Integrators and Robot Adoption: Facts from Hungary*

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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 show how to identify robot integrators, quantify their role, and build 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. We then use our measure of adoption to investigate the lumpiness of robot investments and the geographic concentration of both adopters and integrators. The results in this paper underscore the critical role of intermediaries in broadening access to automation technologies, especially for smaller and medium-sized firms.

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1 Introduction

Robotics is widely considered a general-purpose technology with the potential to drastically alter the fabric of production. Compared to manual workers, industrial robots are stronger, faster, make fewer mistakes and can work nonstop. And yet, for now, their adoption is still limited. Although global robot installations keep growing at a staggering rate, manufacturing firms using robotics technologies are less than 2%, and this figure is even lower in other sectors (IFR Reports). One of the main reasons for the still limited diffusion of robotics is that industrial robots are complex machines that require large investments and specialized skills, making them often not cost-effective outside of mass production. While the importance of scale in the adoption of new technologies has long been emphasized in the literature, other factors that facilitate automation have received much less attention. In this paper, we focus on the role of robot integrators.

Robot integrators help identify automation needs and opportunities, offer engineering services and customize the robots to fit the needs of the end user's application. Robot manufacturers do not usually do this because they do not have the staff or resources to handle the needs of all end users. Integrators fill this gap with specialized design, engineering and programming resources. While integrators are key players in the robotics industry, due to lack of data, we know very little about their quantitative importance.

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, quantify their importance, and we use this information to build a new measure of robot adoption at the firm level.

To organize the empirical evidence, we build 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 import to be chosen more likely by firms that are more productive, that enjoy stronger demand, that 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 the crucial factor not just in the decision to automate, but also for the choice to use integrators.

We then move to the evidence. We leverage administrative data on the universe of

Hungarian firms over the period 2015-2021. We first identify robot integrators from the directories of the main associations in the robot industries, and by linking robot importers and manufacturers to firms selling installation services. Then, we identify the firms buying from these integrators using data on firm-to-firm trade. Since integrators are highly specialized, we are able to use firm-to-firm trade data to trace robot purchases to the final users.

With this data at hand, we document a number of facts about robot integrators. We show how their number has grown over time, and we compare their characteristics to the average firm operating in the same industry. We then turn to robot adopters. We show that the vast majority of firms adopting robots purchase them through integrators. We then provide evidence that firms using integrators differ from other adopters and from non-adopters. Consistently with the model, we find that firms using integrators are smaller, less productive and less capital-intensive than other adopters, but also that these differences tend to vanish when controlling for size. These results suggest that integrators play a crucial role in the diffusion of robots especially for smaller and medium-size firms. Finally, we use our measure of robot adoption to revisit some stylized facts about the lumpiness of automation investment and about the geographical concentration of both 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 has been generally recognized (see for instance Humlum 2021, Brynjolfsson et al. 2023), to our knowledge this is the only paper that measures their activities. This exercise also allows us to document precisely robot adoption at the firm level. Since data on the use of robots by firms are not collected systematically, one of the open challenges in the literature is how to measure it. To overcome this difficulty, different authors have proposed different strategies.

Import data have been used to study the role of robots in firms in Canada (Dixon, Hong, and Wu 2021), France (Acemoglu, Lelarge, and Restrepo 2020; Bonfiglioli, Crinò, Fadinger, and Gancia, 2024), Spain (Koch, Manulov, and Smolka 2021), and Denmark (Humlum 2021). However, as we show in this paper, import data grossly underestimate robot adoption. Moreover, since firms that choose alternative modes of adoption have different characteristics, using import data only may lead to biased results.

The main alternative relies on firm-level surveys. Questions about robot usage have been recently introduced in some countries, but the data is often limited in size, coverage and time span. In the United States, questions on robots were included in the Annual Survey of Manufacturers (ASM) in 2018 through 2020 for a sample of approximately 50,000 establishments (Brynjolfsson et al., 2023). Earlier versions of the Survey of Manufacturing

Technology, conducted in 1988, 1991, and 1993, collected data on robots 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 instead approximately 300,000 firms, but questions about automation technologies are available for the year 2019 only (Acemoglu et al. 2022).

In Germany, the 2019 IAB Establishment Panel, covering around 15,000 establishments, contains information on robot usage between 2014 and 2018 (Benmelech and Zator, 2022, Findeisen, Dauth and Schlenker, 2024). However, the count of industrial robots is available for 2019 only. In Spain, the Encuesta Sobre Estrategias Empresariales (ESEE), an annual survey covering around 1,900 manufacturing firms from 1990 to 2016, features a qualitative question about the use of robots (Koch, Manulov, and Smolka, 2021). A similar question was included in the 2018 survey of almost 4,000 Danish firms from Statistics Denmark (Humlum, 2021). Finally, Bessen, Goos, Salomons, and van den Berge (2023) use a sample of approximately 35,000 non-financial Dutch firms with at least 3 years of data on expenditures on third-party automation services, collected by Statistics Netherlands.

None of these datasets contains quantitative information about robot integrators. Instead, our combined administrative data and firm-to-firm transactions allow us to build a measure of robot adoption for the universe of firms over a relatively long period. With our approach, we can describe robot adoption in country, Hungary, where other firm-level measures of automation are not available. More generally, we believe that our methodology can be used to complement the existing measures of robot adoption in other countries as well.

The rest of the paper is organized as follows. Section 2 presents a simple model that is later used to interpret the data. Section 3 provides a brief description of the Hungarian firm-level data used for the empirical analysis. Section 4 presents some stylized facts about robot integrators. Section 5 focuses instead 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.

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.[1] Consider a firm i that faces a demand function with a constant price-elasticity,

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

$y_i = A_i p_i^{-\sigma}$. 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. 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:

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

The first-order conditions for capital and labor are:

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

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

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 task 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 $f_i^b < f_i^d$. 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 A, 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 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, those that 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.[2]

[2] We assumed 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 applied to the automated tasks only, the parameter α_i would disappear from condition (7).

3 Data

To carry out our analysis, we combine various Hungarian administrative firm-level datasets. Hungary is an ideal case for studying the diffusion of robotics at the firm level. While still lagging behind other countries in terms of robot density, the average number of automated units per 10,000 employees jumped from 18 to 84 over the period from 2010 to 2018 (IFR). Moreover, the presence of a large manufacturing sector, which employs around 25% of the total workforce, implies a strong scope for robot adoption. This is especially true given the importance of the automotive industry, where automation is widely used and which accounts for roughly 30-40% of total manufacturing output.[3] At the same time, Hungary is not an important manufacturer of automation technologies, so robots are almost entirely purchased from foreign firms.

We use VAT data on the universe of domestic firm-to-firm transactions to track firms' purchases from robot integrators and to accurately measure robot adoption at the firm level.[4] We combine these data with customs data at the product-country level to measure robot imports by each Hungarian firm and to control for their involvement in international trade. Finally, we use NAV balance sheet and income statement data, covering financial information on the universe of corporations in Hungary, to construct some of the main outcomes at the firm level, including sales, employment, labor productivity and capital stock per worker. The balance sheet and customs data cover the period 2000-2021, the VAT data the period 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 in various ways. First, we take the list of robot integrators operating in Hungary in 2021 from the online platform HowToRobot and from the IFR's 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 International Federation of Robotics (IFR) is a global industry

[3]Major automotive companies such as Audi, Mercedes-Benz, Suzuki and BMW, as well as their TIER1 suppliers like Bosch, Valeo, or Continental, have manufacturing plants in Hungary. Another large manufacturing sector is electronics (e.g. Flextronics, Samsung, Siemens).

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

association that serves as the primary voice and representative body for the robotics industry. We included IFR members with affiliates in Hungary or with partners located in Hungary. The list from these sources, excluding duplicates, comprises 200 companies included in our dataset.

We complement this list with information on robot imports from custom data. In particular, we also consider as integrators firms importing significant amounts of robots and operating in industries whose main business is the sale of machinery equipment or technical services to other firms.[5] More precisely, we consider firms with an average share of robot imports in the fourth quartile of the distribution 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". With this definition, we identify 10 additional integrators. Finally, leveraging our firm-to-firm data, we also include firms operating in the above industries and having significant purchases, in top quartile of the industry distribution, from robot manufacturers or distributors identified from the HowToRobot-IFR list. Excluding overlaps, this gives us a total of 352 robot integrators in our sample. Their size ranges from a few employees to several hundreds (in our sample up to 4000). They include domestic engineering-focused firms, domestic distributor-focused ones, and affiliates of multinationals. The number of integrators present in each year has increased from 234 in 2015 to 309 in 2021 (+32%).

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:

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

where i denotes a firm; j indicates the 4-digit NACE industry in which the firm operates; and t stands for time. Y_{it} is an outcome and Int_{it} 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 com-

[5] The Hungarian customs data follows the Combined Nomenclature (CN) classification, where trade in industrial robots is recorded under two 8-digit product codes: CN 84795000 and CN 84798950. Our main results remain robust under an alternative (broader) definition of robot imports, which includes CN products corresponding to machines designed to perform activities aligned with the robot application categories defined by the IFR.

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	1.125***	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	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 dummies 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.

prising at least one integrator and for five major outcomes that can be directly constructed from the data: (i) log sales, (ii) log employment, (iii) log sales per worker and (iv) log value added per worker and (v) log capital stock per worker.[6]. We always control for 4-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 ttwo 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 control flexibly for common trends among firms with similar characteristics. We estimate (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, both in term of employment and sales (+0.318 and +0.378 log points respectively in the specifications with controls), have a higher labor productivity, as measured by value added per worker (+0.119 log points), and use more capital per worker (+0.154 log points). This suggests that robot integrators are important players in the industry where they operate.

4.3 The Import Network of Integrators

Robotics relies on technologies and equipment that is largely produced outside of Hungary. It is therefore instructive to look at the import network of robot integrators. Differently from other firms, all integrators in our sample report some imports, a result confirming the importance of foreign suppliers in the industry. Imports tend to be quite concentrated. On average, about 80% of integrators source at least 50% of imports from a single country. The most popular source countries for imports of all products are Germany, the US, Austria,

[6] Foreign-owned firms are those with foreign ownership share above 50%. Capital stock is the stock of tangible assets of the firm.

Switzerland and China. Focusing on imports of industrial robots only, the most important suppliers are Germany, Austria, Sweden, Japan and the Netherlands. More details are in Table B1 in the Appendix. These lists comprise countries that are located close to Hungary and/or that are major world suppliers of parts and hi-tech machinery. The observation that integrators rely on very few suppliers but that there is heterogeneity in their location, suggests that integrators may be subject to different supply shocks.

5 Integrators and Robot Adoption

Consider now firms making purchases of 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 have a total of 6809 unique buyers, excluding integrators. By year, the number of unique buyers has grown from 1766 in 2015 to 3216 in 2021 (see Table B2 in Appendix). This corresponds to an increase of +82% over a 7-year period.[7]

Table 2 provides some information about the sectors served by integrators. Of the total number of robot purchases, 53% come from manufacturing firms, 19% from the wholesale-retail sector, 14% from services, 11% from construction-utilities and less than 3% from the transport, postal and warehousing industry. In terms of value of purchases, the manufacturing sector accounts for 65% of the total, followed by wholesale-retail (20%), services (7%), construction-utilities (5%) and transport, postal and warehousing (around 2%).

The distribution of purchases across sectors confirms that automation is most prevalent among manufacturing firms, although service industries have also started to make significant investments in robotization. For instance, retailers have been investing heavily 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, the typical manufacturing firm buys from 2.5 distinct integrators, while this figure is close to 1 in all other industries. This confirms that integrators sell very specialized services and equipment, which is typically 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.

[7] One issue with the identification of integrators is that some firms involved in robotics are large diversified multinationals like ABB or Panasonic. As a robustness test, we excluded firms with 500+ employees (6) from the list. This resulted in a decline of unique buyers only by about 3%, a proportional response.

Table 2: 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	Number
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.

5.1 Robot Adopters

Adopters are firms that either directly import industrial robots (and are not classified as integrators) or make a purchase from an integrator in any of the sample year. To avoid noisy results driven by very small transactions, we impose also here the minimum threshold. That is, for a firm to be classified as an adopter, the sum of its imports plus purchases from integrators needs to be larger than 15000 Euros in at least one year. To make sure that the results are not affected by changes in the composition of the sample over time, in this section we restrict the analysis to a balanced sample of firms that are active for the entire 7-year period from 2015 to 2021 (see Appendix B for details). This leaves us with 3762 adopters, accounting for 1.1% of all firms in the full (unbalanced) sample and for 12.3% of firms in the balanced sample. The number of adopters in the unbalanced sample is broadly in line with evidence from other countries. For instance, using survey data from the U.S. Census, Acemoglu et al. (2021) report that about 2% of firms use robotics for automation. Using data from the Annual Survey of Manufacturers, Brynjolfsson et al. (2023) find that approximately 11.1% of plants reported having one or more robots in 2019. The difference between the balanced and the unbalanced sample is due to the fact that firms that stay in the sample in all years are larger, and robot adoption is significantly higher among larger firms. Importantly, out of the total number of adopters, only 177 (4.7%) are importers while the remaining 3585 buy from integrators. These figures underscore the quantitative importance of integrators for correctly measuring robot adoption: if we focused on importers only, we would miss 95% of adopters.

Table 3: 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 15 thousand 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 15 thousand 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 dummies 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 3 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.

5.2 Comparing Robot Adopters

We now compare the economic characteristics of adopters who procure robots from integrators with those who import robots directly and with firms who do not use robots. To this end, we defined three distinct groups of firms for our analysis: (1) adopter-importers, which are adopters whose robot imports exceed 15,000 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-adopter, 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 industry-year fixed effects. As before, in some specifications, we also control for time dummies interacted separately with the import, export or multinational dummies and with the initial level of sales. The results are in Table 3, 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 4-digit industry with the same size, and globalization status, robot adopter-importers and adopter-buyers are significantly larger, both in term 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 are also more productive, as 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 differeces disappear when controlling for size. Finally, adopters are also more capital intensive, as measured by capital per worker (+0.392 and +0.233 log points, respectively, in the specification with controls).

It is also useful to compare different types of adopters. Without controls, adopter-buyers are on average smaller, less productive and less capital intesive 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 results are consistent with the predictions of the model and underscore the importance of scale for both the decision to automate and the mode of adoption. They also highlight that integrators are especially important for smaller firms, which may lack the scale to justify setting up the expertise needed to import and install robots directly.

5.3 The Lumpiness of Robot Adoption

The literature has also discussed the lumpiness of robot adoption. As a final application, we use our novel data on adoption to revisit this fact. Automation requires a significant investment, which may involve some organizational change. Moreover, robots are indivisible and the price of a single unit is significant. Indeed, in our balanced sample, the average robot purchase is a considarble 3.8% of the value of sales. As a result, investments of this size may occur unevenly across time. Documenting the lumpiness of robot adoption satisfactorily requires a precise measure of robot adoption. Cross sectional data or surveys are often inadequate for this task while import data may be too sparse. With our transaction data, we can study the distribution of robot purchases over time in much greater detail.

To define a "spike" in robot adoption, we focus on the ratio between the maximum robot purchase of a firm (computed among purchases above the 15000 Euros threshold) and its average, computed across all seven years, including those with zero purchases:

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

If robot purchases of a firm are uniform over time, this ratio would be equal to one. On the contrary, if a firm purchases robots only once, this ratio would be equal to the number of years in the sample, that is, seven. We then define as a "spiky adopter" a firm for which this ratio is greater than 3.5. This corresponds to a distribution of purchases more skewed than two equal purchases over the sample period. We find 2495 spiky adopters in our sample, which corresponds to two-thirds of all adopters. Of these, 1355 (54.3%) have a single purchase over the sample period.

Table 4: 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

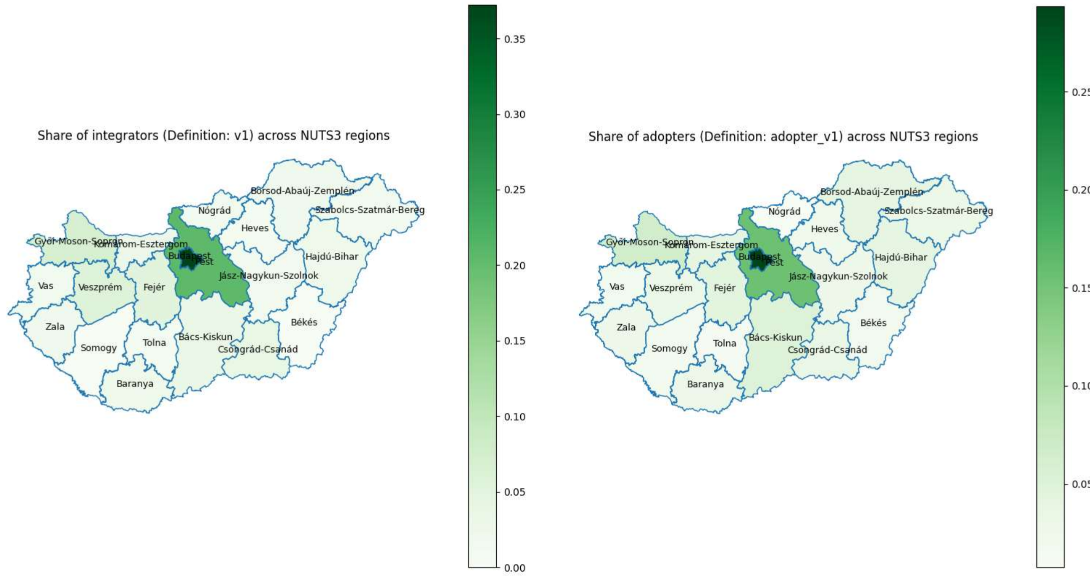
The table shows the distribution of robot adopters, importers and buyers across bins of the ratio between the maximum and the average purchase of robots over the sample period (*spikiness*).

Table 4 reports the distribution of our measure of "spikiness" S_i, i.e., the ratio of max-to-average robot purchase of each firm, for all adopters, adopter-importers and adopter-buyers. As already discussed, a value of S_i between 1-2, i.e., in the first bin displayed in the table, corresponds to firms that buy robots rather continuously. As shown in the table, only 8.7% of adopter-buyers and 19.2% of adopter-importers fall in this group. More generally, adopter-importers follow a pattern of purchases that tends to be less lumpy than adopter-buyers. In particular, the majority of adopter-importers are not classified as "spiky adopter" while the opposite is the case for adopter-buyers. Moreover, 39% of adopter-buyers have $S_i \geq 6$, while this number is just 18.6% for adopters-importers.

These findings confirm that robot adoption tends to be lumpy. However, it also highlights that there is a significant number of firms that invest in robots more uniformly. Moreover, the fact that these firms are adopter-importers, which are larger than adopter-buyers, suggests that the scale of operation may be an important determinant not just of the decision to automate, but also of the frequency of these investments.

5.4 The Geography of Adopters and Integrators

Brynjolfsson et al. (2023) have shown 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 with our data. To this end, in Figure 1 we have drawn maps with the share of adopters and integrators across 20 NUTS3 regions. The maps show a significant degree of geographic concentration. In particular, most firms using robots are located close to the capital, Budapest, and in other industrial regions. Moreover, the location of integrators mirrors closely that of adopting firms.



Each map reports the distribution of robot integrators and robot adopters by NUTS-3 region

Figure 1: Distribution of Robot Integrators and Robot Adopters across NUTS-3 Regions

6 Conclusions

This paper documents some 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 five main takeaways.

First, the paper highlights that most firms adopting robots in Hungary do so through integrators, rather than by directly importing robots. This suggests that most firms lack the expertise to directly install industrial robots and that integrators are a key component in the supply chain of automation technologies. Second, the paper shows that smaller and medium-sized firms, which may not have the scale to adopt robots independently, benefit significantly from the presence of integrators. This highlights the importance of intermediaries in broadening access to advanced technologies in the economy beyond larger, more capital-intensive businesses. Third, we find that robot integrators tend to be larger and more productive than other firms in their industries. They are also more capital intensive, which is consistent with their role in facilitating technological upgrades in client firms. Fourth, given the difficulty of tracking robot adoption using traditional data sources, the paper shows how to use firm-to-firm transaction data to build an accurate measure of robot adoption at the firm level. This methodology could be applied in other countries to improve our understanding of automation trends. Fifth, we use our measure of robot adoption to revisit some results on the lumpiness and the geographical concentration of automation investment.

A natural application of our data would be to study the effects of automation on adopting firms. However, since this question is fundamentally different from the role of intermediaries in facilitation adoption, we left it to 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 could help overcome barriers to technology adoption.

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A Model

Figure 1 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 under which a firm will prefer direct adoption to using integrators ($\pi_i^d > \pi_i^n$) is:

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

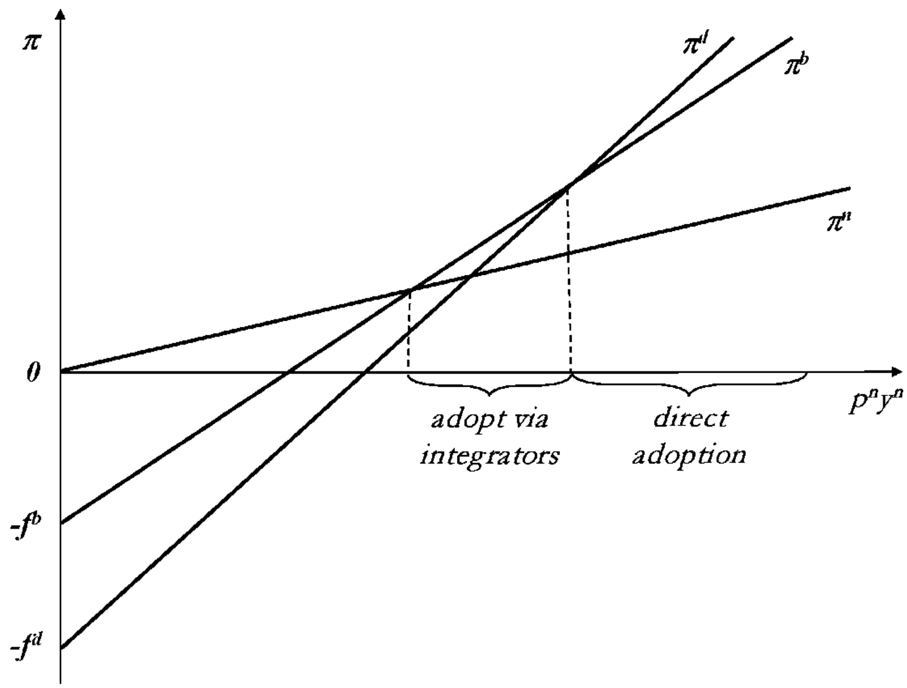
B Data Description

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.[8]

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

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



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

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.

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 300k EUR). In

2017, the threshold for imports was increased to 170 million.

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 of 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 5 employees or report having less than two employees in some year, as well as firms whose sales are always below 250000 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.

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.

C Additional Empirical Results

Table B1: 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 B2: 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 15 thousand euros in a given year.