The Knowledge-Content of Machines: North-South Trade and Technology Diffusion

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Abstract

This paper examines the impact of imported technologies on productivity for a sample of transition and developing countries in Central and Eastern Europe and in the Southern Mediterranean. The paper departs from earlier studies of international technology diffusion by focusing on the technology embodied in imported machines. It first develops a theoretical model which examines jointly the choice of foreign technology and its impact on domestic productivity. It then estimates the model for a set of manufacturing sectors in the sample countries. The technology of imported machines is proxied by their unit values and is estimated with respect to a technological frontier, namely the same machines imported by the US. The paper finds a constant or increasing gap between the frontiers and the machines imported by the sample of developing countries. It also finds that productivity growth in manufacturing depends positively on the type of machines imported and not on the share of imported equipment on total investments. This contradicts earlier empirical findings which did not take into account the technological characteristics of imported factors of production.

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1. Introduction

This paper examines the impact of imported technologies on productivity growth in developing countries. Many studies analyze trade related channels for transferring technologies and knowledge and their effects on productivity[1]. In contrast to this earlier literature, we focus on the technological content of imported factors of production rather than on imports per se. We also explicitly model the choice of technology and therefore we deal with the endogenous nature of the relationship between imported technologies and productivity growth[2].

We study the effects of knowledge, the 'weightless' good (Quah, 1999), when it is embodied in machines, the most physical of all factors of production. We use an indirect measure to capture the amount of knowledge contained in machines: the average unit value per ton of machine imported[3]. Does this measure, relating the value of a weightless good to the weight of its container, make sense? Federal Reserve Chairman Alan Greenspan once noted that through the second half of the twentieth century, the US tripled the real value of its output with no increase in the weight of the material produced (Washington Post, 2000). Indeed, *at any point in time*, the price of machines reflects their relative productivity. If we enter any computer shop we'll find that the price of computers grows with their megahertz or other embodied features.

However, *over time* the relative price of equipment falls and the increasing productivity of increasingly weightless (knowledge intensive) machines is not mirrored in their prices (Gordon, 1990, Eaton and Kortum, 2001). The cost of computers has been declining for years, although their capacity to process information has skyrocketed. Thus, the evolution of unit values of machines over time fails to capture their technological content. To overcome this problem, we normalize the unit values of the machines imported by our sample countries by the unit value of the same machines imported at the same point in time by the US, assumed to be the technological frontier. We consequently derive an

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[1] These channels are imports (Coe and Helpman, 1995; Coe Helpman and Hoffmaister, 1997; Keller, 2000; Djankov and Hoekman , 1996, 1997; Mody and Yilmaz, 2001; Schiff, Wang and Olarreaga, 2002), foreign direct investments (Blomstrom and Kokko, 1998) 1 and exports (Clerides, Lach and Tybout, 1998, Bernard and Jensen, 1999, Aw, Chung and Roberts, 2000, Kraay, 1996). Also see Barba Navaretti and Tarr, 2000 for a review

[2] Also.

index, measuring the distance of imported machines from their technological frontier at any point in time, that can be used for comparisons across countries, industries and time.

We specifically analyze the machines exported by the EU to a sample of neighboring developing and transition countries in Central-Eastern Europe and in the Southern Mediterranean. We find that although developing economies buy increasingly productive machines overtime the technology embodied in these machines persistently lags behind the one purchased by the US.

What drives these choices, and how do they affect productivity and growth? We develop a theoretical model that analyses the choice of technology and relates it to the expected productivity outcomes. The model is then tested, using industry specific data for our sample countries. We find that the choice of lower technologies is optimal for developing countries, given local skills and factor prices. However, an increase in the level of complexity of the machines imported has a positive impact on TFP growth, which turns out to be larger than an increase in the share of imported machines in total investments.

This study contributes in several ways to the literature on trade-related technology spillovers—including Coe and Helpman (1995) and other papers building on their framework such as Coe, Helpman and Hoffmaister (1997), Keller (2000), and Schiff, Wang and Olarreaga (2002). First, it clearly distinguishes between quantity and quality of imports by measuring the knowledge content of imported machines. The impact of the technological content of imported machines has been rarely examined in this literature[4]. Imagine a country A importing the same total value of goods (or capital goods) from two countries, B and C, that have the same R&D stock. The impact of imports from both countries on domestic productivity is the same in the Coe and Helpman framework. However, the composition of goods imported from B and C may be different. For instance, imports from B may consist of fewer but more knowledge-intensive (more productive) machines than

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[3] Unit values per ton of machine are very highly correlated to unit values per number of machines, but the latter are only available for a limited number of machines and countries.

[4] Eaton and Kortum, 2001deals with the choice of capital equipment and its impact on productivity. A recent paper by Caselli and Wilson (2003), classifies imports of capital equipment according to the R&D intensity of the capital equipment producing industry. However, in their framework, all capital equipments imported of a

those from C. Whether imports from B or C have a greater impact on A's productivity will depend on the elasticity of TFP with respect to the knowledge intensity of machines and with respect to the quantity of machines. This is one of the issues examined in this paper.

Second, studies based on the Coe-Helpman framework treat the choice of technology as exogenous. This paper explicitly models the choice of technology—the knowledge-intensity of machines—by relating it to its potential effect on productivity growth.[5]

This paper extends earlier works analyzing the choice of the vintage of imported machinery (Barba Navaretti, Soloaga and Takacs, 2000) and the impact of imported machines on export performance (Barba Navaretti, Galeotti and Mattozzi, 2000).

The remainder of the paper is organized as follows. In section two we present a theoretical model of the choice of technology and its impact on productivity. In the next section we discuss our data set and sample countries. We then construct our measure of embodied technology and present some descriptive evidence on trends imported technologies. Section four examines the impact of imported technologies on total factor productivity and the determinants of the choice of imported technologies for a sample of manufacturing sectors. Section 5 concludes.

2. A Model of Knowledge Production and Choice of Machines

This section develops a simple model of supply of knowledge-embedded machines by developed countries and (import) demand by developing countries. Among other things, the model tries to explain two empirical observations: i) even though machines with greater knowledge content are more expensive at a given moment in time, they are cheaper over time; and ii) countries with higher levels of human capital import more knowledge-intensive machines.

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given type are technology invariant, whereas in our framework we specifically take into account differences in technological content within specific categories of machines.

[5]Eaton and Kortum, 2001 analyze both the choice of imported capital equipment and its impact on productivity. Caselli and Wilson, 2003 analyze the choice of technology and its link to per-capita income. Papers looking at the link between productivity and exports explicitly recognize that the choice of exporting is endogenous relative to the effects of productivity on exporting (Clerides, Lach and Tybout, 1998, Bernard and Jensen, 1999, Aw, Chung and Roberts, 2000, Kraay, 1996) .

2.1. Supply

Assume a developed country industry where each firm's cost of producing additional knowledge at time t, ΔS_t (its expenditure on R&D), is c_t. Knowledge is transmitted by embedding it in a machine (e.g., manufacturing equipment or a CD-ROM). The cost of a knowledge-free machine is $m_t = m, \forall t$.

The production of knowledge and machines takes place in a competitive setting. Each firm produces only one machine. In other words, the are no contemporaneous economies of scale in knowledge production at the firm level.[6] Then, the cost of a knowledge-embedded machine is

$$C_t = m_t + c_t = m + c_t. \tag{1}$$

Machines can only absorb a fixed amount of additional knowledge $\Delta S_t = \Delta S, \forall t$ (e.g., fixed space in a CD-ROM), and they depreciate after one period while knowledge does not. Then, knowledge at time t

$$S_t = \sum_1^t \Delta S_t = \sum_1^t \Delta S = t * \Delta S. \tag{2}$$

All firms know S_{t-1} at the start of period t. In other words, private knowledge in period t - 1 becomes public knowledge at time t (possibly due to reverse engineering). S_t is not known publicly at time t. Any firm that wants to obtain and sell S_t at time t has to produce ΔS_t.

Additional knowledge ΔS_t increases with c_t, the expenditure on R&D, and with S_{t-1}, the stock of publicly available knowledge at the start of period t. The assumption is that privately produced additional knowledge is complementary to the existing stock of publicly available knowledge. For instance, a high-knowledge economy is likely to more easily produce an advanced piece of knowledge than a knowledge-scarce economy. Thus, knowledge production benefits from increasing returns at the industry level. We have:

[6]However, as shown below, the model incorporates increasing returns at the industry level over time.

$$\Delta S_t = f(c_t, S_{t-1}),\ f_1,\ f_2,\ f_{12} > 0. \tag{3}$$

For simplicity, assume

$$\Delta S_t = c_t * S_{t-1}. \tag{4}$$

From equations (2) and (4), we have

$$c_t = \Delta S / S_{t-1} = 1/(t-1), t > 1. \tag{5}$$

Thus, the cost of producing additional knowledge c_t falls over time, and so does the cost of machines C_t (equation (1)), despite the fact that their knowledge content increases. The reason is that i) the cost of machines is related to the cost of producing *additional* knowledge and not to the stock of knowledge because the stock of knowledge in the previous period is publicly available at zero cost, and ii) the increasing stock of publicly available knowledge reduces the cost of developing additional knowledge.

From equations (1) and (5), we have

$$C_t = m + 1/(t-1). \tag{6}$$

At time t, firms can build "new" machines embedded with the latest knowledge S_t at cost C_t, or they can build "old" machines with publicly available knowledge S_{t-1} at cost $C_t^* = m$.[7] Thus, in equilibrium, two types of machines will be built (at most).

Note that the difference in the cost of the two types of machines is

$$C_t - C_t^* = 1/(t-1). \tag{7}$$

The cost difference declines over time. Consequently (as is shown formally below), the proportion of new machines used increases over time.

[7] The "old" machines are not old but the knowledge embedded in them is. Firms can also build machines with older knowledge at cost m but that is never optimal.

2.2 Demand

Downstream firms in developing countries need to buy a machine in every period in order to be able to produce. They demand either an old or a new machine. A downstream firm's choice of type of machine depends on its knowledge-absorption capacity f and on country-specific human capital H. The higher is a firm's f, the more effectively it can make use of the latest knowledge in its production process and the greater the likelihood that it will buy the latest (new) machines. Similarly, the higher is the level of country-specific human capital H, the easier it is for a firm to productively absorb new knowledge.

Even though S_{t-1} is public knowledge for all the firms in the knowledge-producing industry of the developed country, it is not public knowledge for the downstream firms in developing countries which produce other goods and services. Their knowledge-absorption capacity f_t at time t is assumed to depend on a firm-specific exogenous component ε and on whether they are using old or new machines at t -1. The reason is that if firms use the latest machines at t - 1, they acquire a greater capacity to adopt new knowledge and be more effective in using the latest machines at time t. Thus:

$$f_t = f_t(e, M_{t-1}^i), f_1, f_2 > 0, \tag{8}$$

where M_{t-1}^i denotes the effect of a machine of type i ($i = OLD, NEW$) at $t - 1$ on a firm's knowledge-absorption capacity at time t, and $M_{t-1}^{NEW} > M_{t-1}^{OLD}$. For simplicity, let

$$f_t = e * M_{t-1}^i. \tag{9}$$

Assume that, at time t, the productivity gain that downstream firms obtain from additional knowledge ΔS_t is ΔR_t. Normalizing firm output and sales price to unity, the added profits from ΔS_t is (approximately) ΔR_t, and is given by

$$\Delta R_t^i = g(f_t, H_t) = f_t(e, M_{t-1}^i) * H_t = e * M_{t-1}^i * H_t, \tag{10}$$

where the subscript i of ΔR_t^i refers to the type of machine used by the firm at t - 1.

Downstream firms choose a new (old) machine at time t as long as the productivity gain is larger (smaller) than the additional cost, i.e., as long as $\Delta R_t^i > (<) C_t - C_t^* = 1/(t-1)$.

The critical value e_{ct}, the exogenous component of a firm's knowledge-absorption capacity, where the firm is indifferent between the two types of machines at time t, is given by the condition $\Delta R_t^i = 1/(t-1)$ or

$$e_{ct} = 1/[(t-1) * M_{t-1}^{i} * H_t], \tag{11}$$

The higher a country's level of human capital H_t, the lower the critical firm-specific value of e_{ct} where firms switch from old to new machines, i.e., the lower the share of old machines and the smaller the average age of machines.

If a downstream firm's $e < e_{ct}$, then $\Delta R_t < 1/(t-1)$ and it buys an old machine at time t. A firm using an old machine at t - 1 has a higher value of e_{ct} (equation (11)) and is thus more likely to continue using an old machine at time t. Given that the cost of additional knowledge falls over time (equation (5)), e_{ct} falls over time (equation (11)). When e_{ct} has fallen to the point where the inequality is reversed ($e > e_{ct}$), the firm switches to new machines forever (assuming no sudden fall in H_t). On the other hand, if at first, $e > e_{ct}$, the firm buys new machines from the start.

Thus, the productivity of firms with low values of e is hurt in two ways. First, because of the low value of e, and second because firms with low values of e tend to buy old machines. Similarly, a low level of human capital hurts a firm's productivity twice, first, because of the lower level of human capital itself, and second, because it raises the value of e_{ct} and increases the likelihood that the firm will buy old machines.

With this setting and the distribution of firm-specific knowledge-absorption capacity e, we can determine the share of a given type of machine (old or new) imported by any country. Let the distribution of e be uniform, with $e \in [0,1]$. Then, a given country's share of old machines is

$$e_{ct} = 1/[(t-1) * H_t * M_{t-1}^{OLD}]\,. \tag{12}$$

Given that the age of new machines is zero and that of old machines is one, the average age of the stock of machines is also e_{ct}. Thus, the critical value e_{ct} is equal to the share of old machines and is also equal to the average age of machines. It is inversely proportional to a country's level of human capital. [8]

The average cost of machines is given by

$$AC_t = C_t^* * e_{ct} + C_t * (1 - e_{ct}) = m * e_c + (m + c_t)(1 - e_{ct}) = m + c_t (1 - e_{ct}) . \quad (13)$$

A country with a very high level of human capital (a country at the frontier) would have a very low critical value of e_{ct}. From equation (12), $e_c \to 0$ as $H \to \infty$. Thus, in an economy at the frontier, all firms use new machines. Then, the average cost of machines relative to the average cost at the frontier, RAC_t, is

$$RAC_t = \frac{m + c_t (1 - e_{ct})}{m + c_t} \quad (14)$$

RAC_t reflects the average quality of machines in a given country relative to that at the technological frontier, and is used in the empirical analysis. It falls with e_{ct} and thus rises with the level of human capital (equation (12)), and it falls with $c_t = 1/(t-1)$, the cost of producing additional knowledge. Given that c_t falls over time, RAC_t increases and so does the share of new machines.

In the empirical analysis that follows, we estimate a combination of equation (10), which relates productivity gains to the choice of machines, and equation (12) which shows the (average) choice of machines made by any given country.

[8] In reality, the negative link between human capital and age of machines may be even stronger because countries with lower levels of income and human capital will tend to have more low-productivity firms.

3. Data and sample countries

The study focuses on six Central and Eastern European (Bulgaria, Hungary and Poland) and Southern Mediterranean (Egypt, Israel and Turkey) countries and on their imports of machines from the European Union for the period between 1989 and 1997. The sample countries differ in terms of their level of development, with GNP per capita varying from 1,380 US $ in Bulgaria to 16,180 US $ in Israel in 1997.

Economic integration increased between the EU and the sample countries in this period, with growing flows of trade and FDI. All our sample countries have preferential trade agreements with the EU which is by far their major trading partner and source of imported technologies: 60 to 90% of their machines are imported from the EU (Barba Navaretti, Galeotti and Mattozzi, 2000). Eaton and Kortum 2001 also provides evidence that world production of machines is highly concentrated in a few number of countries and that developing countries are almost invariably net importers of such machines.

3.1. Measuring technological complexity

One issue is how to measure the level of technological complexity of imported machines. The theoretical section showed that the average level of technological complexity of machines used by any given country is measured by their average cost. We proxy the technological complexity of imported machines by their average unit values, which is constructed from trade statistics on imports. The EU trade statistics (Eurostat-Comext) provide sufficiently disaggregated data in both values and quantities. Quantities of machines are measured in metric tons[9].

The use of unit values as a proxy of technological complexity raises several concerns. *First*, how closely does this indirect measure capture differences in technological complexity? As shown in the theoretical model of section 2, in a competitive market differences in the price of similar machines (e.g. numerically controlled horizontal lathes) should reflect differences in their knowledge content and productivity. Indeed, if we correlate the unit values of the metalworking machines exported from the US with the skill index of

[9] For some countries, machines quantities are also measured in terms of number of machines, but these data are not as widely available as the former ones. Unit values computed using the two quantity units are very highly correlated anyhow.

technological complexity discussed above, we find very high correlation ratios. These vary from 0.60 to 0.95, depending on the level of aggregation of the categories of machines.

A *second* issue is the use of unit values to compare different types of machines at any point in time and the same machines across time. Different types of machines have different prices because they are inherently different (a loom vs. a lathe) and not only because they are more or less complex. Also, the price of a given machine is known to decline with time due to obsolescence. To control for these effects, we construct a unit value index by normalizing the unit values of machines imported by a given country, classified at the six digits level in trade statistics (harmonized code), by the unit value of the same machines imported by the US, assumed to be the technological frontier. Specifically, the unit value index for a six digit machine i imported by country c at time t is given by:

$$UVI_{ict} = (UV_{ict}/UV_{iUSt}), \tag{15}$$

where the denominator is the unit value of the same machine i imported by the US at time t. This is essentially the relative average cost of machines as defined in (14).

A *third* issue is that unit values might capture market imperfections such as market power or trade barriers, which also affect prices. However, our countries are small and we can reasonably assume that the price of machines is given for them. Moreover, we use f.o.b prices in current Ecu at the EU border, and these should not be distorted by trade and other policies in the importing country.

Once unit values indices UVI are computed, it is necessary to derive correspondences at the industry level between categories of machines imported and the industries using them in production. For example, if we are interested in computing the UVI for the textile industry, we must aggregate it over all textile machines. We are able to do so at the three digit (ISIC) industry level by matching data on productivity derived from industrial statistics (UNIDO) and data on imports of technology derived from trade statistics (COMEXT-Eurostat)[10]. The industry matching is available for thirteen sectors, and is

[10] General machines like computers, which are used by all industries and cannot therefore be attributed to any are omitted from the index.

reported in Appendix 1. Thus, the average unit value index of the machines used in the 3 digit ISIC industry j in country c at time t is given by:

$$UVI^{6}_{jct} = \sum_{i=1}^{n} (UVI_{ict} \frac{V_{ict}}{V_{jct}}) \qquad (16)$$

where n is the number of six digit categories i corresponding to the ISIC three digit category j, and V_{ict} is the value of machines i imported by c at time t and V_{jct} is the total values of machines used in j imported by c at time t.[11]

3.2. Trends of unit value indices

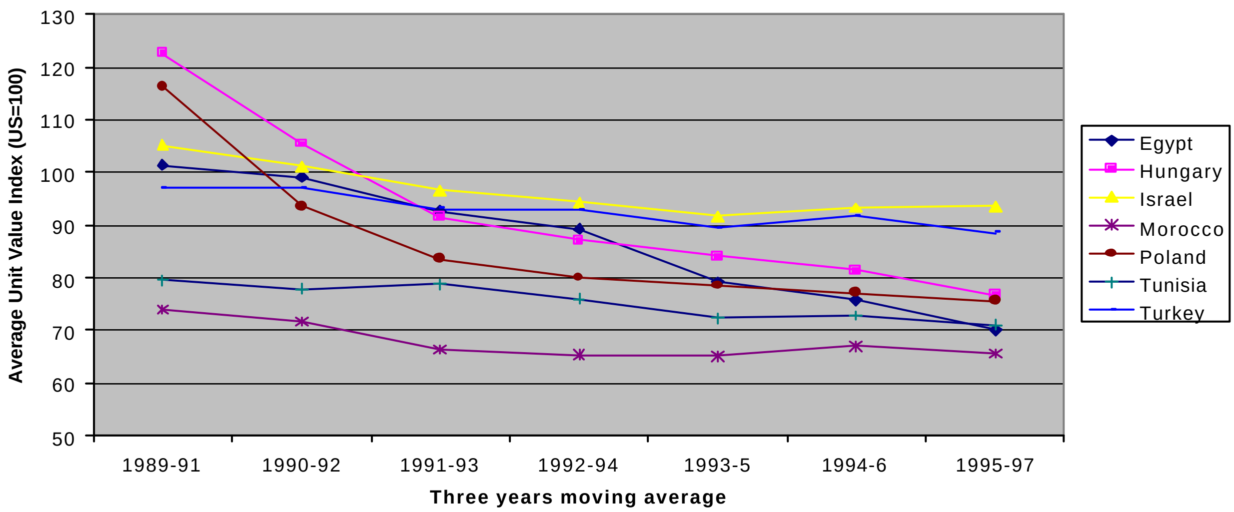
It is useful to observe how the UVI^6 indices behave across countries and over time. Figure 1 reports the trends of the average of unit value indices for the sample importing countries and some other Southern Mediterranean countries. The US index is set at 100. For most years and countries, the index is lower than 100 and declining. These trends support the theoretical prediction that developing countries import on average less technology intensive machines than those imported by the US. The country with the smallest gap is Israel, the one with the highest income per capita in the sample

Note also that the technology gap widens for all the countries in the sample and quite dramatically so for Hungary and Poland, although their trend is affected by the dramatic turn around of these economies after 1989[12].

[11] Note that this index is subject to a composition effect. The index can increase with time either because countries buy the same bundle of machines, and the value of each or some of them increases, or because bundles change towards machines with a higher average unit value. To avoid this problem it is possible to construct Tornqvist price indices, where weights are fixed over time, normally the period average weights (Aw and Roberts, 1986). However, our unit values are already normalised across machines. Thus an increase in the index due to a composition effect does indeed capture a process of technological upgrading that we want to observe.

[12] A possible explanation of the abrupt decline of the index in Poland and Hungary (we have similar figures for Bulgaria) which is consistent with earlier findings based on the skill index (Barba Navaretti, Galeotti and Mattozzi, 2000) is as follows. Eastern European countries used to buy most of their machines within the Soviet Bloc. They would only import top technology machines from Europe. The first years observed in our data may capture this earlier distortion. Once trade was liberalized with the EU, a geographical re-orientation of imports took place and later most machines were imported from Europe. Consequently the average quality of the machines imported from the EU fell.

Figure 1
Trends in Average Unit Values



Appendix 4 examines the persistence in the technology gap of imported machines in an alternative way. It compares UVIs with their values lagged one, two and seven years, and shows a striking persistence in the technology gap.

5. Do embodied imported technologies boost productivity? Econometric analysis

We have shown some descriptive evidence that developing countries import machines embodying simpler technologies than does the US. The theoretical model in section 2 shows that technology imports and productivity are two endogenous choices to be analyzed jointly. The use of more advanced technologies is expected to increase productivity, but firms will only buy them if the increase in productivity is worth the cost.

We examine the impact of machine imports on total factor productivity in those industries (j) using them as factors of production[13]. We work with a panel comprising 13 industries, six countries and 8 years (1989 to 1996). Appendix 2 describes how we computed total factor productivity and Appendix 3 reports the data sources and the basic descriptive statistics of the variables used in the estimations.

Total factor productivity at time t is assumed to depend on lagged productivity (which proxies the exogenous component of the knowledge absorption capacity), on productivity at the frontier, on the types of machines used in production at t and earlier and on the overall level of development of the importing country. It can be empirically implemented as follows:

$$Ln(TFP_{cjt}) = a_1 + a_2(\sum_{t=1}^{n} LnTFP_{cjt-t}) + a_3 LnTFP_{USjt-1} + a_4 LnIMP_{cjt-1} + a_5 LnUVI_{cjt-1} + a_5 LnDOMINV_{ct-1} + \\ + a_6 LnGDP_{ct-1} + a_7 Dj + a_8 Dc + a_9 Dt + e_{cjt} \quad (17)$$

where TFP_{cjt} is total factor productivity for industry j in the importing country c at time t; TFP_{USjt} measures TFP for industry j of the US, the technological leader, which captures the effects of technological progress at the frontier on TFP in c[14]; IMP is the share of imported machines in total investments in industry j, which controls for the relative importance of imported machines; UVI is the unit value index as defined in (15) which proxies the complexity of the machines imported and used in sector j in the importing country c at time t; DOMINV is a variable controlling for the technological content of domestic investments. As this is not observable, we use domestic consumption of electricity as a proxy. GDP is per capita GDP and measures aggregate demand and the overall level of development of country c at time t and it proxies human capital (as well as infrastructure and institutional development). Dj, Dc and Dt are industry, country and time dummies, respectively.

We also need to analyze the choice of embodied technology, as a function, among other things, of expected productivity, given that the two are jointly determined. Equation (14) in the model shows that the proximity to the technological frontier of the machines imported each year by country c, and consequently their relative average cost, is affected by the ability of importers to use high tech technologies efficiently. This latter terms is made of firm specific components, i.e. the firm's absorption capacity, and of country specific components. A firm's absorption capacity, and thus the gains in productivity achievable through the new technologies, depends on its past productivity (TFP_{t-1}), on the technologies

[13] Appendix 2 reports industry matching. Appendix 3 describes the methodology we have followed to construct TFP.
[14] Given how UVI is constructed, if both machines imported by the US and c improve at the same pace with time, UVIc remains constant even if c imports increasingly productive machines. To partially control for this effect, we include industry specific TFP in the US.

used in the past (UVI_{t-1}) and on other factors, e.g. its relationship to foreign firms (OPT_{t-1}).As we do not have consistent sector specific data on FDI, we measure it indirectly by looking at the share of exports of sector j from country c which is dassified as outward processing trade (OPT). OPT captures flows of temporary trade between subcontractors and between parent companies and subsidiaries[15]. The country specific components include the overall level of development, as proxied by GDP per capita (GDP_{t-1}). We also include relative factor prices (w/r) to control for the relative labour intensity of different types of technologies[16]. We thus have:

$$LnUVI_{cjt} = b_0 + b_1(\ln UVI_{cjt-1}) + b_2 Ln(\frac{w_{cjt}}{r_{ct}}) + b_3 LnTFP_{cjt-1} + \\ + b_4 GDP_{ct-1} + b_5 LnOPT_{cjt-1} + b_6 Dj + b_7 Dc + b_8 Dt + n_{cj} \qquad (18)$$

As for productivity, all technological choices are observed at the sector level. Equations (17) and (18) define a system that jointly determines the choice of imported technologies and productivity.

We face several econometric problems *First*, our results may be driven by spurious correlation, in that there may be unobserved time-invariant factors affecting both productivity and the choice of technology. One factor could be the share of foreign investors in the industry, or the degree of export orientation. Although we may control for some of these variables, others may remain unobservable. *Second*, as discussed in the theory there is persistence over time in both productivity and choice of technology, which is not necessarily related to the learning process associated with high tech machines. *Third*, there is

[15] It is quite likely that local subcontractors or local subsidiaries of western companies use more advanced machines for a variety of reasons, including standards imposed on them by their foreign partners/parents

[16] In some specification of our empirical estimations we use the wage rental ratio: $\frac{w_{cjt}}{P_{USjt}(1 + r_{ct} + d)}$. This measure allows us to control for the effects of δ a fixed yearly depreciation rate of 10% and P_{USjt}, the price of the machines imported by the US in sector j at time t (a proxi of the price of the top tech machines). Unfortunately this latter variable is also in the denominator of UVI, thus a source of spurious correlation. We also used alternative measure of labour cost controlling for the skill composition of the labour force using the ILO's Labour Statistics Database. Unfortunately these data are sector invariant, and they are of little scope in cleaning sector specific labour cost data. We had no change in our results when using thes ealternative measures of labour costs.

an endogeneity problem arising from the simultaneity between productivity, the choice of technology and potentially most of the explanatory variables.

To eliminate the effect of time-invariant unobservable factors we carry out the estimations in first differences. To isolate the impact of technological choices on productivity from trend effects, we estimate both productivity and the choice of technology on their lagged values. As for the endogeneity problem, we run two independent regressions where all explanatory variables can be instrumented using the appropriate lagged variables.

This can be done by using the GMM-Instrumental Variable - GMM-IV - method developed by Arellano and Bond (1991) for dynamic panels[17]

The two first difference equations to be estimated are obtained by transforming equations (17) and (18) as follows:

$$\Delta Ln(TFP_{cjt}) = a_1 \Delta Ln(TFP_{cjt-1}) + a_2 \Delta LnTFP_{USjt-1} + a_3 \Delta LnUVI_{cjt-1} + a_4 \Delta LnIMP_{cjt-1} + \\ + a_5 \Delta LnDOMINV_{ct-1} + a_6 \Delta LnGDP_{ct-1} + a_5 Dt + \Delta e_{cjt} \quad (19)$$

$$\Delta LnUVI_{cjt} = b_1 \Delta LnUVI_{cjt-1} + b_2 \Delta Ln(\frac{w_{cjt}}{r_{ct}}) + b_3 \Delta LnTFP_{cjt-1} + b_4 \Delta LnOPT_{cjt-1} + b_5 \Delta LnGDP_{ct-1} + \\ + b_6 Dt + \Delta n_{cjt} \qquad (20)$$

The results of our estimations are reported in Table 1 for productivity (equation (19)) and Table 2 for the choice of technology (equation (20)). Both regressions perform well. The non-significant Sargan tests indicate that the instruments are appropriate. The estimations also successfully take care of the serial autocorrelation of disturbances, given that there is no second order auto-correlation.

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[17] We also estimated a system of simultaneous equations where productivity and technology are jointly determined. These estimations give similar results to the GMM IV ones, but they have the major shortcoming that we cannot control for the endogeneity of other variables except for TFP and UVI.

We first focus on the determinants of TFP in Table 1. Regressions (1) and (2) include the import share. As this variable has many missing observations (see Appendix 3), to test the robustness of our results we also report regression (3), which does not include the import share and has many more observations, a number similar to those used in estimating the choice of technology. We find that embodied technologies, as measured by the unit value index of the machines imported, have a positive effect on TFP. The coefficient is significant and robust in the three regressions (and in alternative specifications not reported). Import shares have a positive but not significant coefficient (and not robust to changes in this specification), thus confirming our presumption that what matters for productivity and growth is the quality of the machines imported, and that once we control for quality, quantities are not important. TFP in the US also has a positive effect on TFP in the importing country, showing that technical progress in the leader generates spillovers onto the laggard, independently of the two countries' trade relations. GDP has a positive effect in regression (1), confirming the prediction that country specific factors related to the level of development enhance the efficient use of advanced technologies. However this variable is sector invariant and almost time invariant and thus not very robust in our estimations. It is no longer significant in (2) where we include electricity consumption per capita, a proxy of the quality of domestic investments. Also this latter variable is not significant in (2), probably because it is highly correlated to GDP per capita. GDP per capita is also not signficant in (3).

Table 1. Determinants of TFP

Dependent variable: Diff Ln Total Factor Productivity			
	(1)	(2)	(3)
Lag Diff Ln Total Factor Productivity	-0,008 (0,075)	0,076 (0,588)	0,277*** (3,34)
Lag Diff Ln Unit Value Index	0,228*** (2,59)	0,166** (2,14)	0,169** (2,06)
Lag Diff Ln Import Shares	0,024 (1,20)	0,018 (0,999)	
Lag Diff Ln Gross Domestic Product per capita	1,021** (2,00)	0,503 (1,04)	0,181 (0,538)
Lag Diff Ln Total Factor Productivity US	0,556** (2,47)	0,516*** (2,53)	0,339* (1,85)
Lag Diff in electricity consumption per capita		0,471 (1,07)	
N observations	153	153	345
Wald (joint)	23,99 [0,000]	57,91 [0,000]	26,81 [0,000]
Sargan test:	37,36 [1,000]	36,36 [1,000]	53,59 [0,708]
AR (1) test	-2,078 [0,038]	-2,220 [0,026]	-2,560 [0,010]
AR (2) test	1,638 [0,101]	1,836 [0,066]	1,741 [0,082]

Notes: The table includes results from the first step of two-stage GMM-Instrumental Variables estimates plus the Sargan test derived from the second step. "Diff" indicates first-order differencing. Time dummies are included in all the equations. Absolute value of t statistics into brackets. ***99% significance, **95% significance, *90% significance

a) All the explanatory variables (except for TFP US) are treated as endogenous. GMM-type, level instruments are their lags at (t-2) and earlier.

b) the Wald statistics is a test on the joint significance of the independent variable asymptotically distributed as χ^2 with k degrees of freedom (K is the number of coefficients estimated excluding time dummies), under the null of no relationship.

c) Sargan test of overidentifying restrictions is distributed as a χ^2 with as many degrees of freedom as the number of overidentifying restrictions, under the null of the validity of the instruments. The test based on the two-step GMM estimator is heteroskedasticity-consistent.

d) The GMM estimations were performed using the programme DPD for OX (J.Doornik, M. Arellano and S.Bond, 1999).

We now move on to the analysis of the choice technology. Results are reported in Table 2. Lagged TFP has a positive and significant effect on the Unit Value index or choice of technology. Firms buy high tech machines if they have enough skills to use them in a sufficiently productive way. Factor prices have no effects. We use alternatively the ratio of real wages on real interest, and the wage rental ratio as described in footnote

11. The latter is the best measure of relative factor costs, but it includes the price of US machines, which is also at the denominator of the dependent variable, thereby causing spurious correlation. Results though, are unaffected by the use of these alternative measures.

Table 2. Choice of Technology

Dependent variable: Diff Ln UVI^6	(2)	(4)
Lag Diff Ln Unit Value Index	-0,081 (0,60)	0,041 (0,662)
Lag Diff Ln Total Factor Productivity	0,259* (1,93)	0,256** (2,10)
Lag Diff Ln Wage Rental	0,048 (0,84)	
Lag Diff Ln Real Wage over Real Interest Rate		-0,091 (1,12)
Lag Diff Ln Outward Processing Trade	0,925 (0,47)	-0,877 (1,11)
Lag Diff Ln Outward Processing Trade square	-2,553 (0,853)	
Lag Diff Ln Gross Domestic Product per capita	0,744** (1,97)	0,035 (0,09)
N observations	379	379
Wald (joint)	17,80 [0,007]	11,16 [0,048]
Sargan test:	55,71 [1,000]	62,21 [1,000]
AR (1) test	-4,571 [0,000]	-4,312 [0,000]
AR (2) test	-0,465 [0,642]	1,203 [0,229]

Note: See Table 1.

As for OPT, which captures the involvement of foreign firms, this variable is also non significant, even when we check for non-linearity by introducing the square of OPT.

Finally, as expected, GDP has a positive impact on the choice of technology, confirming that frontier technology are purchased only when the overall level of development, and implicitly human capital, is high. However, as in the estimation of the determinants of TFP, this result is not robust to changes in the specifications of the model. The coefficient of GDP is not significant when we measure relative factor costs as real wage over real interest rates.

6. Conclusion

In this paper, we explored the impact of imported technologies on productivity in manufacturing sectors for a sample of developing and transition countries in Central and Eastern Europe and in the Southern Mediterranean. These countries have recently integrated their economies with the European Union.

Our analysis, which is based on a theoretical model of the choice of technology, departs from earlier studies of international technology diffusion by focusing on the technology embodied in the imported machines. The technological level of the imported machines is proxied by an index relating the unit value of the machines imported by a given country to the unit value of the same machines imported by the US. We find very strong regularities in the pattern of imported machines. Unit values are generally stable across time, except for countries facing dramatic shocks in the period observed, like the Eastern European ones. There is a constant and even increasing gap between the unit value of the machines imported by the US and the machines imported by our sample of developing countries. The increasing gap may be partly due to the fact that productivity grew unusually fast in the US in the 1990s.

The technology gap reflects two inherent characteristics of technological progress in the last decade. On the one hand, the price of machines has been stable over time despite the rise in their technological content. On the other hand, at any point in time, the prices of machines increased with their technological content. Therefore, as the price of technology has fallen over time, developing countries have imported increasingly more advanced machines, while the gap *vis a vis* the technological leaders has remained approximately constant. We show that this gap is significantly persistent and that it is higher the lower the level of development of the importing country.

We also show that productivity in manufacturing depends positively on the type of machines imported in a given industry. Thus, the cheaper and less sophisticated machines that developing countries import result in a lower TFP than frontier technologies, even though the choice may well be optimal given their relative factor prices and their reduced ability to use frontier technologies.

In contrast with earlier studies we find that importing machines per se does not enhance importers' productivity. Once we control for the quality of imports, quantity does not seem to matter.

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Appendix 1. Matching machines and products

Table 1. Matching between machines and products

Machines			Products		
Harm.	SITC/3	Description	Nace	ISIC rev.2	Description
8437/38(excluding 84384)/79	727	Food machinery, non domestic	411-423	311	Food
84384/842121/842122/8435	727	Food machinery, non domestic	424-28	313	Beverages
847810/90	72843	Tobacco working machines	429	314	Tobacco
8444-51	7244/5/6/7	Textile machinery	431-9	321	Textile
8452	7243	Sewing machines	453-6	322	Clothing
8453	7248	Skin, leather working machines	441-2/ 451-2	323+324	Shoes and leather
84793/8465/6	72812/72819/ 72844	Machine tools for working woods and wood treating machines	461-7	331+332	Wood and wood furniture
8439/41	725	Paper etc mill machinery	471/2	341	Paper and Pap. Prods.
8440/2/3	726	Printing and binding machry	473	342	Printing
8456-8463/8466	731/3/5	Machine tools for metal	312-9/321-8/ 351-3/361-5	381+382+384	Metal products and Machines (incl transport excl electrical)
8454/5/8468/8515	737	Metalworking machinery	221-3 311	371	Iron and steel
8475/84642019	72841	Glass working machinery	247	362	Glass
8477	72842	Rubber and plastic working machines	481-3	355/356	Rubber and plastic

Appendix 2: Empirical Derivation of Total Factor Productivity

Measuring changes in total factor productivity.

The estimation procedures used are very straightforward. We assume that sectoral GDP *(Yj)* is produced using two factors, physical capital *(K)* and labor *(L)*, using a Cobb-Douglas production function:

$$(1) \qquad Y_{jt} = A_{jt}(0)e^{l_{jt}}(K_{jt}^{ajt} L_{jt}^{1-ajt})$$

where j indicates sector, $A_j(0)$ represents initial conditions, λ_j is the rate of technological progress in sector j, a_j measures the importance of physical capital in output, and $1-a_j$ the importance of labor. After taking logs and differentiating with respect to time, we have:

$$(2) \qquad d\ln(Y_{jt}) = l_j + a_j d\ln(K_{jt}) + (1-a_j)d\ln(L_{jt})$$

We estimated (2) by sector j and time t. We pooled data for all c countries in our sample, added a time trend dummy (Dt) a country dummy (Dc), and, by country, a dummy for periods of recession in the economic activity(DR_{cjt}) which takes value 1 whenever $Y_{cjt} < Y_{cjt-1}$. The final equation estimated is:

$$(3) \qquad d\ln(Y_{cjt}) = l_{cjt} + a_j d\ln(K_{cjt}) + (1-a_j)d\ln(L_{cjt}) + Dc + Dt + DR_{cjt} + e_{cjt}$$

To gain in efficiency, we take into account the simultaneous correlation between the disturbances in different sectors (due to, for instance, common shocks) by estimating all the sectors as a system, by SUR.

Changes in TFP by country and by sector were calculated as:

$$(4) \qquad \Delta TFP_{cjt} = d\ln(Y_{cjt}) - \hat{a}_j\, d\ln(K_{cjt}) - (1-\hat{a}_j)d\ln(L_{cjt}) - \hat{D}c - \hat{D}t - \hat{DR}_{cjt}$$

Values estimated for a (the contribution of capital), varied from a minimun of 0.25 for the food sector to 0.75 for the machinery sector.

DATA:

TFP was estimated for 13 sectors disaggregated on the basis of the three digits ISIC rev. 2 code. (see appendix 2), for the peiod between 1980 and 1996. Becasue of data availability TFP at the sector level could only be computed for Bulgaria, Egypt, Israel, Hungary, Poland, Turkey and the US. Capital stocks were calculated according to the perpetual inventory method, The data source is UNIDO Industrial Statistics data base.

Appendix 3. Variable description data sources and descriptive statistics

	Variables description	***Data Source***
Total Factor Productivity (TFP)	Total factor productivity (see appendix 3)	Unido Industrial Statistics
Total Factor Productivity US	Total factor productivity in the United States (see appendix 3)	
Unit Value Index (UVI)	Ratio between the unit value of machines imported by a country from the EU and the unit value of machines imported by the US.	Comext, Eurostat
Wage Rental Rate	$\frac{w_{cjt}}{P_{USjt}(1+r_{ct}+d)}$ where Pus is the unit values of machines imported by the US, r_{ct} is real interest rate, and δ is a fixed 10% depreciation rate	Unido Industrial Statistics and Comex-Eurostat
Real Wage	Interest rate deflated wages	Unido Industrial Statistics and Comex-Eurostat
Import Share (IMP)	Average share of imported machines on total investments	Comext, Eurostat and Unido Industrial Statistics
Outward Processing Trade (OPT)	Shares of outward processed exports on total exports of the sample country.	Comext, Eurostat
Gross Domestic Product per capita (GDP)	Real gross domestic product of the importing country.	World Development Indicators, World Bank

All variables, except for GDP, measured for sector j in country c at time t,

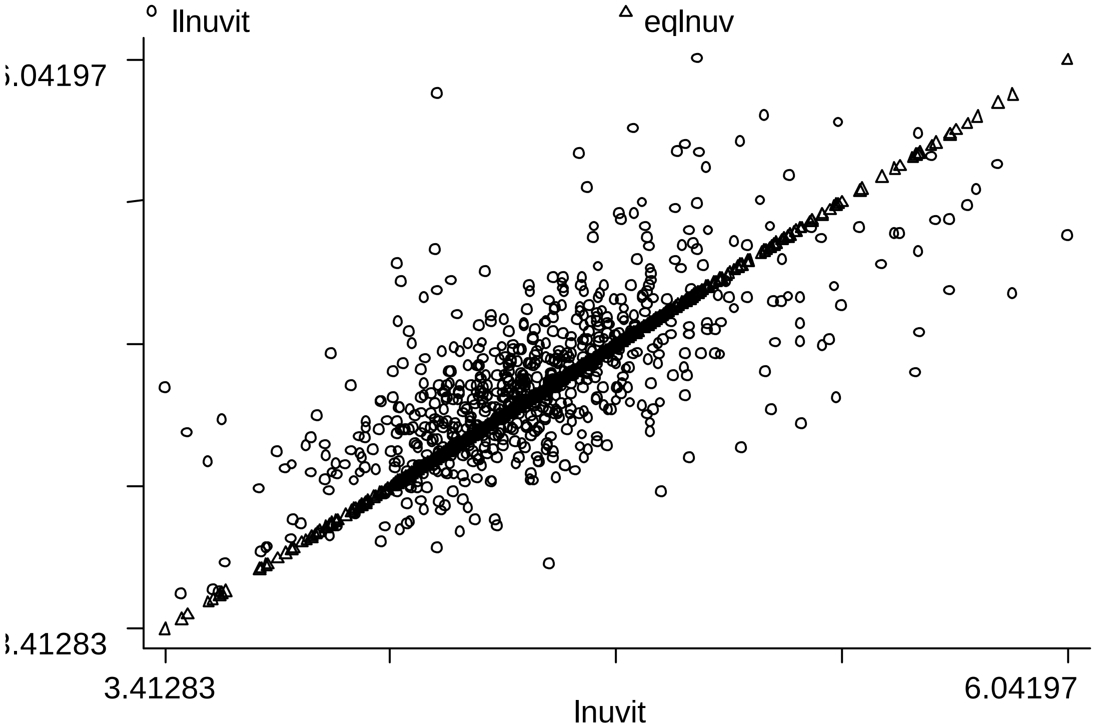
Descriptive Statistics

Variable	Obs	**Mean**	**Std. Dev.**
Total Factor Productivity (TFP)	489	91.22	16.96
Total Factor Productivity US	504	107.39	13.33
Unit Value Index (UVI)	648	96.54	40.15
Wage Rental Rate	540	215.32	222.56
Real Wage	573	249.47	382.54
Import Share (IMP)	340	0.38	0.24
Outward Processing Trade (OPT)	648	0.06	0.14
Gross Domestic Product per capita (GDP)	648	6609.63	4326.49

Appendix 4.

An alternative way to assess the persistency in the technology gap of the machines imported is to compare sector and country specific unit value indices with their lags. We plot the unit value indices of machines imported at time t (horizontal axes) with the unit value indices of the same machines imported 1 year earlier in figure (a), 2 years earlier in figure (b), and 7 years earlier in figure (c) (vertical axes). The thick line is the diagonal. The figures show a striking persistence in the gap. The indices are positively correlated with their lagged values, even with 7 years lags. Moreover, note that a large share of the dots lie above the diagonal, and that this share increases the longer the lag. This implies that for many sectors and countries the gap is increasing.

Figure a, b.
Persistency of the technology gap
1 year lag



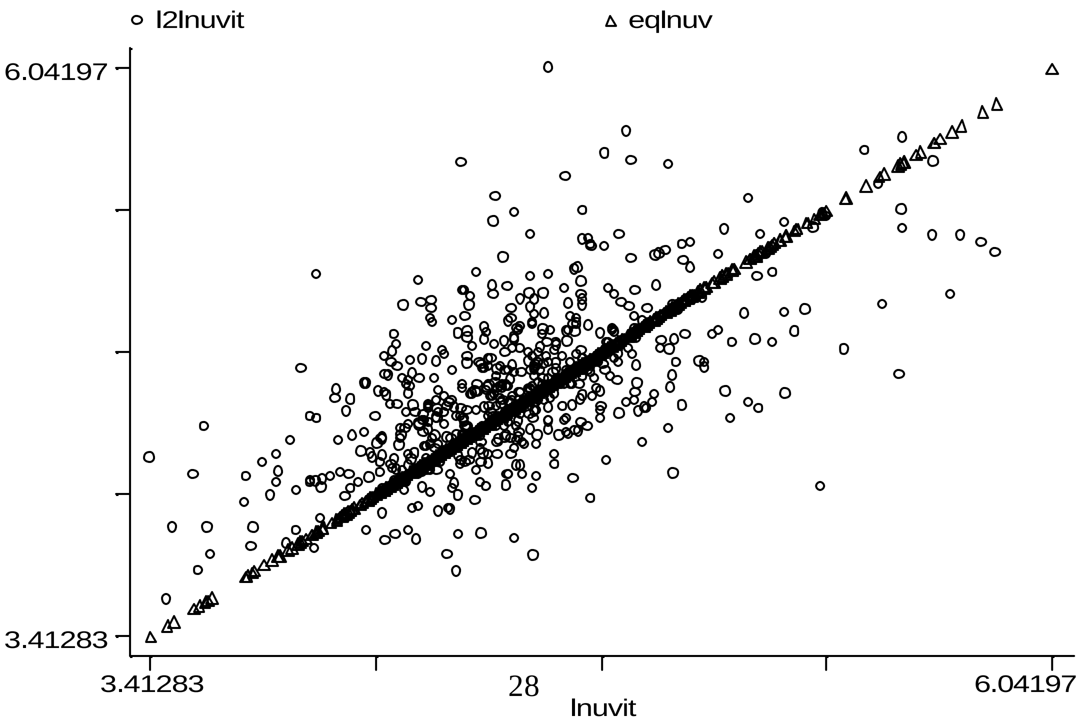


Figure c

Persistency of the technology gap

7 year lags