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JEL Classification: R12, F14, D22

Keywords: machine imports, impact of technology adoption, trade-related spillovers, agglomeration

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Machine imports, technology adoption and local spillovers

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Abstract

In less developed economies import can be the primary source of adopting new technologies in the form of modern production equipment. This paper explores the spread of manufacturing machinery across locations and investigates the effects of previous importers on the firms' decision to import certain types of foreign machines. Using a uniquely compiled Hungarian firm-level dataset for the 1992-2003 period, we find that the probability of importing a particular piece of sector specific machinery is positively affected by the presence of local firms previously importing the same machine. A similar pattern is found with regards to the choice of source country. While these results offer evidence of positive externalities, we find that these benefits are concentrated in large and foreign owned companies.

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1 Introduction

Capital goods, machines and manufacturing technologies are produced in a few developed economies. Countries who do take part in developing these technologies can benefit from them via knowledge spillovers as suggested by endogenous growth theories which highlight the external nature of technology (see Romer, 1990; Rivera-Batiz and Romer, 1991). For developing countries, who do not produce manufacturing technology themselves, a key vehicle for spillovers and growth are imports. Indeed, Coe and Helpman (1995); Acharya and Keller (2009) find large spillover effects from imports from foreign, R&D-abundant countries on domestic productivity at the aggregate and sector levels. Importing technology embedded in machines, materials leads to increased productivity also at the level of the firm (see Halpern et al., 2013, 2015).

This paper looks at how accumulated knowledge of machine imports affects new adoptions and dissects channels of this spillover. Focusing on the imports of machinery allows to gain a better understanding on a possible source of productivity gains and development. In particular, we investigate how investment to a particular machinery may be encouraged by earlier imports of the same machine carried out by local firms. As more and more local firms have imported a particular machine, the easier it is for another firm to be informed about the advantages and the specifics of the technology. In addition, if the machine is available from many countries, firms learn whether it is worth substituting a machine from one country with one from another. If these learning channels are at work, we hypothesize that in the absence of peers a firm would be less inclined to import a given machine or it would import it much later.

To answer these questions, we compile a dataset that matches machine level import observations to Hungarian manufacturing firms for 1992-2003. The period provides several advantages. It starts with Hungary's early transition years, prior to which foreign machinery was not generally available to domestic firms. Possibly, every machine imported in the early 1990's can be regarded as technologically more modern and more advanced than previously installed machinery. In addition, the transition invited waves of foreign direct investments, which introduced new imported machines and technology to many sectors. This is not only true for green-field investment, but also for a portion of the privatized companies as well where firms upgraded their production facilities through imports. In the examined period, foreign machinery indeed plays an important role in manufacturing investments. The share of machinery investment of manufacturing firms is over 60 percent, see Figure 6 in the Appendix.

Our results indicate that the presence of a previous importer of a specific machine in the close vicinity increases the probability of a firm importing the same machine. The presence of such peers within 1 km of the firm increases import probability by 0.3 percentage points. This effect decreases with the distance of the peers and increases in the number of peers. An additional peer within 1 km of the firm increases the probability of same machine import by 0.27 percentage points. Compared to the baseline probability of machine import, peer presence suggests a 26 percent increase.

We also investigate how the decision about the country from which the chosen machine is to be imported from is influenced by peer presence. The results show that firms tend to import a particular machine from the country with 0.6 percentage points higher probability if there is a firm in the vicinity which have already imported the machine from the same country.

To better understand the nature of the spillovers we investigate both the heterogeneity of firms and that of the peers. Our analysis suggests spillovers go from more to less productive firms, as local first importers of a specific machinery are more productive than followers. We also find that the probability of choosing the machine that others have already imported in the vicinity is higher if the firm is exporter, larger in size or is foreign owned. Also, we find that the presence of exporting, large and foreign peers have a higher impact on import probabilities.

This study contributes by broadening the scope of spillovers in trade behavior in showing that they not only encourage exporting behavior but can affect the importing technology embedded in machines. We build on previous findings in the trade spillover literature. For exporters, empirical evidence suggests that location can be an important factor influencing internationalization. Agglomeration economies can help firms overcome up-front costs and engage in trade.[1] Benefits arise from sharing indivisible goods and facilities and a larger variety of more specialized inputs, from better matching of the right employment or intermediate inputs and services and from learning and the diffusion of knowledge about, e.g., production technologies and market opportunities (Duranton and Puga, 2004). A positive effect of agglomeration for exports was documented in Mexico (Aitken et al., 1997; Cardoso-Vargas, 2017), in Argenina (Pupato, 2007) in France (Koenig et al., 2010) in Belgium (Dumont et al., 2010) in China (Fernandes and Tang, 2014; Mayneris and Poncet, 2015) and in Hungary (Harasztosi, 2016).

There is ample evidence on the productivity enhancing effect of imports also at the firm level.[2] The sources of these positive effects can be different mechanisms. Some explain the increased productivity with the technology embedded in the inputs and the wide variety imports make accessible (Halpern et al., 2015; Goldberg et al., 2010; Bas and Strauss-Kahn, 2011). Others highlight the R&D-generating nature of imports. MacGarvie (2006), e.g., uses patent citations to show that importing firms are more likely to generate new patents. More recently, Halpern et al. (2013) shed light on the productivity-enhancing effect of the imported technology on machines.

[1] Agglomeration economies can either increase the firms' productivity or can decrease the fixed costs of trade entry, or both.

[2] Amongst others, Kasahara and Rodrigue (2008) find evidence for Indonesia, Amiti and Konings (2007) for Chile and Kugler and Verhoogen (2009) for Columbian firms.

Despite the advantages only a fraction of firms import. For firms to be able to trade internationally, they need to be competitive and highly productive. This is often explained by the sizable up-front cost that only the most productive ones can afford. See, e.g., Bernard and Jensen (1999), Bernard et al. (2007), Amiti and Konings (2007) or Castellani et al. (2010). Also, future trading firms are already bigger, employ more skilled and better paid workers and are more capital intensive than their peers in the same sector who do not trade.

We know little about the effect of agglomeration on importing activity at the firm level, especially for capital items, even though importers may face a harder challenge than exporters. First, evidence suggests that the productivity premium needed to start importing is higher than in the case of exporting (Altomonte and Békés, 2010). Second, while exporters often experiment their profitability on foreign markets for a year or two (Eaton et al., 2011), machine importers make long term investment decisions which might result in a higher fixed cost. Firms deciding to invest in an imported technology face the screening cost of potential foreign suppliers, the cost of the technology itself and adapting equipment to foreign conditions and standards. They also require information about the skill requirements for workers and operating difficulties (see Eaton and Kortum, 2001; Bas and Berthou, 2012). While this information may be available via the manufacturer, local industry experience with a given machine may also prove beneficial and encourage adoption. Recent empirical evidence for Sweden suggests positive local effect of peers on import activity (Pateli, 2016). There is also evidence on the effect of peers on the country choice of Hungarian importers located in the capital city, as shown by (Bisztray et al., 2018) for a smaller set of countries.

There is some evidence at the firm level that the characteristics of the location affect the adoption of advanced machinery.[3] These studies, however, do not relate machinery adoption to trade activity. They suggest that the rate and beneficial effects of technology diffusion differ across location characteristics: regions distant from the innovation leader adopt the technology much later, while successful adoption depends on other location characteristics such as the level of existing knowledge and technology, the absorption capacity of the location and the availability of a skilled workforce. Kelley and Helper (1999) show a positive effect of localized economies on the numerically controlled machine adoption of U.S. firms. Also, No (2008) takes a similar approach and investigates the adoption of advanced manufacturing technologies (design, fabrication and inspection) across Canadian firms.[4]

The rest of the paper is structured as follows. Section 2, which discusses empirical strategy is followed by section 3 introducing the dataset. It gives details on data compilation and the construction of the main variables and portrays spatial distribution of

[3]For an aggregate approach see, e.g., Comin et al. (2012); Keller (2002)

[4]There is some evidence on the import of manufacturing scheme, but not machinery. Holl et al. (2010, 2013) who focuses on the adoption of the Japanese just-in-time strategy in Spain and reveal considerable role of location and congestion.

machine imports. Section 4 discusses the results, Section 4.4 offers additional insight to the sources and heterogeneity of the spillovers, and finally section 5 concludes.

2 Empirical Strategy

In this section, we explain the empirical setup used for the main exercise in this paper.

2.1 The estimation setup

Consider an economy made up of $s \in S$ sectors. Each sector is defined by its technologies and in relation to that, the set of machines it uses. In each sector, firms may choose to upgrade their technology by importing a machine from this set. To choose one or any machine the firm balances the cost of import and installation against the future benefits. We assume that imported machinery is always a technology upgrade and that firms are uncertain about the net benefit due to lack of information. Without information firms may not perceive the benefits at all.

Empirically, first we will focus on core machines only - those that we map to a single sector only. As a next step, we will expand to all machines ever imported in the sector.

Firms can gather information about machines from peers – firms in the same industry located in their proximity – who have imported them previously. Experience of these importer peers can reveal the true benefits of importing. Importing and using a particular machine shows that it could be a good business decision to consider.

If there is information in machinery use of peers, firms can benefit from knowledge spillovers, and hence, firms that have peers with experience in a particular machine are more likely chose to upgrade technology with this particular machine. This implies that comparing two machines in the firm's choice-set, the one with greater available information from peers is more likely to be imported by the firm.

To do this comparison, we follow Bisztray et al. (2018) and model the effect of peer presence on the probability that firm i at a given location chooses new import machine m from the set of machines it has not imported at time t as linear hazard and so compare machine choices within the firm:

$$y_{imt} = \beta_0 + \sum_r \beta_r \mathbf{X}^r_{imt} + \alpha_{it} + \mu_{mt} + \varepsilon_{imt} \quad (1)$$

where y_{imt} is an indicator variable for first import of machine m by firm i at time t and $\mathbf{X}^r$ is a vector of spillover variables representing the presence of machine importers in the past years in vicinity r before the firm's import decision at t. The unit of observation is a firm-machinery-time triple (denoted with subscript imt). Dimension m is defined at the sector of the firm and includes all machines ever used in sector s. Time dimension t is defined for the machine m imported by firm i. This means that for a machine who never gets imported y_{imt} is zero for all years the firm is observed. For machine importers y_{imt} takes on the value one the year m is imported, zero before.

As a first approach we calculate $\mathbf{X}$ as a vector that comprises of a set of dummy variables indicating the presence of imports of m before time t by other firms within the distances of r_1, r_2, .. (in km) to firm i. In a later step, vector $\mathbf{X}$ is also calculated as a vector showing the number of other firms having imported machine m that are located within the distance of r_1 to firm i, the number of importers outside the radius r_1 but within the distance r_2 and so on.

Equation 1 also includes firm and machine specific interactions with time to control for the average propensity of a firm to import and that of a machine to be imported.

In equation 1, the coefficients of interest, β_r, shall show the effect of previous machine adopters within distance r on the probability of firm i importing machine m. This effect is identified by comparing various machine purchase options *within* firms. In this setup, β_r confers the effect of the existence previous adopter of machine m on the percentage points increase in the probability of importing at time t. We will make a variety of efforts to partial out confounders and get as close to causal interpretation as possible.

Second, we are also interested in the peer effect on the country choice - how local experience from importing a given machine *from a given country* could affect import choice. In this case, we estimate:

$$y^*_{imct} = \beta_0 + \sum_r \beta_r \mathbf{X}^r_{imct} + \alpha_{it} + \mu_{mt} + \mu_{ct} + \mu_{mct} + \varepsilon_{imct} \tag{2}$$

where country of origin c for the imported machine is added as an extra dimension. Here, $\mathbf{X}^r_{imct}$ is a vector of dummy variables indicating the presence of other firms within distances of r having imported machine m from country c before time t. Alternatively, vector $\mathbf{X}_{imct}$ can also specified to counts the number of firms other than i that have imported the same machine. The peers, similarly to same-country peers, are summed over various distances: within r_1 km, between distances r_1 and r_2, r_2 and r_3 and so on. Equation 2 also introduces additional set of fixed effects controlling for county-specific and machine-country specific propensities detailed in the next subsection.

The idea here is to compare import decisions within a firm conditional on firm, machine and country characteristics when local experience varies in terms of country source. It is important to note, the sample is constructed to be conditional on machine imports. Without this restriction **X** would surely have the joint task of explaining the choice to import and the country choice. We concentrate only on the latter.

In all estimations, we cluster standard errors at the location level, defined by longitude-latitude coordinates.

2.2 Controlling for potential confounders

In this section, let us review the efforts we took to partial out confounding factors.

First, let us consider **location effects**: unobserved local features may cause both past and present adoption. These time-varying location effects are captured by a location $\times$ time fixed effect in both equations. Location is defined at the municipal level (in Hungary, there are over 3 thousand municipalities for 10 million inhabitants).

Such fixed effects shall capture a variety of issues, such as local policies that facilitate investments, creation of special clusters or introducing favorable municipal tax schemes.[5] The availability of scientists or abundant skilled labor who help adopting and operating new machinery can also be such an unobserved factor. Reliable infrastructure (electricity supply), sufficient local input suppliers or local customers can also make installing a new machinery worthwhile. In addition, the spaciousness of the location influences how close are the firms to each other and what the probability of knowledge flow is.

In addition, the positive correlation between the number of past and present importers can also be caused by local business cycles. If certain regions in a given period of time are experiencing economic boom while others are in downturn then the positive correlation between the presence of past and present importers can be purely driven by a series of region-specific shocks. Series of persistent local productivity shocks will be a common accelerator of machine imports for all local firms. However, these underlying shocks need not to be necessarily persistent to cause a problem. If local shocks have effect for over two calendar years, a positive correlation will occur that we would falsely identify with spillovers. In addition, such shocks can be foreseen by managers and adjust labor, capital and other firm characteristics accordingly.

Second, location-specific unobserved heterogeneity may cause identification problems jointly at the industry levels. These **sector specific effects** will be captured by sector $\times$ time and sector $\times$ location $\times$ time and sector$\times$ machine$\times$ time effects.

For example, certain sectors are more eager capital users than others, in which case it is more likely that local firms have already have imported the necessary machines.

[5] The Hungarian corporate tax code (Act LXXXI of 1996), encourages investment in backward and developing regions by facilitating local tax credit schemes. The scheme was especially generous in the pre-2002 era. See Békés and Harasztosi (2012).

The number of machines we investigate varies per sector, too. This is especially worrisome, if the sector that depends on the specific machine heavily is concentrated. Then the region hosting these firms will show correlation between past and present import, without firms actually learning from each other. In addition, the propensity to import a machines may differ in various sectors.

Third, to manage various **country effects**, we add country and country$\times$machine interactions with time. We also add country $\times$ location $\times$ time fixed effects in Equation 2. The purpose of these additional fixed effects is to capture that notion that it is easier to import a machine from Germany than from China because of language barrier and distance. However, this may be correlated with locations: there could be factors that can help local access to certain countries, such as geographical or cultural proximity, e.g. presence of embassies or trading houses. This relative differences can vary over time, or even over machines.

3 Data and descriptive statistics

This section gives a detailed description about the compilation of the dataset used to estimate equations 1 to 2. The section describes the main variables and provides a descriptive portrait of the spatial distribution of machine imports.

3.1 Compiling the dataset

The empirical analysis is based primarily on the Customs Statistics (CS). It contains the universe of exports and imports by Hungarian economic agents between 1992 and 2003. It gives information on yearly trade aggregated to the 6-digit Harmonized System product level and gives the country of origins and destinations as well. The quantity measurements allow the calculation of unit prices. It is important to point out that while trade data is available after 2003, its structure and classifications change after Hungary's EU accession in 2004. This hinders the investigation to go beyond that date.[6]

This dataset is merged with firm level information from CeFiG-IEHAS database[7], a panel of Hungarian manufacturing firms between 1992-2003 with very detailed firm-

[6]The classification of the country of origin is replaced in 2004 in the trade statistics to sender country, which affects import statistics by country considerably. Investigation of the 2004 data, the year where both classifications are available, reveals major changes especially in overseas trade. For example, share of China in imports drops significantly as products manufactured there are traded through European countries, e.g. Germany. For statistics, see e.g. Csermely et al. (2012).

[7]IE-HAS is the Institute of Economics of the Hungarian Economy of Sciences. CeFiG is a research project and community, Center for Firms in Global Economy, which is a joint effort of academic and researchers at Central European University and IE-HAS.

level information on balance sheets. It allows to include the following firm level characteristics into the empirical estimations: firm size defined by the average annual employment, foreign ownership indicating majority foreign share in the subscribed capital of the firm and total factor productivity (TFP).[8] The dataset provides sectoral classification of NACE rev. 1. For more details on this data see Békés et al. (2011).

To identify events of machine import we rely on the Standard International Trade Classification (SITC) rev. 3. which we match to CS. No. 7 group of SITC classification titled *Machinery and transport equipment* defines capital products used in sector specific production. As in this study the focus is on manufacturing machines only, transport equipment and vehicles are excluded. Anyway, vehicles are less production-specific and most widely available via wholesalers in Hungary and importing them is less likely than procuring them locally. This leaves us with a range of machinery listed in SITC classification from *Power generating machinery and equipment* (71) to *Electrical machinery, apparatus and appliances* (77).

As a next step, we allow the list of machinery imported by specific sectors to be borne out of the data. We consider only a subset of the manufacturing sectors and omit industries where the imported machinery can be in fact materials to firms' final product, i.e. *Manufacture of machinery and equipment*. See Table 1 for the list of manufacturing sectors considered. We match the set of machines from SITC 71-77 at the 5 digits to each sector by looking at actual machine imports from 1992-2003. A machine is matched to the sector if it is imported by at least 3 firms. Additionally, machines for general industry purposes such as computers, air conditioning are excluded. We have also checked that the machine is in line with industry activity. That is, matches like *Manufacture of textiles* (17) and *gas-operated metalworking machinery* (73742) are not considered for the analysis. The matching resulted in allocating 143 individual machines to industries, with Tobacco industry having only 3 and the Food and Beverages sector having the maximal number of 37 machines. In Table 1 the sum of machines is 210, which implies that we matched one machine to more than one sector. For example industrial sewing machines can be used by both textiles and wearing apparel industries.[9] For details on the list of machines, see Table 20 (In the Online appendix).

Given the list of machines per sectors one can look at machine importing events at the firm. Only the first import of a machine is considered, subsequent imports afterwards are omitted. To improve reliability of the data and improve economic significance of the research we omit firms with less than 10 employees on average.

We also make some restrictions on the country dimension. For each machine we

[8]To calculate total factor productivity we rely on the control function approach proposed by Levinsohn and Petrin (2003)

[9]When creating peers we will not concentrate only on within sector peers for two reasons. One is that a machine in a related industry can equally inspire imports as within sectors import do. Second, Hungarian sector classification only shows main activity and not second and third product line of a company. Hence, firms in different but close sectors can actually be in the same sector.

Table 1: Number of machines allocated to manufacturing sectors

NACE sector		number of machines	%
15	Manufacture of food products and beverages	37	17.62
16	Manufacture of tobacco products	3	1.43
17	Manufacture of textiles	15	7.14
18	Manufacture of wearing apparel	10	4.76
19	Tanning and dressing of leather	7	3.33
20	Manufacture of wood and wood products	8	3.81
21	Manufacture of pulp, paper and paper products	16	7.62
22	Publishing, printing	13	6.19
24	Manufacture of chemicals and chemical products	14	6.67
25	Manufacture of rubber and plastic products	4	1.9
26	Manufacture of other non-metallic mineral products	10	4.76
27	Manufacture of basic metals	16	7.62
28	Manufacture of fabricated metal products	40	19.05
36	Manufacture of furniture	17	8.1
Sum		210	100.00

consider only the 15 most important trade partners ranked by volume share of imports for that particular machine and only those machines are considered that are imported from at least 3 countries. This ensures that firms have country choices. The partner list consist of 35 countries with Germany, Italy and Austria as chief suppliers of imported machinery. The list of countries are provided by Table 15.

3.2 Descriptions of machines and machine importers

Only a small fraction of manufacturers import machinery directly. Table 2 shows the number of firms in the selected manufacturing sample. It shows that only about half of the firms import any goods from abroad, intermediate goods included. Machine importers are even scarcer. Only about fifth of the firms import machines. Note that these are only those firms who import from our list, which actually underestimates their share.

Table 2: Number of firms by import activity

	firms	importers	machine importers
1992	4800	2595	1205
1993	5290	2810	996
1994	5442	2968	923
1995	5647	3049	844
1996	5870	3184	839
1997	6129	3377	872
1998	6206	3504	928
1999	6292	3538	866
2000	6173	3637	840
2001	6038	3679	775
2002	5965	3673	706
2003	5747	3513	618

On average, a firm that ever imported (in our period), will on average import 1.7 machines a year. When we look at the firm activity, we observe an importing firm for 6 years on average, and the firm will import a total of 6 different machines. On average firms import from 3.2 different countries. The largest number of different machines imported by one firm is 31, and the firm that imports machine from the highest variety of sources imports from 16 countries all together.

Table 3 provides statistics on importing firms by the number of machines they import. The upper panel concentrates on core machines (used in a single sector) only. We find that while more firms import only one machine, more than 53 percent of importers are multi-machine importing firms. About 10 percent of them import 5 or more machines. Looking at imports in shorter period or even in a single year reveals that about 17 to 27 per cent of the importers import multiple machines in a given year. This provides sufficient within firm variation for our estimation strategy, even when only core machines are considered.

The lower panel shows corresponding statistics for any machine imported. Patterns are similar to the core machines. As the variety of machines considered increases, consequently the number of firms that import a single machine only decreases. About one third of the importers import more than one machine in a year.

Table 3: Share of importers by the number of machines imported

	one	two	three	four	5 or more
core machines					
1995	73.3	17.2	5.0	1.7	2.8
1997	76.3	15.3	6.5	0.9	0.9
1999	77.9	19.1	2.0	1.0	
2001	82.9	10.9	3.4	1.7	1.1
1993-1997	61.3	18.8	8.2	2.9	8.7
1998-2003	63.1	19.8	8.7	2.7	5.7
full period	56.5	20.9	8.4	4.1	10.0
all machines					
1995	69.6	17.9	7.9	1.6	3.0
1997	66.4	19.9	7.5	3.9	2.2
1999	67.5	20.3	6.9	2.6	2.6
2001	70.1	17.6	6.7	2.5	3.1
1993-1997	46.3	21.9	12.5	6.2	13.1
1998-2003	46.4	20.6	11.5	7.3	14.2
full period	38.8	21.5	11.7	7.7	20.3

The table shows the percentage share of importing firms by the number of machines imported. Statistics are calculated for selected years, periods. The upper panel counts only core machines - imported only by the sector if the firm. Each row totals to 100.

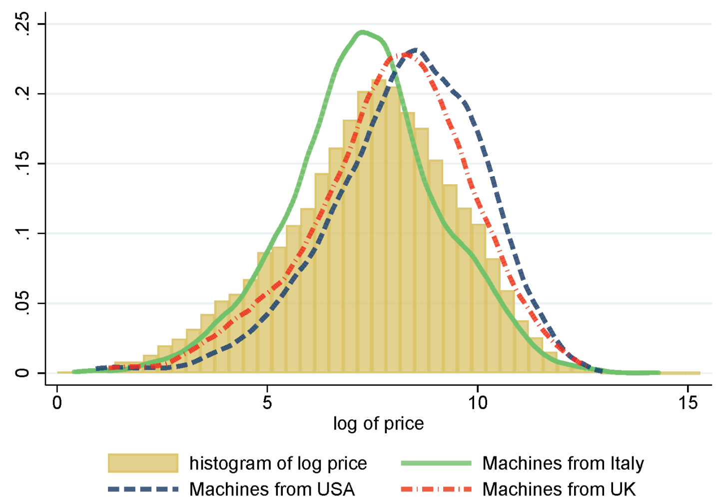
As earlier evidence suggests[10], when we compare importing firms to non-importers, we shall find that these firms are larger and have superior productivity. Regressing a dummy of being machine importer on firms characteristics, we find that machine

[10]See, e.g., Castellani et al. (2010), Mayer and Ottaviano (2008) for a broader take, and (Békés et al., 2011) for previous estimations on Hungarian firm level data

importing firms are 110% larger in terms of number of employees) and 40% more productive (in terms of total factor productivity) - see details in Table 13 of the Appendix.

The data allows to describe the distribution of the unit prices of the machines firms import. The prices show considerably heterogeneity both across and within the machine category. Average within machine category standard deviation of log price equals standard deviation of all the prices. They vary considerably across countries as well, for at least two reasons. Import prices are recorded including cost, insurance and freight (CiF) which suggest that duties and distance increase the price of the machines. Also, prices vary due to the value added and the price of technology embedded in the machines. Figure 1 illustrates this showing the difference in the price distribution of machines from Italy, USA and UK. The difference in the average price between Italy and the U.S. can be most probably explained by the difference in shipping costs and the varieties. While, the difference in the average price between Italy and the UK may be mostly attributed to the difference in machine varieties and qualities as the distance is considerably less in their relation.

Figure 1: Distribution of machine unit prices (in logs and 1992 terms)

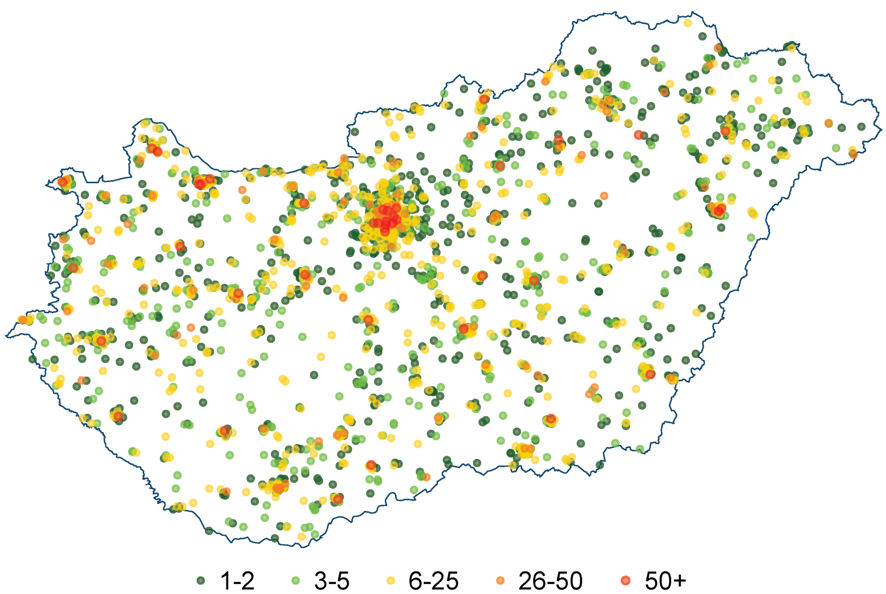


3.3 Location of peers

Investigating the effect of peers on importing activity requires heterogeneity across space. If machine imports exhibit stickiness in space, that is, a new machine importer is influenced by previous importers, new importers should be relatively close to previous ones.

The data also includes the location of the firm's headquarter at the municipality level including postcode.[11] Using this information we geo-code the location information and assign geographical coordinates to each firm at the level of postcode using *Geonames.org* dataset and using Google Earth. In Hungary most settlements have single post-codes, here the coordinates refer to the center of the settlement. Most larger cities and agglomerations, however have multiple post codes.[12] Also there is small share of settlements that share the same postcode, hence it is important to define location by both postcode and settlement. Geo-coding firms this way enables measuring the shortest distance between them. [13]

Figure 2: Number of imported machines by location



Machine importing activity is observed in 2,329 locations defined by postcode - settlement coordinates. This is about 63% percent of all 3,658 locations where any production activity in the selected manufacturing sectors can be detected. This is illustrated in Figure 2 which displays the map of Hungary and shows the distribution the total number of machines imported in each location over the sample period. In over forty locations more than 50 machines gets imported. These are predominantly located in larger townships in Hungary. About 100 location imports between more than 25

[11]Identifying firms' location by headquarters can be problematic in the case of multiple-site firms. This possibility is investigated in Békés and Harasztosi (2013) who find that in the case of manufacturing sector the share of multi-site firms in Hungary negligible.

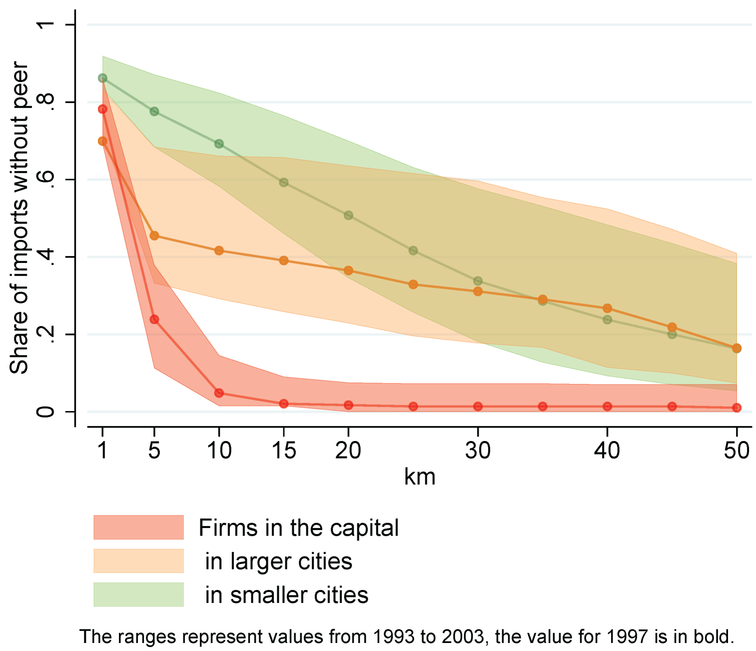
[12]Budapest, the capital city has 160 post codes, Miskolc has 21, Debrecen has 17, Szeged has 15, Győr has 13 and Pécs has 20.

[13]We kept only firms in the sample that do not change location over the period: only 3 percent of all firms have two or more location.

but less than 50 machines, over 670 locations imports less than 25 but more than 5 machines. The remaining locations, a bit more than 1500, import 5 machines or less.

As a next step, we look at machine import instances and categorize them according to the existence of previous activities. We use threshold values starting from 1km to 50 km with 5km steps to investigate within what distances peers are most likely to locate. Figure 3 shows the share of imported machines in selected years that do not have peers within a specific distance. As distance of peers can be dependent on the size of a given agglomeration, we show results by three size categories: for firms in the capital, for firms in the larger cities (20 county capitals) and all locations smaller. The red line shows the results for firms in Budapest, the capital city. We find that in 1997, 80 percent of the machine imports without same machine peers within 1 km, this ratio sharply drops to about 20 percent when we look at 5 km distance, decrease to a close to zero level around 15km and we find that almost all imports have peers within the 30 km radius. The red shaded area shows the corresponding ratios for 1993 and 2003 for the beginning and the end of our sample; the count of peers being cumulative the peerless ratios are always lower for a later point in time.

Figure 3: The share of machine imports without peers at various km distances



This figure shows the share of machine imports that happen without firm presence separately three groups of firms based on their location: Firms in the capital city, Budapest. Firms in larger and firms in smaller cities. Results for Budapest firms (in red) suggest that almost all imports have peers within the 15km radius.

The statistics for larger cities are presented in yellow. Here, in 1997, about 70 percent of the machine imports without same machine peers within 1 km, and then drops to about 45 percent within 5 km before decreasing gradually to 20 percent within the 50 km radius. Interestingly, the band around the 1997 value is rather wide in Figure 3 for larger cities, which suggest a significant variation in the presence of peers over time.

For smaller cities and settlement, results show the highest share of firms without peers, over 85 percent in any year. This ratio gradually decreases with the distance and statistics become similar to those calculated for larger cities when distance exceeds the 30km radius.

The take-away message of the graph is that distance matters a great deal, and firms with fewer peers close by (small cities) will benefit from spillovers from further away (flatter decay) than those in larger cities, or especially in the capital.

While the findings from Figure 3 already give motivation to use distance thresholds 1km, 5km, 15km and 30km for the analysis, it is still worth looking at the distribution of peers from a different perspective. Instead of the share of peerless imports within a distance Table 4 looks at the distance of the closest peer for the same three time periods. The table has two panels, the left one shows the distribution of machine imports by closest same-machine peers, while the right panel looks at imports by the spatial distribution of same machine-same country peers.

Table 4: Share of imports with and without previous importers in selected years

	peer type					
	same machine			same machine & country		
distance of the closest peer	1993	1997	2000	1993	1997	2000
within 1km	11.5%	19.7%	23.0%	4.6%	8.3%	8.0%
between 1 to 5km	16.3%	21.8%	23.8%	8.9%	11.7%	12.2%
between 5 to 15km	12.3%	15.9%	15.8%	7.6%	8.8%	10.1%
between 15 to 30km	12.0%	15.9%	15.3%	6.5%	8.5%	9.0%
between 30 to 50km	15.3%	13.4%	13.1%	10.2%	9.4%	11.6%
further than 50km	31.5%	13.4%	8.9%	33.2%	23.8%	24.1%
no peer at all	1.1%	0.0%	0.0%	29.1%	29.4%	25.0%

The table categorizes country-machine firm level imports by the existence of peers by distance. The panel on the left looks at machine import, while the panel on the right looks peers by importing country. Each column adds up to 100 per cent.

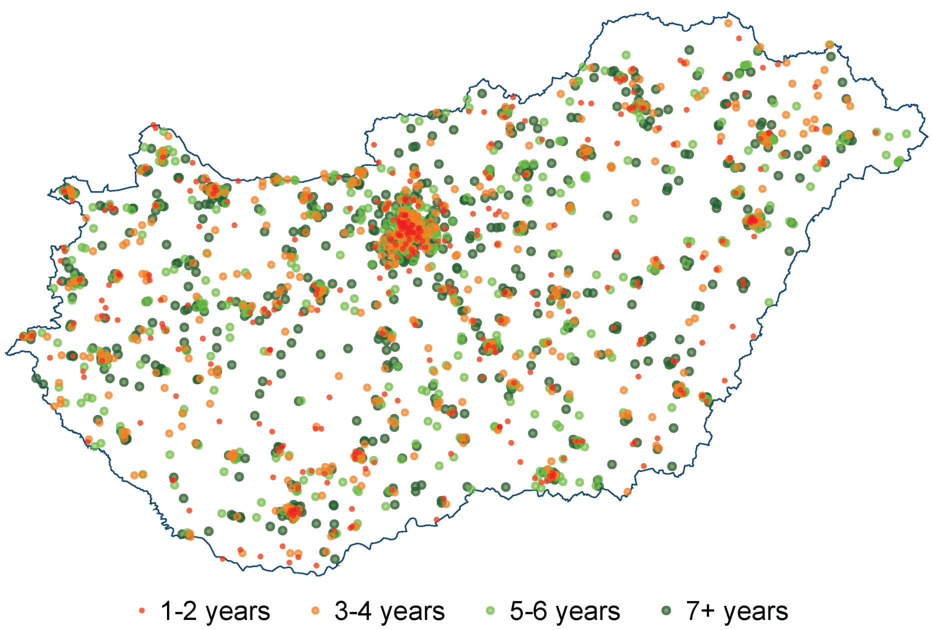
Even in the second year of our sample, in 1993, 11.5 percent of the importing events are involving machines that have been imported in the previous year by other firms within the 1km vicinity and more than half of them have peers within the 30km radius. As time advances the chance of not having any a peer diminishes, and more and more firms have local peers when they import machines. By 2000, half of the imports take place in locations where there was previous import in the 5km radius.

Additionally, Table 4 shows that even in 1993, at least 70 percent of the machine imports had same-country peers. About 5 percent of the imports have peers within 1km, while 27 percent of them within 30km. We find an accumulation of peers with the 1 to 15 km range. As time passes, the share of imports with immediate (1km) same-country peers increases to 8 per cents, those with peers within 15km, increases to 30 percent from a previous 20 percent by 2000.

3.4 Timing of imports

Investigating the effect of peers on importing activity requires an additional heterogeneity: across time. If a new machine importer is influenced by previous importers, those who import earlier should be closer to peers than those who import later.

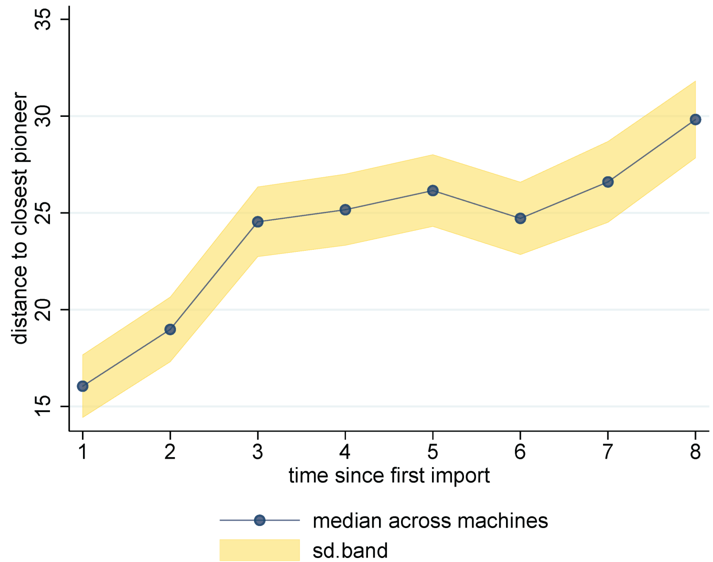
Figure 4: Time average machine being imported after the pioneer



The Figure show the average time elapsed for machines imported in a municipality after the specific machine is imported first in the country at all. It is at a zipcode coordinate level.

To investigate the timing of machine imports first, let us plot how many years pass after the first import of machine *m* until the same machine is first imported in location. Figure 4 shows the average of years passed for any technology imported in a given location. The distribution of timing shows considerable variation. It shows that, on average, timing is negatively correlated with city size: average early adoption (1-2) years is concentrated around agglomerations such as the capital city and important manufacturing centers. At the same time, late adoption (7+ years) is found in smaller settlements and in the greater vicinity of agglomeration. That is, foreign machinery is adopted in smaller municipalities later than in larger cities. In fact, in major cities the imported machine arrives first, in 1992 or 1993. New machines get imported in smaller settlements much later, in some cases even in the 2000's. Nevertheless, there are some pioneering small municipalities.

Figure 5: The average distance a machine travels a year after the first import



The figure shows the average kilometer distance of a new machine import from the first imports of that machine in Hungary. Standard errors are gained from regressing distance from pioneer importer on time dummies indicating time elapsed from pioneer importer of the product at import observation level.

We examine the possible spatial dependence of imports by looking at average distances between importers in kilometers over time. Figure 5 investigates how far technology as embodied by machines travels in time. The distance is calculated in the following manner. Assume that at time zero (1992 in our case) K firms import machine m. The next year new firms import machine m. Measure their distance from the closest firm of the existing K. If the new importers is in the same location as any of the previous K importers the distance can be assumed to be zero. An average of the distances so calculated will tell us how much a machine travels a year. The distance is calculated for each year after the first import of a given m, always with respect to the original K firm. If the locations of the successive waves of imports are independent of location of the pioneer importers distance should be uniform over time. Figure 5 shows that in years immediately after the first import followers are located closer on average than in later years. It shows that if new machine imports tend to be close to old ones within 3-4 year of the first import. Additionally, it also shows that investigation should cover the 15km to 30km radius in addition to the very close peers. The 15km to 30km radius can be considered to cover a group of settlements (an urbanized center) or a micro-region (See Table 14 in the Appendix).

All-in-all, these results are consistent with the idea that machine imports exhibit peer effects and learning takes place in a rather limited geography, even allowing time for information spillover.

One idea behind the spillover effects, as mentioned above, is that peer effects can lower the fixed cost of importing for following firms and as a consequence relatively lower productivity firms can catch-up. This would suggests that firms that import are more productive than the ones that follow. Table 5 tests this idea and compares firm productivity by the relative timing of the machine imports. The baseline group consist of firms that import machine 5 years or later than the pioneer. The pioneer is the firms that import a given machine within a given distance first. The first column compares firms at any distance, the second compares firms within 30km distance to each other, and the third uses 15km distance. The last column looks at firms within the 1km neighborhood. Consequently, the initial sample size containing all firm-pairs decreases as the size of the neighborhood shrinks.

Table 5: Relative productivity advantage of machine importer pioneers

dep: var TFP	peers within the distance				
	any	30km	15km	5km	1km
pioneer	0.990***	0.360***	0.319***	0.253***	0.413***
	[0.267]	[0.0603]	[0.0653]	[0.0569]	[0.0701]
lagging 1-2 years	0.373**	0.287***	0.286***	0.243***	0.227**
	[0.163]	[0.0727]	[0.075]	[0.0791]	[0.105]
lagging 3-4 years	0.378***	0.200***	0.207***	0.159**	0.0147
	[0.123]	[0.066]	[0.071]	[0.0700]	[0.113]
dummy: year	yes	yes	yes	yes	yes
dummy:location	yes	yes	yes	yes	yes
firm controls	yes	yes	yes	yes	yes
Observations	1 461 691	120 402	78 463	32 683	15 639
R-squared	0.366	0.26	0.225	0.264	0.331
Adj. within R.	0.134	0.0969	0.0966	0.115	0.132

This table compares firm productivity by the relative timing of the machine imports. The pioneer is the firms that import a given machine within a given distance first. The first column compares firms at any distance, the second compares firms within 30km distance to each other, the third uses 15km distance. The last column looks at firms within the 1km neighborhood. Firm controls include firm age, firm size and foreign ownership dummy. The baseline group consist of firms that import machine 5 years or later than the pioneer. Regressions are of log-dummy type, hence 0.99 coefficient (column 1) implies that pioneers are 170=100*(exp(0.99)-1) percent more productive then firms following 5 or more years later.

Results shows that pioneer exporters are always more productive than followers, especially more than those that import 5 years or later. This is a common finding across all distances we look at, but in some cases result are more pronounced. For example, in the first column, where firms are compared in productivity with respect to their time lag to the country level pioneer, pioneers are 170 percent more productive then firms following five or more years later. Even firms that follow 1 or 2 years later or firms that follow 3-4 years later are more productive, by about 45 percent each.

When the analysis is restricted to comparing follower firms to local pioneers, the differences are smaller but still robust as in the case of the smallest distance examined. When firms within 1km of each other are compared, the productivity premium of the pioneers is 51 percent that of the firms lagging behind by 1 or 2 years has only 25 percent productivity advantage over the base group. Eventually, there does not seem to be significant productivity difference across firms that import the machine 3-4 year or 5 or more years later than the local pioneer.

3.5 Peer effects in import decision

This work focuses on understanding the drivers of machine selection - comparing choices within the firm. Before we turn to our main results, we shall take a look at the basic question of how local spillovers could affect the choice to become a machine importer at all - whether firms with local experienced peers are more likely to import machines.

In Table 6 we look at the probability that firm imports any machine from its choiceset depending on the local presence of past importers. We focus only on core machines, which specifies the peers to be same sector importers. We look at three cross-sections and allow the dependent variable to take on the value one if the firm imports for the first time in any of the years in of the 3 year periods. In each period we regress the import dummy on four indicator variables separately which measure the existence of past imports at various distances.

Table 6: Propensity to import any machinery

Dep. Var: dummy for import in period	1994-1996	1997-1999	2000-2002
peers within 1km	3.802*	3.225**	4.856***
	[2.069]	[1.624]	[1.527]
peers within 5km	3.510**	2.257*	3.466***
	[1.519]	[1.220]	[1.104]
peers within 15km	3.243**	1.842	1.085
	[1.374]	[1.185]	[1.098]
peers within 30km	0.205	0.588	2.356**
	[1.291]	[1.195]	[1.040]
Observations	2998	3748	3966

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors, clustered at location level, are in parentheses
The table shows results from 12 separate linear probability regressions, where import dummy is regressed on a single peer indicator. Regressions include sector fixed effects. The coefficient are multiplied by 100 to express percentage points.

Results in Table 6 suggests that the firms with local peers present are more likely to import a core machine. Compared to the baseline probability of machine import, an average of 11 percent in the examined years, peer presence suggests an over 30 percent increase. We also find that the correlation is higher the smaller the distance at which peer presence is measured.

In this specification peer presence means the existence of previous firms who have imported any core machinery. This means that while peer presence is indicated, past importer could have not actually imported machine m, but another one from the set. Hence, findings are rather indicative than precise. We commence with a more specific inquiry.

4 Results

This section presents the results of our empirical investigation on machine specific spillovers. The first subsection will discuss results regarding the effect of previous importers of the machine m on present import decisions about m. The second subsection collects results from exploring the effect of country choice of peers on the country choice of new machine importers.

4.1 Results on machine import spillovers

Now we look at the effect of peers on machine imports. We estimate multiple variants of equation 1. These results are collected in Table 7.

Table 7: Machine import spillover estimation

Dep. var: import dummy	[1]	[2]	[3]	[4]
	core machines		all machines	
same machine peers				
within 1km	0.308***	0.301***	0.389***	0.382***
	[0.099]	[0.098]	[0.069]	[0.069]
between 1 to 5km		0.196***		0.175***
		[0.066]		[0.052]
between 5 to 15km		0.156**		0.082*
		[0.065]		[0.048]
between 15 to 30km		0.056		0.071**
		[0.043]		[0.033]
between 30 to 50km		0.027		0.012
		[0.033]		[0.028]
further than 50km		-0.018		0.039
		[0.048]		[0.041]
Observations	402,765	402,765	917,803	917,803
R-squared	0.156	0.156	0.134	0.134

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors, clustered at location level, are in parentheses
Each column contains results from separate linear probability regression. Columns (1) and (2) include interactions with time for firm, machine, sector and location. Columns (3)-(4) include additionally interactions with time for machine-sector and location-sector. The coefficient are multiplied by 100 to express percentage points.

First, we employ a single dummy variable indicating peer presence within 1 km of the firm on a subset of machines choices for each firm. The subset, includes core machines only that are in the choice-set of firms in a single sector only. We find a positive correlation between importing a specific machine and the presence of past importers within close range.

To capture the meaning of the estimated coefficient, let us compare two machinery import options for a firm in a given sector offering a set of core machinery import use possibilities. Controlling for machinery and time characteristics, we find that importing a machinery that was previously imported by a peer has 0.308 percentage points greater chance, on average. Note that in the tables, we present coefficient as multiplied by 100 to express percentage points not percentage for ease of interpretation. Compared to the average hazard of importing machine is about 1 percent, our results mean an 30 percent increase in the probability of machine import in a given year.[14]

Table 8: Machine import spillover estimations in numbers

Dep. var: import dummy	[1]	[2]
same machine peers		
# of peers within 1km	0.269***	
	[0.065]	
1 peer within 1km		0.318***
		[0.066]
2 peers within 1km		0.657***
		[0.177]
3 peers within 1km		0.886***
		[0.338]
4+ peers within 1km		1.124**
		[0.450]
Observations	917,803	917,803
R-squared	0.134	0.134

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Standard errors, clustered at location level, are in parentheses
Each column contains results from separate linear probability regression, each include interactions with time for firm, machine, sector and location and additionally interactions with time for machine-sector and location-sector. Results on the included peer variables in further than 1km are omitted. The coefficient are multiplied by 100 to express percentage points.

Column (2) includes additional variables extending distance at which peers are considered. In addition to the peers within 1km, we add indicators for peer presence in the distance ranges between 1 and 5 km, between 5 and 15 km and so on. Results show that peer presence is positively related to machine imports even at higher distances up to 15km, however, the size of the estimated coefficients decrease as distance increases. The coefficient on the presence of past importers of machine m within 1 and 5 km range imply 19 percentage point increase in the probability to import the same machine. Peer presence within 5 and 15 km implies only 15 percentage point increase.

[14]Same machine peer variables take into account all previous imports. In Table 17 of the Online appendix we look at how results change we peers are differentiated by the time of import. We do not detect a clear over-time pattern.

As this is estimated in a single shot, coefficient may be added. For firms with peer(s) within 1km as well as within 5km, the cumulative spillover effect is $0.301 + 0.196 = 0.497$.

Columns (3) and (4) show estimates on an enlarged sample, where machines that are considered as part of the choice-set of firms in more than one sectors are included. The specifications are analogous to columns (2) and (3) respectively, including addition controls for machine-sector and location-sector interactions with time. The results are similar to those of the case of core machines: the coefficients imply that peer presence within 1km distance of the firm increases import probability by 0.38 percentage points, peer presence between 1 and 5 km increases the import probability of the same machine by 0.17 percentage points. Presence of previous importers of machine m within the 5-30 km range increases import probability by 0.07-0.08 percentage points.[15]

In the presence of spillover, more peers would imply a higher effect on probability. This is investigated by Table 8. Column (1) shows regression results when instead of dummies, peer variables count the number of firms having imported machine m previously. For brevity only the results on peers within 1km are shown. Results imply that an additional peer increases import probability with 0.26 percentage points.

An alternate approach to investigate this phenomenon is to interact the peer presence dummy variable with categorical variables indicating the number of peers. These results are reported in column (2) of Table 8. Results illustrate how the peer effects increase by the number of peer presence. This relationship is fairly linear, having three peers increase the probability three times a single peer would.

4.2 Results regarding country choices

Once the firm has decided to import machine m it has to make a choice which country should it procure the machine from. This subsection investigates the effect of the choice made by nearby previous importers on firm i's decision about which supplier country it chooses.

We report results obtained from regression based on Equation 2 in Table 9. Results from in column (1) indicate that presence of past importers of machine m from country c within 1 km of the firm increase the probability that the firm imports the same machine from the same country by 2.68 percentage points. Dummy variables for peers that have imported the same machine from the same country but are at a greater distance also report positive and significant coefficients. This specification includes

[15] The positive impact of peer presence is still detected when Budapest firms are excluded (Table 16 in the Online apendix)

the same rich set of fixed effects as columns (3) and (4) of Table 7, which however might not be sufficient when examining country choice.

Columns (2) and (3) of Table 9 gradually introduce additional controls, including county and country-machine interactions with time for the former and additionally location-country interactions with time for the latter. Including additional controls significantly decreases the size of the estimated coefficients and only the peers closest report significant results.

Consider the last model with machine-country-time fixed effects. Here we compare options for a firm of buying a machinery from different countries. The choice set now includes not only the variety of machines but machine-country combinations. We compare import likelihoods to the sample average import likelihood for all machine-country options for a given year. Results in columns (3) suggest that the presence of past importers of machine m from country c within 1 km of the firm increase the probability that the firm imports the same machine *from the same country* by 0.66 percentage points. The increase in probability due to peer presence within 1 and 5 km is estimated at 0.35 percentage points. Similarly to previous results the effect peer presence decreases with distance.

Table 9: Regressions for country choices I.

Dep. var: import dummy	[1]	[2]	[3]
same country & machine peers			
within 1km	2.687***	0.938***	0.660***
	[0.201]	[0.182]	[0.181]
between 1 to 5km	1.614***	0.342***	0.354***
	[0.126]	[0.112]	[0.104]
between 5 to 15km	1.072***	0.129	0.206**
	[0.087]	[0.087]	[0.084]
between 15 to 30km	1.634***	0.0506	0.0284
	[0.089]	[0.086]	[0.079]
dummy: c×t		yes	yes
dummy: m×c×t		yes	yes
dummy: l×c×t			yes
Observations	1,349,414	1,349,414	1,349,414
R-squared	0.046	0.083	0.149

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Standard errors, clustered at location level, are in parentheses.
Each column contain results from separate linear probability regression. Additional fixed effects included are firm, machine, sector and location interactions with time and machine-sector and location-sector interactions with time. The coefficient are multiplied by 100 to express percentage points.

Next we look into two additional issues regarding the measurement of peer effect on country choice. In the left panel of Table 10 we examine whether the inference on same-machine, same country spillovers changes if we include additional peers. Column (2) includes variables for the presence of firms who have imported the same machine but from a different country. The inclusion does not change the results on same-country peer variables, at the same time we find as small general spillover effect due same-machine peers.

In the right panel (columns 3 and 4), we look at the impact of additional peers by including measures that count the number of previous importers. We find that an additional peer within 1km distance from the firm increases the probability of the import of machine m from the same country by 0.46 percentage points. [16] Results do not indicate that peers that import from other country would have any impact.

Table 10: Regressions for country choices II.

Dep. var: import dummy	[1]	[2]	[3]	[3]
Peer measure:	Binary		Continuous	
same machine and country peers				
within 1km	0.660***	0.640***	0.463***	0.454***
	[0.181]	[0.181]	[0.151]	[0.151]
between 1 to 5km	0.354***	0.346***	0.114*	0.111*
	[0.104]	[0.105]	[0.067]	[0.067]
between 5 to 15km	0.206**	0.203**	0.015	0.005
	[0.084]	[0.083]	[0.028]	[0.027]
same machine peers, other country				
within 1km		0.270***		0.018
		[0.064]		[0.016]
between 1 to 5km		0.077		-0.003
		[0.061]		[0.007]
between 5 to 15km		-0.022		0.005
		[0.051]		[0.004]
dummy: c×t	yes	yes	yes	yes
dummy: m×c×t	yes	yes	yes	yes
dummy: l×c×t	yes	yes	yes	yes
Observations	1,349,414	1,349,414	1,349,414	1,349,414
R-squared	0.149	0.15	0.149	0.149

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Standard errors, clustered at location level, are in parentheses.
Each column contain results from separate linear probability regression. Additional fixed effects included are firm, machine, sector and location interactions with time and machine-sector and location-sector interactions with time. The coefficient are multiplied by 100 to express percentage points. Results on the included peer variables in further than 1km are omitted.

This result helps us understand what we shall consider as an imported product. Firms use spillover at the machine-country level, i.e. a conveyor belt from Germany and from China is not the same investment decision. Information is useful as long as it corresponds to a specific product (proxied here by machine code-country pairs), not just the technology.

[16] The investigation is not complemented in this case by examining peer number categories as in the previous section due to the low number of cases with more than 2 peers.

4.3 Limitations in identification

As detailed in section 2, we have made considerable effort to control for a great deal of alternative stories. There are, nevertheless, some threats to the identification.

First, spatial clustering of machine imports especially that of the same country machines, can also occur when firms are subject to promotion activity. If a regional sales agent of a foreign manufacturer for a particular machine is especially efficient, then her activity will result in a positive correlation between current and past machine imports. Not being able to track regional sales records for each machine, a solution could be to include machine $\times$ country $\times$ location effects. Since our main explanatory variable has the same dimension, we do not have sufficient remaining variation to include such effects. Note that the presence of an active sales agent does not necessarily mean that spillovers are not at work. Firms may learn from each other whether a machine is indeed a good fit for production and contact the agent to facilitate import.

Nevertheless, a potential solution to control for the promotion activity is to capture the machine dimension with sector level control (e.g., sector $\times$ country $\times$ location effects). In Table 18 of the Online appendix we investigate this by the inclusion of country-sector and location interaction terms in addition to our wide set of controls. We assume that sales representatives are responsible for larger areas, such as counties and entire regions and thus define locations accordingly. We use NUTS4 and NUTS3 classifications. Results remain similar to our baseline specifications.

Second, note that this paper considers only machine purchases via direct import. This implies that a possibly important source of machine acquisition is not in the scope of the study, namely indirect import. Firms can acquire imported foreign technology via a domestic wholesaler of specific machines. Though, we have limited the machine imports to industry-specific equipment by leaving out widely domestically available items, such vehicles and information technology, the one has to bear in mind that this study can capture only a part of the underlying economics.

Third, firms may strategically locate to enjoy spillover benefits. Thus, future importers will be found in locations which is abundant of importers of m, a positive correlation between the number of past and present importers appears. Such a self-selection of firms may bias the estimation of spillover effects.

A possible solution can be to assume that if firms start business in certain places specifically to benefit from spillovers, one can expect them to start importing soon after they are born. Having this in mind, Table 19 of the Online appendix, looks at how our baseline results change if we exclude firms that import within the first 3 or within the first 5 years after they are born. The estimated coefficient on the within 1km peers remain positive and significant in both cases, however we find that the magnitude is smaller.

4.4 Spillover effects and absorptive capacity

This section examines the heterogeneity of the spillover effects across firms. Our aim is to capture what drives absorptive capacity - what types of firms could benefit from peer effects. First we look into whether the heterogeneity in the importing firm make a different in the assessment of spillover effect. We look into three firm characteristics.

We start by looking at firms of different sizes. Size may be an important indicator of the firm's absorptive capacity.[17] Another indicator could be ownership - foreign firms may find it easier to learn about importing as they already have some capacity to deal with internationalization. Finally, we differentiate between exporting and non-exporting firms. While the former have general knowledge about and expertise in foreign trade and may have permanent partners the latter does not. The result on importing firm heterogeneity are reported in Table 11.

Table 11: Machine import spillover: importer heterogeneity

Dep. var: import dummy	[1]		[2]		[3]
same machine peers - within 1km					
small	-0.145**	domestic	0.059	non-exporter	-0.362***
	[0.062]		[0.063]		[0.051]
medium	0.736***	foreign	1.044***	exporter	0.904***
	[0.142]		[0.159]		[0.115]
large	2.138***				
	[0.416]				
Observations	917,803		917,803		917,803
R-squared	0.136		0.136		0.136

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors, clustered at location level, are in parentheses. Each column contains results from separate linear probability regression, each include interactions with time for firm, machine, sector and location and additionally interactions with time for machine-sector and location-sector. The coefficient are multiplied by 100 to express percentage points.

Column (1) includes cross-terms of presence dummy with the indicator variables expressing firm size.[18] We use three firm categories: small below 50 and above 10 employees, medium-sized over 50 and below 250 employees and large firms above.[19] Results indicate that the probability of importing increases with firm size in response to peer presence. For the largest firms peer presence increases import probability by 2.13 percentage points, for the medium sized firms results indicate 0.73 percentage points. In contrast, smallest firms are discouraged from importing machinery if in their vicinity another firm has already imported the same machine.

[17] Results from Table 13 in the Appendix suggest size is an indicator of the inclination to import machinery.

[18] For convenience we report only the peers within 1km, the inclusion or omission of the other peer variables do not alter the results.

[19] See http://ec.europa.eu/enterprise/policies/sme/facts-figures-analysis/sme-definition/

Column (2) includes cross-terms of presence dummy with the indicator variables of firm ownership. We find that foreign owned firms are more likely import the same machine as the peer within 1km distance already has.

Column (3) includes cross-terms of presence dummy at various distances with the indicator variable on firm export indicator. Results imply that the probability of importing machine *m* increases by 0.9 percentage points for exporting firms as a result of peer presence. For non-exporting firm the results, however, suggest a decrease in import probability.

Second we look into how the heterogeneity of the peers affect our results. To do this we recalculate the peer variables $\mathbf{X}^r$ in equation 1 so that it takes into account the characteristics of the previous importers. As in the previous subsection, we look into the same three characteristics: size, ownership and export activity. For instance, when it comes to size, we only consider firms that have imported machine *m* within the 1k radius *and* that are small sized and count them. Hence results can be compared to those in Table 8.[20]

Table 12: Machine import spillover: peer heterogeneity

Dep. var: import dummy	[1]		[2]		[3]
same machine peers - within 1km					
small	0.136	domestic	0.169**	non-exporter	0.0858
	[0.083]		[0.074]		[0.102]
medium	0.414***	foreign	0.368***	exporter	0.315***
	[0.113]		[0.087]		[0.068]
large	0.259***				
	[0.092]				
Observations	917,803		917,803		917,803
R-squared	0.136		0.136		0.136

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors, clustered at location level, are in parentheses
Each column contains results from separate linear probability regression, each include interactions with time for firm, machine, sector and location and additionally interactions with time for machine-sector and location-sector. The coefficient are multiplied by 100 to express percentage points.

The results on peer heterogeneity are reported in Table 12.[21]

Column (1) is reporting results on peer effects by the size of past importer shows that only the presence of medium and large sized firms increase the probability of machine import. We also learn that an additional medium sized firm increases import probability by 0.4 percentage points, while the effect of an additional large peer is smaller.

[20] The reason for using count variables is that using dummy variables would be insufficient to relate results in Table 7. Count allows for an easier interpretation if the peer presence indicator stands for more than one type of firm.

[21] For convenience we report only the peers within 1km, the inclusion or omission of the other peer variables do not alter the results.

Column (2) shows results by the ownership characteristics of the peers. We find that both additional domestic and foreign owned peers increase the probability of machine import. Results imply that while an additional domestic peer increases probability by 0.17 percentage points, the effect from an additional foreign peer is almost double in size.

Column (3) shows results when the number of peers are separated by exporting activity. We find that an additional exporter peer increases import probability of machine m by 0.31 percentage points, while non-exporting peers have non-significant effect.

The past two tables provide evidence regarding the heterogeneity of the spillover effects. The variation on the receiving end is substantial: peer effects are concentrated among larger and/or foreign owned firms. The source of knowledge matters as well, import experience from large firms matter more, too. This marked heterogeneity and the rather limited role of domestic firms is rather stark and important finding.

5 Concluding remarks

This paper investigated whether firms' decision to import a sector-specific machine is influenced by the local accumulation of the same machine. Local experience in a particular technology embodied in particular machinery can help firms reduce search and adaptation costs and hence, improve chances of technology upgrade via imported machinery.

Using very detailed product level import dataset the paper has identified the firms' first investment into a specific foreign machinery. The results suggested that an additional local importer in the firm's vicinity increases the probability of importing that machinery substantially. We also found that firms learnt about a specific product made in a given country, not just the type of the machine.

Distance was important, as decision was primarily affected by peers within a few kilometers away. Firms, especially in small cities learnt from neighboring peers and not from far away partners. Finally, we found that spillover effects tend to concentrate on larger or foreign owned firms, as small and domestically owned firms do not seem to be affected by peer effects.

The paper focused on a particular channel of productivity spillover, that of improvement via technology upgrading. Our results could be indicative for policy-makers interested in indirect impact of technology upgrade subsidy programs. We found that such indirect effects do exist. However, they are centered around large to large firm interactions.

Our results also indicate that while policies promoting foreign direct investment alone might not be sufficient to help firms' technology adoption of firms via machine imports. Smaller sized firms producing for the domestic market do not benefit as much from import spillovers are larger export oriented firms do.

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6 Appendix

Imports vs other firms

Table 13 describes how machine importers relate to other firms. The first column compares importers to the rest of the economy by regressing importer dummy on a set of firm characteristics. In the second column, a machine importer dummy is regressed on various firm characteristics. The machine importer dummy takes on the value one if the firm in a given year has imported any of the machines defined by the choice-set in Table 20 (Online Appendix). The results show that importing firms, machine importing firms included, are on average larger, more productive, pay higher wages and are more capital intensive. These results confirm what we already know about importing firms. The third column, however, considers only importing firms and thus compares machine importer to all importing firms. All in all, one can conclude that firms importing machines outperform other importers in all explored dimensions.

Table 13: Characteristics of machine importers

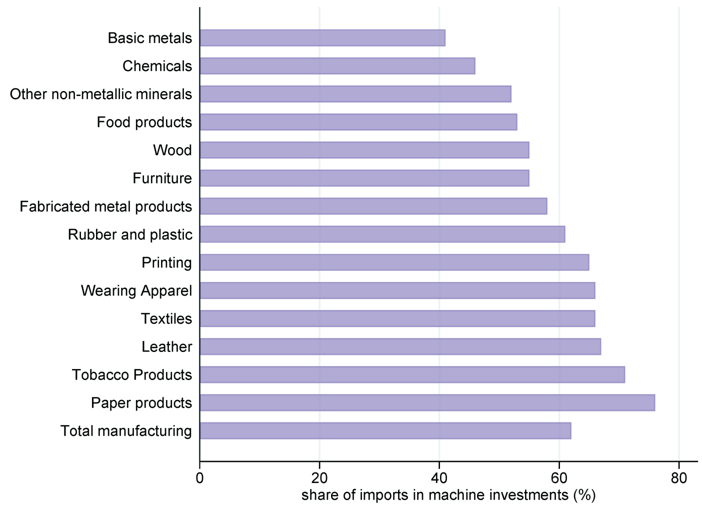
premia of	importers	machine importers	machine importers vs. importers
Log of employment	0.879***	0.780***	0.389***
	[0.011]	[0.015]	[0.019]
Log of value added per worker	0.552***	0.392***	0.163***
	[0.009]	[0.012]	[0.014]
Log of TFP	0.456***	0.355***	0.180***
	[0.008]	[0.011]	[0.013]
Log of average wage	0.292***	0.162***	0.0461***
	[0.006]	[0.009]	[0.012]
Log of capital per worker	0.766***	0.703***	0.334***
	[0.018]	[0.023]	[0.027]
Number of exporter goods			2.639***
			[0.221]
Number of destinations			2.026***
			[0.147]
Observations	37,320	37,320	18,124

Each row shows coefficient estimates of variables in the first column regressed on importer and machine importer dummies. When independent variables are in logs the coefficient 0.879 with the log of employment implies: exp(0.879)-1 = 140% higher employment on average in machine importers firms compared to importing firms.

In Hungary most internationalized firms are two-way traders, that is, most importing firms do export as well. This allows for an additional comparison along the dimensions of export activity. We learn that firms importing machines show higher average export activity in terms of sold goods (defined at HS6 level) and serve a higher number of destination countries on average.

Additional descriptive statistics

Figure 6: The share of imports in the volume of machine investments, (1992-2003 average)



Source: Central Statistical Office, Hungary

Table 14: *Summary of Hungarian administrative spatial zoning*

EU level units	Hungarian equivalent	number	avg. size km^2	avg. radius (km)
NUTS2	EU admin. region	7	13861	66.42
NUTS3	countries (megye)	20	4651	38.47
NUTS4 (LAU1)	micro regions (kistérség)	150	620	14.0
NUTS5 (LAU2)	municipalities	3125	30	3.09

Table 15: Countries investigated

Country	# of machines	country	# of machines
Austria	137		
Belgium	71	Croatia	2
Bulgaria	1	Luxembourg	1
Canada	4	Netherlands, the	74
Switzerland	113	Norway	1
China	17	New Zealand	1
Czech Republic	67	Poland	13
Germany	148	Portugal	2
Denmark	46	Romania	11
Spain	31	Russia	3
Finland	15	Sweden	58
France	123	Slovenia	5
Grat Britain	114	Slovakia	26
Ireland	1	Thailand	1
Israel	1	Turkey	3
India	1	Taiwan	23
Italy	143	Ukraine	1
Japan	76	United States	124

ONLINE APPENDIX

Table 16: Machine import spillover estimation: Budapest excluded

Dep. var: import dummy	[1]	[2]	[3]	[4]	[5]
	machine choice		country choice		
peers					
within 1km	0.430***	0.421***	3.128***	1.265***	0.870***
	[0.099]	[0.100]	[0.256]	[0.230]	[0.227]
between 1 to 5km		-0.097	2.579***	0.600***	0.443***
		[0.071]	[0.223]	[0.188]	[0.169]
between 5 to 15km		-0.204*	1.918***	0.333**	0.185
		[0.112]	[0.160]	[0.162]	[0.142]
between 15 to 30km		-0.077	1.862***	0.071	-0.068
		[0.089]	[0.108]	[0.106]	[0.099]
Observations	197,338	197,338	1,063,151	1,063,151	1,063,151
R-squared	0.141	0.141	0.048	0.089	0.173

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Standard errors, clustered at location level, are in parentheses.

Each column contains results from separate linear probability regressions. The two columns in the left panel correspond to columns [3] and [4] of Table 7, the three columns in the right panel correspond to columns of Table 9 each ran on the sample excluding Budapest based firms. Coefficient represent percentage point changes in probability of import.

Table 17: Machine import spillover estimation - timing

Dep. var: import dummy	[1]	[2]
same machine peers		
peers within 1km	0.389***	
	[0.0692]	
peers within 1km (t-1)		0.354***
		[0.121]
peers within 1km (t-2)		0.294**
		[0.121]
peers within 1km (t-3)		0.499***
		[0.127]
peers within 1km (t-4 or older)		0.389***
		[0.0823]
Observations	917,803	917,803
R-squared	0.134	0.134

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Standard errors, clustered at location level, are in parentheses.

Each column contains results from separate linear probability regressions. Column [1] replicates the result of Table 7 (Column 4) while column [2] decomposes the dummy variable of [1] by the timing of latest peer import event.

Table 18: Regressions for country choices: agent activity

Dep. var: import dummy	[1]	[2]	[3]
same machine & country peers			
within 1km	0.660***	0.542***	0.900***
	[0.181]	[0.184]	[0.183]
between 1 to 5km	0.354***	0.17	0.267**
	[0.104]	[0.108]	[0.113]
between 5 to 15km	0.206**	-0.0413	0.114
	[0.084]	[0.0913]	[0.0929]
between 15 to 30km	0.0284	0.067	0.045
	[0.0798]	[0.0782]	[0.0781]
dummy: s $\times$ c $\times$ t $\times$ NUTS4		yes	
dummy: s $\times$ c $\times$ t $\times$ NUTS3			yes
Observations	1,349,414	1,349,414	1,349,414
R-squared	0.149	0.19	0.126

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Standard errors, clustered at location level, are in parentheses.

Each column contains results from separate linear probability regression. The columns use varying location definitions. Column [1] replicates the result of Table 9. Column [2] adds l$\times$s$\times$c$\times$t to the specification of [1] using NUTS4 as location, while column [3] uses NUTS3.

Table 19: Machine spillover regressions: controls for location selection

Dep. var: import dummy	[1]	[2]	[3]
first import year - firm birth	any	more than 3	more than 5
same machine peers			
peers within 1km	0.382***	0.199***	0.120***
	[0.069]	[0.052]	[0.040]
Observations	917,803	913,259	905,899
R-squared	0.134	0.127	0.127

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Standard errors, clustered at location level, are in parentheses.

Each column show results from separate regressions. The first regression is identical to last regression of Table 7, the others have the same specification but exclude firms based on the years lapsed between firm birth and first import. Column (2) excludes firms that import within the first 3 years they are born. Column (3) excludes firms that import within the first 5 years. Regressions include peer indicator of other distances only results are omitted. Coefficient represent percentage point changes in probability of import.

Table 20: List of machines

sector	SITC code	Description
15	72123	Harvesting and threshing machinery; mowers
	72126	Machines for cleaning, sorting or grading eggs, fruit or other agricultural produce
	72127	Machines for cleaning, sorting or grading seed, grain or dried leguminous vegetables
	72129	Parts of the machines of headings 721.21 through 721.26
	72138	Dairy machinery
	72139	Parts for milking machines and dairy machinery
	72191	Presses, crushers used in the manufacture of wine, cider, fruit juices or similar beverages
	72196	Agricultural, horticultural, forestry or bee-keeping machinery
	72721	Machinery for the extraction or preparation of animal or fixed vegetable fats and oils
	72722	Machinery, n.e.s., for the industrial preparation or manufacture of food or drink
	72729	Parts for the food-processing machinery
	72849	Machinery having individual functions, n.e.s.
	74137	Bakery ovens (including biscuit ovens), non-electric
	74138	Other non-electric furnaces and ovens (including incinerators)
	74139	Parts for the furnaces and ovens of headings
	74143	Indsutrial use refrigerating or freezing chests , cabinets, display counters, showcases
	74145	Other refrigerating or freezing equipment; heat pumps
	74149	Parts of refrigerators, freezers and other refrigerating or freezing equipment (electric or other)
	74186	Driers, n.e.s.
	74187	Machinery for making hot drinks or for cooking or heating food
	74271	Pumps for liquids, n.e.s.
	74291	Parts for pumps
	74311	Vacuum pumps
	74359	Other centrifuges
	74361	Machinery for filtering or purifying water
	74362	Machinery for filtering or purifying beverages other than water
	74367	Machinery for liquids, n.e.s.
	74391	Parts of centrifuges (including centrifugal driers)
	74471	Pneumatic elevators and conveyers
	74473	Other continuous-action elevators and conveyors, bucket-type
	74474	Other continuous-action elevators and conveyors, belt-type
	74479	Continuous-action elevators and conveyers for goods or materials, n.e.s.
	74527	Other packing or wrapping machinery
	74529	Parts of Dishwashing machinery
	74531	Weighing machinery, including weight-operated counting and checking machines
	74565	Other appliances for projecting, dispersing or spraying liquids or powders
16	72843	Machinery for preparing or making up tobacco, n.e.s.
	72853	Parts for the machinery for preparing or making up tobacco
	74527	Other packing or wrapping machinery
17	72435	Other sewing-machines
	72442	Machines for preparing textile fibres
	72443	Textile-spinning, doubling or twisting machines; textile-winding (including weft-winding) or reeling machines
	72449	Machines for extruding, drawing, texturing (parts)
	72451	Weaving machines (looms)
	72452	Knitting-machines and stitch-bonding machines
	72453	Machines for making gimped yarn, tulle, lace, embroidery, trimmings, braid or net and machines for tufting
	72454	Machines for preparing textile yarns for weaving machines, knitting-machines, stitch-bonding
	72455	Machinery for the manufacture or finishing of felt or non-wovens
	72461	Auxiliary machinery for machines of Machines for extruding, drawing, texturing and weaving
	72467	Accessories of weaving machines (looms)
	72468	Accessories of machines for gimped yarn, tulle, lace
	72474	Indsutrial machinery for washing , cleaning, wringing, pressing etc.
18	72435	Other sewing-machines
	72439	Sewing-machine needles; furniture, bases and covers specially designed for sewing-machines

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sector	SITC code	Description
	72452	Knitting-machines and stitch-bonding machines
	72453	Machines for making gimped yarn, tulle, lace, embroidery, trimmings, braid or net and machines for tufting
	72468	Accessories of machines for gimped yarn, tulle, lace
	72473	Drying machines, each of dry linen capacity exceeding 10 kg
	72474	Indsutrial machinery for washing , cleaning, wringing, pressing, bleaching, dyeing etc.
	72485	Machinery for making or repairing articles of hides, skins or leather, other than footwear
19	72435	Other sewing-machines
	72481	Machinery for preparing, tanning or working hides, skins or leather
	72483	Machinery for making or repairing footwear
	72485	Machinery for making or repairing articles of hides, skins or leather, other than footwear
	72488	Machinery for preparing, tanning, or working hides, skins or leather
20	72812	Machine tools for working wood, cork, bone, hard rubber, hard plastics
	72819	Accessories suitable for machines of working stone, ceramics, bone, rubber and plastics
	72844	Presses for the manufacture of particle board or fibre building board of wood
	72849	Machinery having individual functions, n.e.s.
	72852	Parts for the machinery for working rubber or plastics
	73166	Other sharpening (tool- or cutter-grinding) machines
	73177	Sawing or cutting-off machines
21	72512	Machinery for making or finishing paper or paperboard
	72521	Cutting machines
	72523	Machines for making bags, sacks or envelopes
	72525	Machines for making cartons, boxes, cases, tubes, drums or similar containers
	72527	Machines for moulding articles in paper pulp, paper or paperboard
	72591	Machinery for making pulp of fibrous cellulosic material
	72599	Machinery for making up paper pulp, paper or paperboard
	72631	Machinery, apparatus and equipment for typesetting, for making printing blocks
	72635	Printing type, blocks, plates, cylinders and other printing components, etc.
	72659	Offset printing machinery (other than reel or sheet)
	72668	Machines for uses ancillary to printing
	72681	Bookbinding machinery (including book-sewing machines)
	72699	Parts for offset typing
	74527	Other packing or wrapping machinery
	74529	Parts of Dishwashing machinery
22	72529	Paper mill and pulp mill machinery
	72599	Machinery for making up paper pulp, paper or paperboard
	72631	Machinery, apparatus and equipment for typesetting, for making printing blocks
	72635	Printing type, blocks, plates, cylinders and other printing components, etc.
	72651	Reel-fed offset printing machinery
	72655	Sheet-fed, office-type (sheet size not exceeding 22 x 36 cm) offset printing machinery
	72659	Offset printing machinery (other than reel or sheet)
	72667	Other printing machinery
	72668	Machines for uses ancillary to printing
	72681	Bookbinding machinery (including book-sewing machines)
	72689	Parts for bookbinding machinery
	72691	Parts for type-founding or typesetting
	72699	Parts for offset typing
24	72449	Machines for extruding, drawing, texturing (parts)
	72832	Machinery for crushing or grinding earth, stone, ores etc.
	72833	Machinery for mixing and kneading earth, stone, ores etc.
	72839	Accessories for sorting, screening, separating, washing, crushing earth, stone etc.
	72842	Machinery for working rubber or plastics or for products from these materials, n.e.s.
	72846	Machinery for treating metal (including electric wire coil-winders), n.e.s.
	72849	Machinery having individual functions, n.e.s.
	72852	Parts for the machinery for working rubber or plastics
	72855	Parts, n.e.s., for the machines of headings 72348, 72721, 72844, 72846 and 72849
	74173	Distilling or rectifying plant

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sector	SITC code	Description
	74174	Heat-exchange units
	74183	Medical, surgical or laboratory sterilizers
	74186	Driers, n.e.s.
	74527	Other packing or wrapping machinery
25	72812	Machine tools for working wood, cork, bone, hard rubber, hard plastics
	72819	Accessories suitable for machines of working stone, ceramics, bone, rubber and plastics
	72832	Machinery for crushing or grinding earth, stone, ores, etc. substances in solid form
	72842	Machinery for working rubber or plastics or for products from these materials, n.e.s.
26	72831	Machinery for sorting, screening, separating or washing earth, stone, ores or other mineral
	72832	Machinery for crushing or grinding earth, stone, ores, etc. in solid form
	72833	Machinery for mixing and kneading earth, stone, ores , etc. in solid form
	72834	Machinery for agglomerating, shaping or moulding solid mineral fuels, ceramic paste etc.
	72839	Accessories for sorting, screening, separating, washing, crushing, kneading earth, stone etc.
	72841	Machines for assembling electric or electronic lamps, tubes or valves or flash bulbs, in glass envelopes
	72842	Machinery for working rubber or plastics or for products from these materials, n.e.s.
	72849	Machinery having individual functions, n.e.s.
	72851	Parts for the machines for assembling electric or electronic lamps
	72855	Parts, n.e.s., for the machines of headings 72348, 72721, 72844, 72846 and 72849
27	72849	Machinery having individual functions, n.e.s.
	73177	Sawing or cutting-off machines
	73311	Forging or die-stamping machines (including presses) and hammers
	73312	Bending, folding, straightening or flattening machines (inc. presses), numerically controlled
	73313	Non-numerically controlled bending, folding, straightening or flattening machines (inc. presses)
	73391	Draw benches for bars, tubes, profiles, wire or the like
	73399	Machine tools for working metal, sintered metal carbides or cermets, without removing material, n.e.s.
	73513	Work holders
	73515	Dividing heads and other special attachments for machine tools
	73595	Parts for machine for metal, sintered metal carbides or cermets
	73712	Casting machines
	73719	Parts for converters, ladles, ingot moulds
	73729	Rolls and other parts for metal-rolling mills
	73737	Other metalworking machines for electric , laser or other light or photon beam machine group
	73739	Parts for metalworking machines (Electric, laser, photon, ultrasonic..)
28	72846	Machinery for treating metal (including electric wire coil-winders), n.e.s.
	72849	Machinery having individual functions, n.e.s.
	72852	Parts for the machinery for working rubber or plastics
	73131	Horizontal lathes, numerically controlled
	73135	Other lathes, numerically controlled
	73137	Other horizontal lathes
	73143	Drilling machines, n.e.s.
	73145	Boring-milling machines, n.e.s.
	73154	Milling machines, n.e.s.
	73157	Other threading or tapping machines
	73162	Non-numerically controlled flat-surface grinding machines, in which accuracy is of at least 0.01 mm (any axis)
	73163	CNC grinding machines in which accuracy is of at least 0.01 mm (any axis)
	73164	Grinding machines, n.e.s., in which accuracy is of at least 0.01 mm (any axis)
	73177	Sawing or cutting-off machines
	73311	Forging or die-stamping machines (inc. presses) and hammers
	73312	Bending, folding, straightening or flattening machines (inc. presses), numerically controlled
	73313	Non-numerically controlled bending, folding, straightening or flattening machines (inc.presses)
	73315	Non-numerically controlled shearing machines (inc. presses)
	73316	Numerically controlled punching or notching machines (inc. presses)
	73317	Punching or notching machines, n.e.s.
	73318	Presses for working metal or metal carbides, n.e.s.

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sector	SITC code	Description
	73393	Thread-rolling machines
	73395	Machines for working wire
	73399	Machine tools for working metal, sintered metal carbides or cermets, without removing material, n.e.s.
	73511	Tool holders and self-opening die-heads
	73515	Dividing heads and other special attachments for machine tools
	73591	Parts for machine tools working by removing metal
	73595	Parts for machine for metal, sintered metal carbides or cermets
	73721	Metal-rolling mills
	73733	Machines and apparatus for resistance welding of metal, fully or partly automatic
	73735	Machines and apparatus for arc (inc. plasma-arc) welding of metal, fully or partly automatic
	73736	Other metalworking machines for arc welding of metal
	73737	Other metalworking machines for electric , laser or other light or photon beam machine group
	73742	Other gas-operated metalworking machinery and apparatus
	73743	Other machinery for soldering, brazing or welding
	73749	Parts for the machinery for soldering, brazing or welding
36	72435	Other sewing-machines
	72439	Sewing-machine needles; furniture, bases and covers specially designed for sewing-machines
	72812	Machine tools for working wood, cork, bone, hard rubber, hard plastics
	72819	Accessories suitable for machines of working stone, ceramics, bone, rubber and plastics
	72842	Machinery for working rubber or plastics or for the manufacture of products from these materials, n.e.s.
	72844	Presses for the manufacture of particle board or fibre building board of wood or other ligneous material
	72849	Machinery having individual functions, n.e.s.
	72852	Parts for the machinery for working rubber or plastics
	73162	Non-numerically controlled flat-surface grinding machines, in which an accuracy of at least 0.01 mm (any axis)
	73167	Honing or lapping machines
	73177	Sawing or cutting-off machines
	73178	Planing machines, metalworking
	73311	Forging or die-stamping machines (including presses) and hammers
	73312	Bending, folding, straightening or flattening machines (including presses), numerically controlled
	73595	Parts for machine for metal, sintered metal carbides or cermets
	73749	Parts for the machinery for soldering, brazing or welding
	74527	Other packing or wrapping machinery