "Workers, Wages, and Technology," *The Quarterly Journal of Economics*, 112(1), pp. 253-290.

[13] Findeisen, S., Dauth W. and Schlenker O. (2024). "Organized Labor Versus Robots? Evidence from Micro Data," CEPR Discussion Paper No. 19192.

[14] Humlum, A. (2019). "Robot adoption and labor market dynamics," Mimeo, University of Chicago.

[15] Hummels, D., Jorgensen, R., Much, J. and Xiang, C. (2014). "The wage effects of offshoring: Evidence from Danish matched worker-firm data," *American Economic Review*, 104(6), pp. 1597–1629.

[16] IFR (2022). "World robotics reports," https://ifr.org/worldrobotics/ (last accessed: 15 April 2021)

[17] Koch, M., Manulov, I. and Smolka, M. (2021). "Robots and firms," *Economic Journal*, vol. 131(638), pp. 2553–2584.

[18] Koren, M., Csillag, M., Köllo, J. (2020). "Machines and Machinists: Incremental technical change and wage inequality," Central European University, mimeo, 2020.

A Model

Figure A1 shows profits as a function of scale:

$$\begin{aligned}
\pi_i^n &= p_i^n y_i^n / \sigma \\
\pi_i^b &= p_i^n y_i^n \left[\lambda^{-(\alpha_i+\kappa_i)} r^{-\kappa_i} \right]^{\sigma-1} / \sigma - f_i^b \\
\pi_i^d &= p_i^n y_i^n r^{-\kappa_i(\sigma-1)} / \sigma - f_i^d
\end{aligned}$$

where

$$p_i^n y_i^n = A_i^{\frac{1}{\sigma}} y_i^{\frac{\sigma-1}{\sigma}} = A_i \left[\varphi_i \left(1 - \frac{1}{\sigma} \right) r^{-\alpha_i} \right]^{\sigma-1}.$$

Note that the condition

$$\begin{aligned}
\lambda^{-(\alpha_i+\kappa_i)} r^{-\kappa_i} &> 1 \\
r^{-\kappa_i/(\alpha_i+\kappa_i)} &> \lambda
\end{aligned}$$

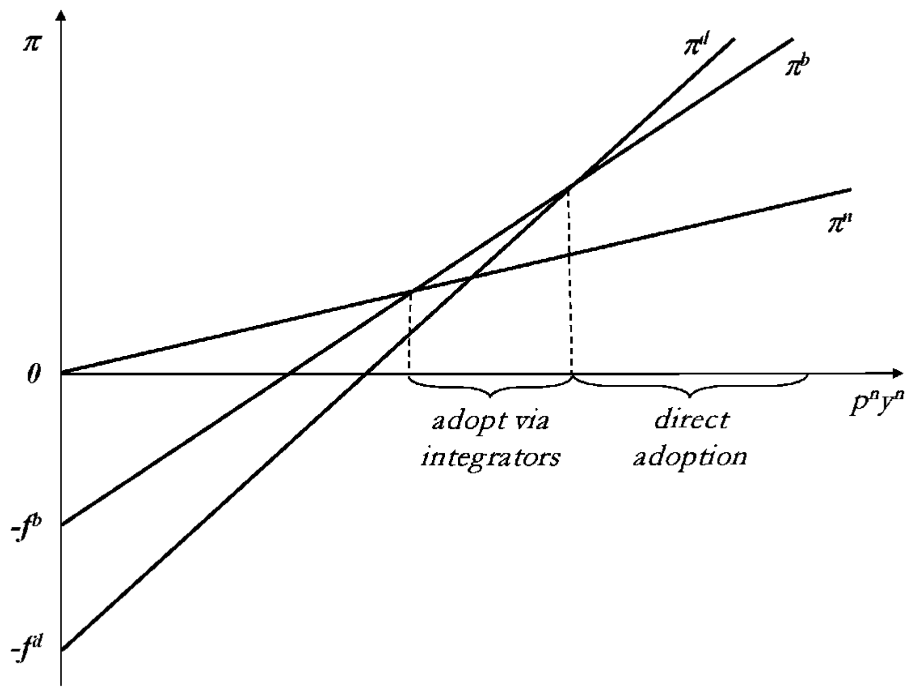
guarantees that the slope of π_i^b is greater than the slope of π_i^n.

We also report here the condition under which a firm will prefer direct adoption to no automation ($\pi_i^d > \pi_i^n$) in terms of exogenous parameters:

$$\pi_i^d > \pi_i^n \Leftrightarrow r^{-\alpha_i(\sigma-1)} \left[r^{-\kappa_i(\sigma-1)} - 1 \right] > \frac{f_i^d}{\xi A_i \varphi_i^{\sigma-1}}.$$

Likewise, the condition for which a firm will prefer direct adoption to using integrators ($\pi_i^d > \pi_i^n$) is:

$$\pi_i^d > \pi_i^b \Leftrightarrow r^{-(\alpha_i+\kappa_i)(\sigma-1)} \left[1 - \lambda^{-(\alpha_i+\kappa_i)(\sigma-1)} \right] > \frac{f_i^d - f_i^b}{\xi A_i \varphi_i^{\sigma-1}}.$$



The figure plots the profits of non-adopters (*n*), adopter-buyers (*b*) and adopter-importers (*d*) against the revenues of non-adopters.

Figure A1: Choice of Adoption: Importers vs Buyers

B Data Description

The data used in this paper are based on official reports filed to Nemzeti Adó- és Vámhivatal (NAV), the Hungarian National Tax and Customs Administration. All data are administrative Hungarian data managed by KSH, the Hungarian Statistical Office. The data are stored in a data room managed together with HUN-REN KRTK. Access is granted by the rights holder, KSH. All monetary values were converted in thousand Euros using average annual Euro-Forint exchange rates.[13]

B.1 Firm-level data

The firm-level data include annual balance sheet and income statements submitted to the tax authority by all (double book-keeping) firms for the whole economy. These data cover the universe of firms. For the period 2015-2021, there are 350-420 thousand firms per year. Beyond statutory financial variables such as revenues, materials and fixed assets, the data include the number of full-time employees. The location of firms—the principal address of the headquarter—comes from the corporate registry. It does not vary over time.

[13] https://www.exchangerates.org.uk/EUR-HUF-spot-exchange-rates-history-2019.html.

B.2 Trade data

The foreign trade product statistics system is composed of two subsystems: the Intrastat subsystem contains trade conducted with European Union member states (intra-EU trade), while the Extrastat subsystem covers trade conducted with third countries (non-EU trade). For intra-EU trade, data are collected from trading companies via questionnaires by KSH, while for non-EU trade, data are collected by the National Tax and Customs Administration (NAV) through customs procedures. The information required for trade within the EU is obtained from the Intrastat reports based on common EU regulations but regulated nationally. The information regarding which economic organizations, not obliged to submit Intrastat reports, conducted product trade with EU member states and at what value (i.e., identifying new data providers) is primarily obtained from the VAT declarations under the "Community acquisition" and "Community supply" fields. The EU regulations require national tax authorities to regularly transmit these data. There is a threshold to report intra EU trade. Companies are only designated to provide Intrastat data for the direction of traffic in which they have a turnover above a threshold of 100 million HUF (about 300 thousand Euros). In 2017, the threshold for imports was increased to 170 million HUF.

B.3 VAT data

The value added tax (VAT) data cover the universe of firms submitting a VAT report to NAV. The data is based on firms regularly reporting transactions as required by law. Reporting, and hence, the raw data is monthly or quarterly depending on firm size. We aggregated transactions at the annual level. The dataset was filtered to keep only supplier-side transactions. The data starts in 2015, and the reporting thresholds (to make it into the database) were cut gradually. Accordingly, for consistency over time, we filtered transactions by reporting firms above an annual value of 1 million HUF (about 3000 Euros). The data include information on domestic firm-to-firm transactions only. It does not include external trade transactions, nor information on the content of the transactions.

B.4 Sample composition and data cleaning

The regressions on adopters (Section 5.2) are based on a consistent sample of firms that are present in the sample over the entire 7-year period from 2015 to 2021. To ensure common support, a few industries with very few adopters are excluded from these regressions, namely, mining, utilities, construction and public service. Very small firms are excluded as well. These are defined as firms that never have more than five employees or report having less than two employees in some year, as well as firms whose sales are always below 250 thousand Euros.

Missing values in employment were imputed using the average of adjacent years when possible. Firms with persistently missing key variables (e.g., sales, employment) were excluded. Extreme values (beyond the 1st and 99th percentiles of the distribution) in key ratio variables (e.g., labor productivity, capital intensity) were winsorized.

Table C1: Characteristics of Robot Integrators - 4-digit NACE × Year FE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log Employment	Log Employment	Log Sales	Log Sales	Log Sales per Worker	Log Sales per Worker	Log VA per Worker	Log VA per Worker	Log Capital per Worker	Log Capital per Worker
Integrator	1.125***	0.318***	2.214***	0.378***	0.828***	0.050	0.670***	0.119***	0.640***	0.154**
	[0.071]	[0.045]	[0.098]	[0.037]	[0.045]	[0.043]	[0.043]	[0.040]	[0.077]	[0.076]
Observations	757936	715217	764811	764811	635306	635306	576032	575849	511186	507483
R-squared	0.14	0.51	0.13	0.76	0.12	0.51	0.08	0.30	0.13	0.19
Ind x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes

The dependent variables are indicated in the columns' headings. *Integrator* is a dummy equal to 1 for robot integrators and equal to 0 for other firms. *Controls* are interations between a full set of year dummies and the initial values of the following firm characteristics: log sales, a dummy for exporting firms, a dummy for importing firms and a dummy for multinational firms. All specifications control for 4-digit NACE industry x year fixed effects; industries without robot integrators are excluded. Standard errors, reported in square brackets, are corrected for clustering at the firm level. ***, **, *: denote significance at the 1%, 5% and 10% level, respectively.

B.5 Data access

The data is not public and is available only in a secured data room based on access granted by the rights holder, KSH. However, any replicator might ask for access to data.[14]

C Additional Empirical Results

Table C2: Characteristics of Robot Integrators - No Large Integrators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log Employment	Log Employment	Log Sales	Log Sales	Log Sales per Worker	Log Sales per Worker	Log VA per Worker	Log VA per Worker	Log Capital per Worker	Log Capital per Worker
Integrator	1.070***	0.291***	2.160***	0.371***	0.834***	0.067	0.704***	0.157***	0.657***	0.169**
	[0.068]	[0.044]	[0.095]	[0.038]	[0.045]	[0.043]	[0.043]	[0.039]	[0.077]	[0.077]
Observations	755,977	713,309	762,902	762,902	633,584	633,584	574,386	574,203	509,647	505,944
R-squared	0.115	0.502	0.102	0.756	0.077	0.502	0.059	0.289	0.110	0.180
Ind x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

The dependent variables are indicated in the columns' headings. *Integrator* is a dummy equal to 1 for robot integrators and equal to 0 for other firms. *Controls* are interations between a full set of year dummies and the initial values of the following firm characteristics: log sales, a dummy for exporting firms, a dummy for importing firms and a dummy for multinational firms. All specifications control for 3-digit NACE industry x year fixed effects; industries without robot integrators are excluded. Integrators with more than 500 employees are excluded. Standard errors, reported in square brackets, are corrected for clustering at the firm level. ***, **, *: denote significance at the 1%, 5% and 10% level, respectively.

[14] Instructions on how to request data access can be found at https://adatbank.krtk.mta.hu/en/.

Table C3: Top Import Origins for Robot Integrators

Top 1 Robot Import Origin			Top 1 All Products Import Origin		
(1)	(2)	(3)	(4)	(5)	(6)
Country	Integrator-years	Frequency	Country	Integrator-years	Frequency
Germany	80	0.28	Germany	1042	0.33
Austria	37	0.13	USA	363	0.12
Sweden	27	0.10	Austria	228	0.07
Japan	25	0.09	Switzerland	190	0.06
Netherlands	22	0.08	China	184	0.06
Denmark	21	0.07	Netherlands	123	0.04
China	12	0.04	Italy	110	0.03
USA	10	0.04	Japan	100	0.03
Taiwan	8	0.03	UK	78	0.02
Italy	7	0.02	Taiwan	73	0.02

The table reports the number and share of integrator-year observations for which a country is the top-1 origin of robot imports or overall imports.

Table C4: Export Supply Shocks and Integrators Size - No Large Integrators

	(1)	(2)	(3)	(4)
	Log Employment	Log Employment	Log Sales	Log Sales
ESS	0.128**	0.120*	0.110*	0.102*
	[0.065]	[0.066]	[0.058]	[0.059]
Observations	1,328	1,328	1,204	1,204
R-squared	0.946	0.948	0.958	0.960
Firm FE	Yes	Yes	Yes	Yes
Ind x Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

The dependent variables are indicated in the columns' headings. *ESS* is constructed as in eq. (9) using data on countries' exports of individual HS 6-digit products to middle-income destinations and the shares of each HS 6-digit product and origin country in the total imports of each integrator in the initial year. *Controls* are interations between a full set of year dummies and the initial values of the following firm characteristics: log sales, a dummy for exporting firms, a dummy for importing firms and a dummy for multinational firms. All specifications control for firm and 3-digit NACE industry x year fixed effects. The sample consists of robot integrators only, excluding integrators with more than 500 employees. Standard errors, reported in square brackets, are corrected for clustering at the firm level. ***, **, *: denote significance at the 1%, 5% and 10% level, respectively.

Table C5: Integrators and Adopters: 2015-2021

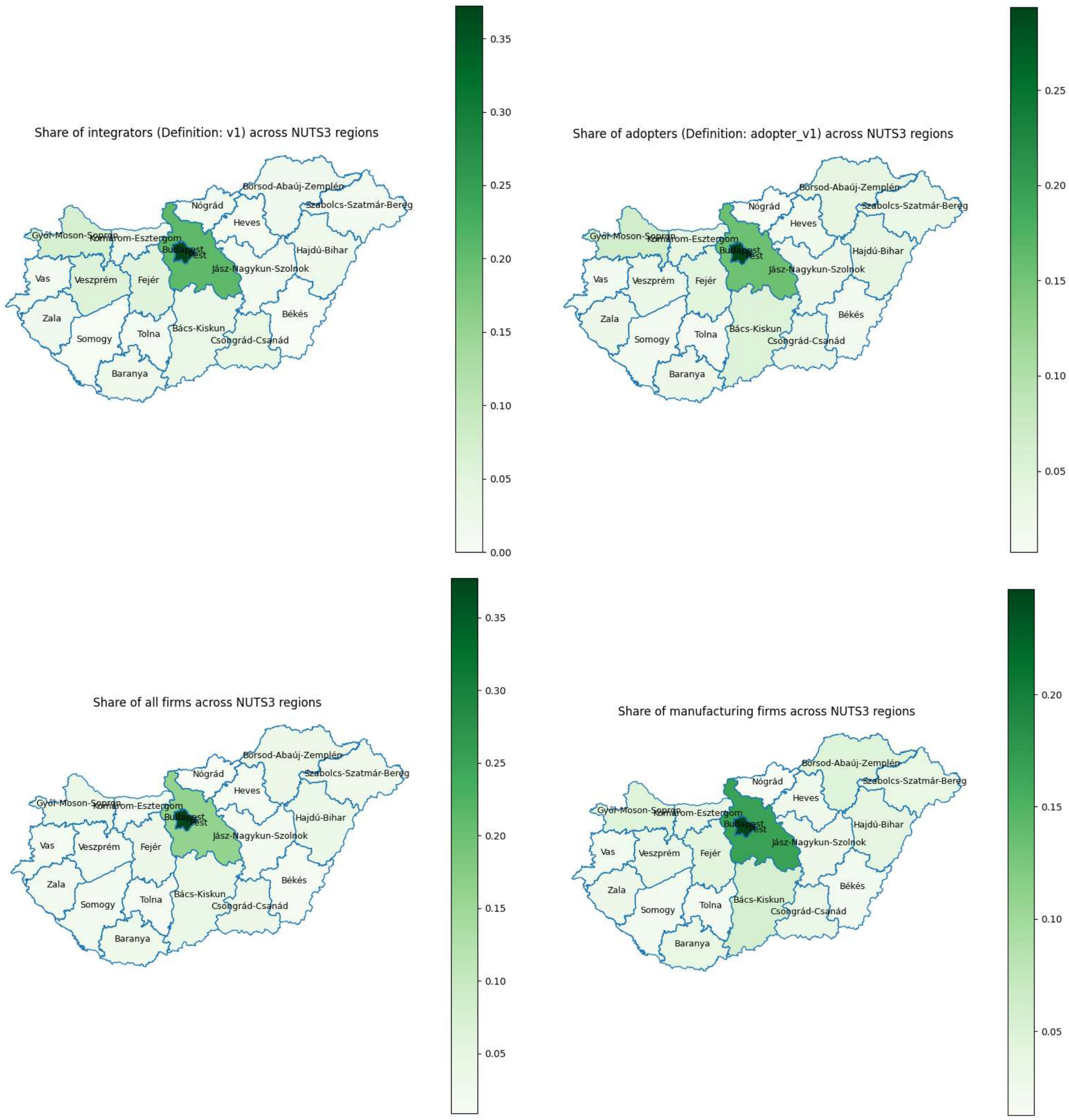
Year	Integrators (Nr.)	Buyers (Nr.)
2015	234	1766
2016	241	1837
2017	255	2152
2018	276	2470
2019	290	2653
2020	300	2812
2021	309	3216

Buyers are firms whose purchases from integrators exceed 15000 Euros in a given year.

Table C6: Characteristics of Robot Adopters - 3-digit NACE $\times$ Year FE

	(1) Log Employment	(2) Log Employment	(3) Log Sales	(4) Log Sales	(5) Log Sales per Worker	(6) Log Sales per Worker	(7) Log VA per Worker	(8) Log VA per Worker	(9) Log Capital per Worker	(10) Log Capital per Worker
Adopter-importer	1.901***	0.570***	2.620***	0.352***	0.721***	-0.213***	0.611***	-0.044	0.937***	0.409***
	[0.104]	[0.057]	[0.122]	[0.035]	[0.054]	[0.053]	[0.040]	[0.044]	[0.072]	[0.078]
Adopter-buyer	1.161***	0.331***	1.665***	0.207***	0.479***	-0.125***	0.399***	0.010	0.686***	0.254***
	[0.022]	[0.014]	[0.027]	[0.010]	[0.014]	[0.014]	[0.012]	[0.012]	[0.023]	[0.025]
Observations	214,594	214,594	195,948	195,948	195,948	195,948	191,384	191,384	184,816	184,816
R-squared	0.296	0.650	0.300	0.865	0.290	0.527	0.172	0.280	0.183	0.235
Diff(importer-buyer)	0.740***	0.239***	0.955***	0.145***	0.242***	-0.088*	0.212***	-0.054	0.251***	0.155**
	[0.105]	[0.057]	[0.123]	[0.035]	[0.054]	[0.052]	[0.041]	[0.044]	[0.073]	[0.076]
Ind x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

The dependent variables are indicated in the columns' headings. Adopter-importer is a dummy equal to 1 for firms with a value of robot imports above 15000 Euros in at least one year over the sample period (2015-2021). Adopter-buyer is dummy equal to 1 for all other firms who have purchased robots in at least one year over the sample period. The excluded category consists of firms whose robot purchases never exceed 15000 Euros over the sample period (non adopters). Controls are interations between a full set of year dummies and the initial values of the following firm characteristics: log sales, a dummy for exporting firms, a dummy for importing firms and a dummy for multinational firms. All specifications control for 3-digit NACE industry x year fixed effects. The sample consists of firms who are active in all years, have more than five employees and sales above 250 thousand Euros. Standard errors, reported in square brackets, are corrected for clustering at the firm level. ***, **, *: denote significance at the 1%, 5% and 10% level, respectively.



Each map reports the distribution of a given set of firms (indicated in the map heading) across NUTS-3 regions.

Figure C1: Distribution of Robot Integrators, Robot Adopters and Other Firms across NUTS-3 Regions