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Weightless Machines and Costless Knowledge An Empiricl Analysis of Trade and Technology Diffusion

Abstract

This paper examines the impact of imported technologies on productivity for a sample of developing and transition countries in Central and Eastern Europe and in the Southern Mediterranean. These economies are getting more and more integrated to the European Union.

The paper departs from earlier studies of international technology diffusion as it focuses on the technology embodied in the machines imported. Earlier works had mostly focussed on spillovers of foreign R&D conveyed through trade, without controlling for the characteristics of the goods imported. The paper jointly estimates the choice of foreign technology and its impact on domestic productivity for a set of manufacturing sectors. The technological level of the machines imported 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. The paper finds 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. It shows that this gap is significantly persistent and that it is higher the lower the level of GDP of the importing country. The empirical analysis also finds that productivity growth in manufacturing depends positively on the type of machines imported in a given industry. Consequently, although the choice of developing countries to buy cheaper and less sophisticated machines is optimal, given relative factor prices and their endowments of technology, this choice has a cost in terms of long run productivity growth.

1. Introduction

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). Accordingly, in a recent paper Danny Quah labels as 'weightless' an economy where knowledge products represent an increasingly large share of national income(Quah, 1999). Knowledge, lacking physical attributes and, to use more standard accounting definitions, being intangible, is a hidden factor of production making economies grow 'weightless'.

Weightlessness has its nominal counterpart: *costlessness*. Every one familiar with a keyboard knows well that the cost of computers in the last ten years remained more or less stable or even declined, although computers' capacity to process information skyrocketed. Thus, knowledge spreads and accounts for an increasing share in income because it is virtually costless. However, this is true only if we allow for a sufficiently long time horizon. Top technologies do not diffuse instantly and it takes time before they become available to everybody at a reasonable price, even when embodied in durable equipment or production machines. Unfortunately, (fortunately for inventors) what matters for diffusion is the link between technologies and prices at any point in time, not the time trend of a given technology. If we enter a computer shop we find that the prices of machines grow with the number of megahertz and other magnificent embodied features. Only a few can buy a top computer of today, even if anyone will be able to afford it sometimes in the future. The prices of technologies at any point in time reflect their relative productivity.

This paper discusses whether developing countries' choices of imported factors of production are influenced by the link between technological complexity and prices and, in turn how these choices affect productivity in manufacturing.

We take the most physical of all factors of production: machines. We use trade data to construct average unit values per ton of machine[1] exported by the EU to a sample of

[1] We can show that unit values per ton of machine are very highly correlated to unit values per number of machines. We use the former, as the latter are available for a limited number of machines and countries only

neighboring developing and transition countries in Central-Eastern Europe and in the Southern Mediterranean . We work with homogeneous groups of machines, by using very disaggregated trade data. We also take the export of EU machines to the US as a top technology counterfactual.

If we look at country averages, the evidence is perfectly consistent with our stylized facts on computers. The unit values in nominal Euros of machines imported by the US from the European Union between 1989 and 1997 rises just marginally, notwithstanding dramatic increases in productivity. However, at any point in time there is a persistent gap between the unit values of the machines imported by the US and those imported by our sample of developing countries. We also find that this gap is inversely correlated to a broad development indicator like income per capita. Thus, although backward economies buy increasingly productive machines, the technology embodied in these machines persistently lags behind the one purchased by the US, as far as unit values are good proxies of embodied technologies.

We then work at the industry level and we analyze jointly the choice of the technological complexity of the machines imported and the impact of embodied technologies on total factor productivity. We find that the choice of lower technologies is optimal for developing countries, given local skills and factor prices. We find that imported technologies have a favorable effect on productivity, but this effect hinges upon the type of technologies embodied in the machines imported. In other words, an increase in the level of complexity of the machines imported has a larger impact on TFP growth than an increase in the share of imported machines on total investments. This implies that the persistent technological gap also generates a persistent divergence of income levels between advanced and industrialized economies.

Many recent contributions empirically analyze how international economic integration creates new channels for transferring technologies and knowledge and how these channels affect productivity[2]. These contributions have looked at the impact of imports as conveyors of R&D spillovers (Coe and Helpman, 1995, Coe Helpman and Hoffmaister,

[2] See Barba Navaretti and Tarr, 2000 for a review

1997, Keller, 2000), of foreign direct investments (Blomstrom and Kokko, 1998)[3] and of exports (Clerides, Lach and Tybout, 1998, Bernard and Jensen, 1999, Aw, Chung and Roberts, 2000, Kraay, 1996).

None of these works, however, have looked at the role of imported machines in transferring embodied technological progress. Take the most quoted reference in this area, Coe and Helpman 1995. The basic idea in their paper, derived form earlier theoretical contributions on endogenous growth in open economies, is that growth in a given country depends both on domestic and foreign stocks of technological knowledge. Foreign knowledge is acquired as a costless externality by importing goods from countries which are rich in R&D. Coe and Helpman construct a trade weighted foreign R&D stock, using the share of imports from each partner country on total imports as weights and they evaluate its impact on aggregate domestic total factor productivity (TFP). Coe, Helpman and Hoffmaister, 1997 carry out a similar exercise, using imports of machines as weights and Keller, 2000, estimates the impact of foreign R&D stocks on TFP at the sector level.

That trade is a great channel to circulate ideas it is a well known and very ancient story. Trade in goods certainly generates parallel channels for the weightless exchange of technological knowledge. Yet, technological knowledge is also embodied in the goods imported. When these goods, like machines, are used as factors of production their technological features are likely to directly influence productivity. The contributions discussed above, by just focussing on externality, somehow misrepresent the process of technology transfer. Imagine a given country importing the same total value of goods (or capital goods) from two countries which have the same R&D capital stock. The impact of imports from both countries on domestic productivity is expected to be exactly the same in the Coe-Helpman, Hoffmeister, Keller framework. But what if the bundle of goods imported from the two countries is different, and in particular what if the machines imported from one of the two countries are much more productive? Then the impact of imports on productivity should be different in the two cases. This is precisely the central result of this paper.

[3] Blomstrom and Kokko 1998 provide a good survey. See also Blomstrom and Persson, 1983, Haddad and

In principle it should be possible to argue that the larger the R&D capital stock of a country the more technologically advanced the machines imported from that country. But we show in this paper that this is not the case in general. If we take the average unit value of the manufacturing machines exported from the European Union they vary quite widely across importing country. Thus the bundle of machines exported from any given country (or group of countries) may vary, independently of this country's R&D capital stock.

The results of this paper are consistent with and extend our earlier work. In Barba Navaretti, Soloaga and Takacs, 2000 we explore the choice of the vintage of the machines imported by developing countries from the US. We find that vintage, like technological complexity is explained by factor prices and skills prevailing in the importing countries. In Barba Navaretti, Galeotti and Mattozzi, 2000 we use a measure of technological complexity related to the skills necessary to use the machines imported and show that this measure of technological complexity has a positive impact on the export performance of textile products for a sample of Eastern European and Mediterranean countries. Compared to these earlier works, here we use a different measure of technological complexity (unit values of importd machines), that can be computed for all machines used in production. We can consequently work on a broad number of manufacturing sectors and focus on TFP as our performance variable.

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. In Appendix 1 we develop a simple analytical framework as a background to the econometric analysis of sections 4.

2. Data and sample countries

The aim of the empirical analysis is to study the determinants of the choice of imported machines and the impact of embodied technologies on total factor productivity for

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Harrison, 1993, Harrison, 1996 and Djiankov and Hoekman, 2000 some manufacturing sectors. The main problem concerning data is to derive correspondences at the industry level between categories of machines imported and the industries using them in production. 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). The industry matching is available for thirteen sectors, reported in Appendix 2. Before deriving an empirical model, we discuss the choice of the sample countries and the construction of the variables measuring imports of technology . We also run some simple descriptive statistics of average unit values of machines imported by our sample countries.

The study focuses on six Central and Eastern European (Bulgaria, Poland and Hungary) and Southern Mediterranean (Egypt, Israel and Turkey) countries and on their imports of machines from the European Union. There has been a dramatic increase in the degree of economic integration between these areas, with growing flows of trade and foreign direct investments. For most of the sample countries the EU is by far the major source of imported technologies: 60 to 90% of their machines are imported from the Union. We do not miss much by not considering their trade with the rest of the world.

The sample countries differ quite much in terms of their pattern of trade liberalization. The Central and Eastern European ones have liberalized suddenly, following the fall of the Berlin Wall. There is overwhelming consensus that the extent of trade reforms has been considerable. Turkey is instead an earlier liberalizer. It implemented extremely liberal policies already in the Eighties and it recently decided to implement a Custom Union with Europe, applying the EU common external tariff to third countries' imports. The other Southern Mediterranean countries have mixed performances. Although some of these countries (Israel, and Egypt) have negotiated or are negotiating reciprocal free trade agreements with Europe, trade regimes have been up to now, and often still are, quite protectionist.

The countries in our sample also differ in terms of their level of development and production structure. GNP per capita varies between 1,380 US $ of Bulgaria to the 16,180 US $ of Israel. We have therefore a sufficiently differentiated picture to understand the role of trade liberalization and of differences in the level of development which may affect technological choices.

3. Measuring technological complexity

Now, how can we measure the level of technological complexity, or, rather the type of technologies embodied in imported machines? In an earlier paper we devised a measure of technological complexity for metalworking machines (Barba Navaretti, Soloaga and Takacs, 2000). This measure was based on the minimum skills necessary to use a machine and it was constructed with the help of specialized engineers. With sufficiently disaggregated trade data, it was possible to assign the skill index to each type of machine. The same measure was also applied to textile machines in a subsequent paper (Barba Navaretti, Galeotti and Mattozzi, 2000). Unfortunately this measure is only restricted to these two industries and cannot be used for the rest of manufacturing. Moreover, it cannot be used to compare technologies embodied in the same type of machines imported by different countries, as all machines in a given trade category would get the same ranking. For example numerically controlled horizontal lathes have a higher index than manually controlled one. But we would be unable to distinguish between more or less advanced numerically controlled horizontal lathes imported by a given country.

In this paper we use a more straight forward measure, the unit values of machines. Does this indirect measure capture differences in technological complexity? In a competitive market we expect that differences in the price of similar machines (e.g. numerically controlled horizontal lathes) reflect differences in productivity. As discussed in the introduction, at any point in time price of machines differ according to productivity. Indeed, if we correlate the unit values of the metalworking machines exported from the US, with the index of technological complexity discussed above, we find very high correlation ratios varying from 0.60 to 0.95, depending on the level of definition of the machines considered.

A second problem is the use of unit values to compare across different types of machines. Different types of machines can have very different prices because they are inherently different (a loom vs. a lathe) not because they are more or less complex. To control for this composition effect, we construct a unit value index by normalizing the unit values of machines classified at the six digits level in trade statistics (harmonized code) imported by a given country by the unit value of the same machines imported by the US. More specifically, the unit value index for a six digit machine i imported by country c at time t is given by:[4]

$$UVI_{ict} = (UV_{ict}/UV_{iUSt})$$

Where the denominator is the unit value of the same machine i imported by the US at time t. To match data on unit values with data on productivity, which are measured according to three digits ISIC classification, we must aggregate all the six digits unit value indices corresponding to all those machines used in any three digit ISIC category. For example, if we are interested in computing the unit value index for the textile industry to see what is its impact on productivity in textile, we must aggregate the unit value index of all textile machines. The correspondence between the harmonized codes of the machines and the ISIC codes of the industries using them is reported in appendix 2. 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:

$$UVI^{6}_{jct} = \sum_{i=0}^{n} (UVI_{ict} \frac{V_{ict}}{V_{jct}}) \qquad (1)$$

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.[5]

[4] Note that if we were to use the skill index discussed above, we could not compare machines whithin a six digit category.

[5] Note that this index is affected by 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 with time, 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 with 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.

A final problem, is that unit values may capture market imperfections like market power or trade barriers, which do have an influence on prices. However, our countries are small and we can reasonably assume that the price of machines is given for them. Moreover prices are f.o.b prices in current Ecu at the EU frontier, thus they should not be distorted by tariffs and other policies in the importing country

Given that the EU trade statistics (Eurostat-Comext) provide sufficiently disaggregated data in both values and quantities, we focus on imports from the EU. As argued, all of our sample countries import most of their machines from the European Union. For example, the average share of textile and clothing machines imported from the EU on total textile machines imported between 1988 and 1996 is never lower than 66% (Barba Navaretti, Galeotti and Mattozzi, 2000). Quantities of machines are measured in metric tons. For some countries, machines quantities are also measured in terms of number of machines, but these dat are not as widely available as the former ones. Unit values computed using the two quantity units are very highly correlated. The analysis is carried out for the period between 1989 and 1997.

It is useful to observe how these indices behave across countries and with time. To do so we compute simple numerical averages for each year for some of the importing countries. We start with row average unit values (not normalised), so as to compare the trend of unit values of machines imported by the US from the EU with those imported by other countries (Figure 1). We observe a stable gap between the unit values of the machines imported by the US and by the other countries. If we exclude Hungary and Poland, we note that for all the other countries unit values are quite stable, although for the US they tend to rise and for the other countries slightly decline. This evidence suggests that the price of machines is stable with time and does not increase with technical progress. But if at any moment in time the price of any given machine is linked to its productivity, developing countries are on average importing less productive machines than the US.

As discussed above, the trends reported in figure 1 may be affected by the composition effect. In figure 2 we therefore report the average of the Unit Value Index (7), where unit values are normalized by the unit values of US imports (Figure 2). We see that the trends are very similar to the one reported in figure 1.

Another way to assess the persistency in the technology gap of the machines imported is to compare unit value indices with their lags. In Figure 3 we plot the unit value indices of machines imported at time t with the unit value indices of the same machines imported 1 (3a), 2(3b) and 7 years earlier (3c). 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 between the machines they import and the machines imported by the US is not only persistent but even increasing.

Figure 1
Trends in Aggregate Unit Values

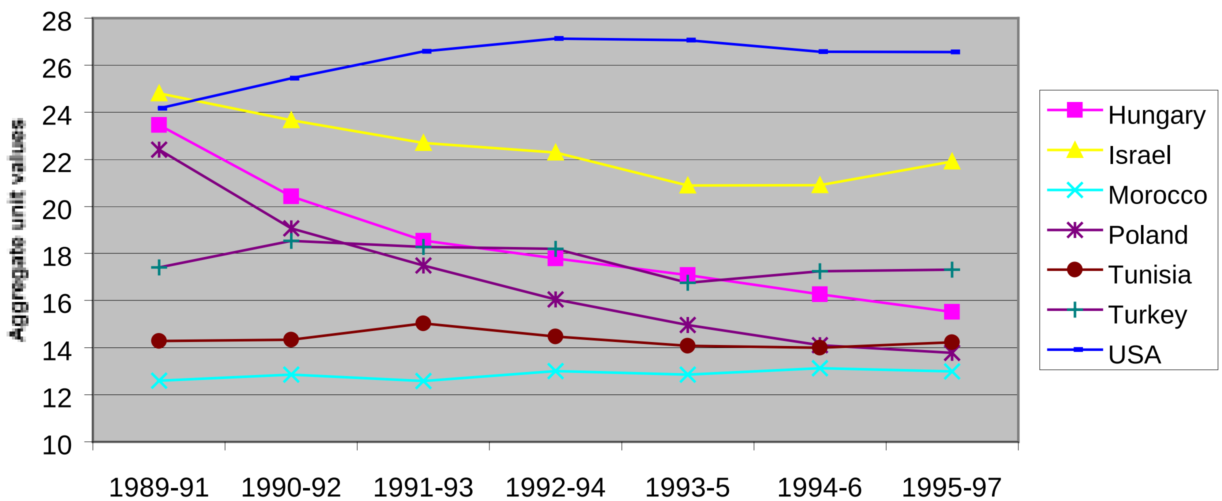


Figure 2
Trends in the Aggregate Unit Value Index

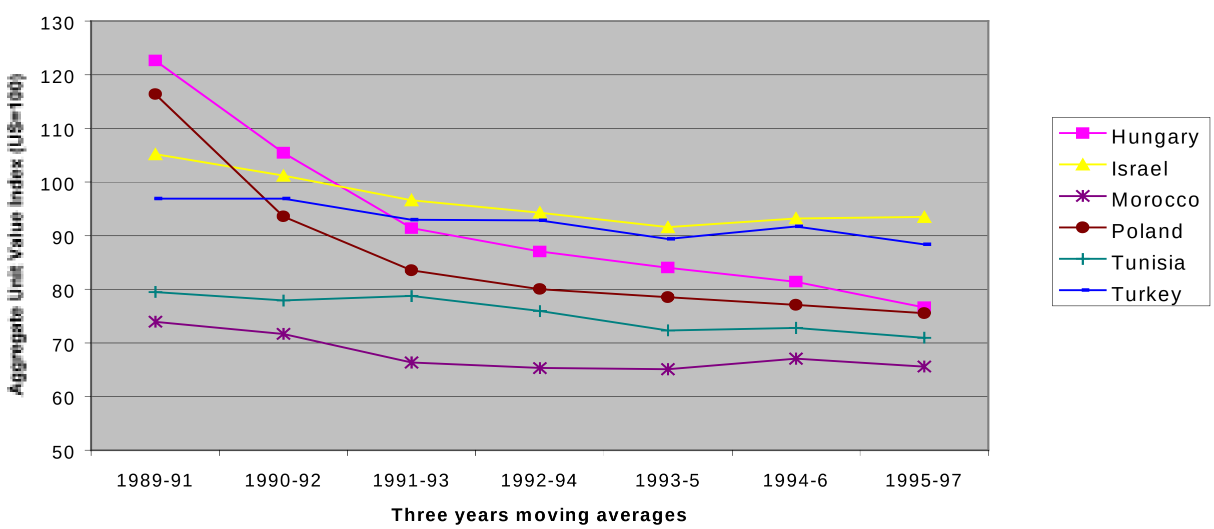
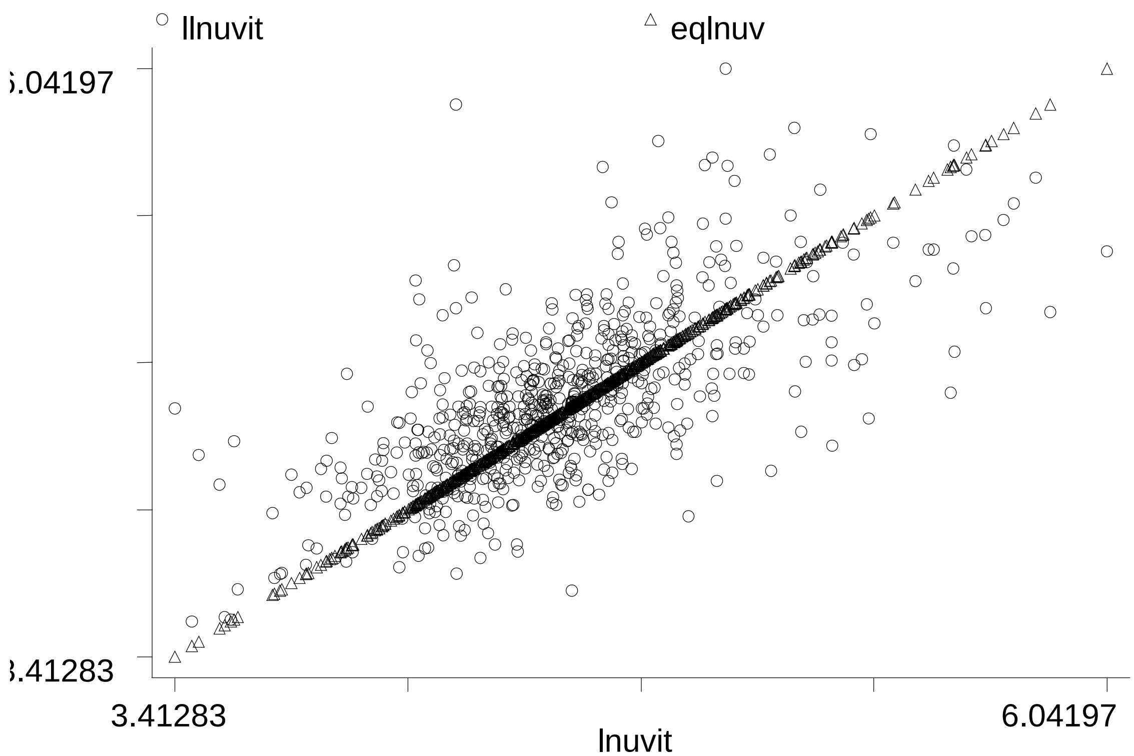


Figure3 a,b
Persistency of the technology gap
1and 2 year lags



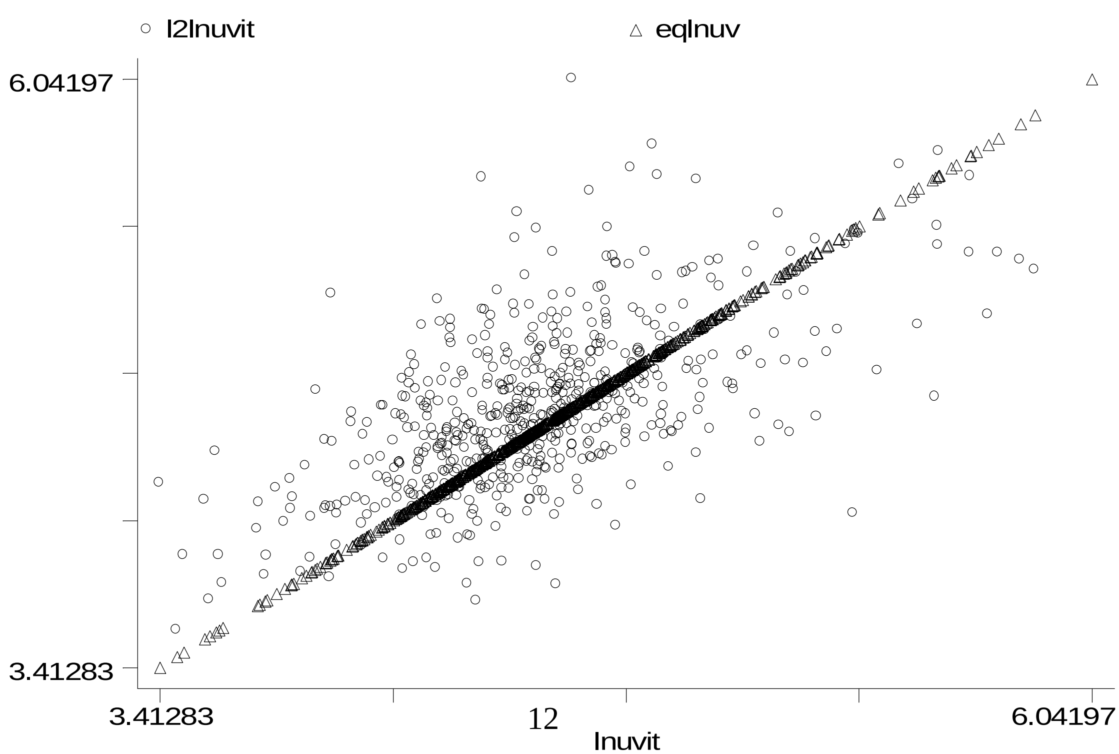
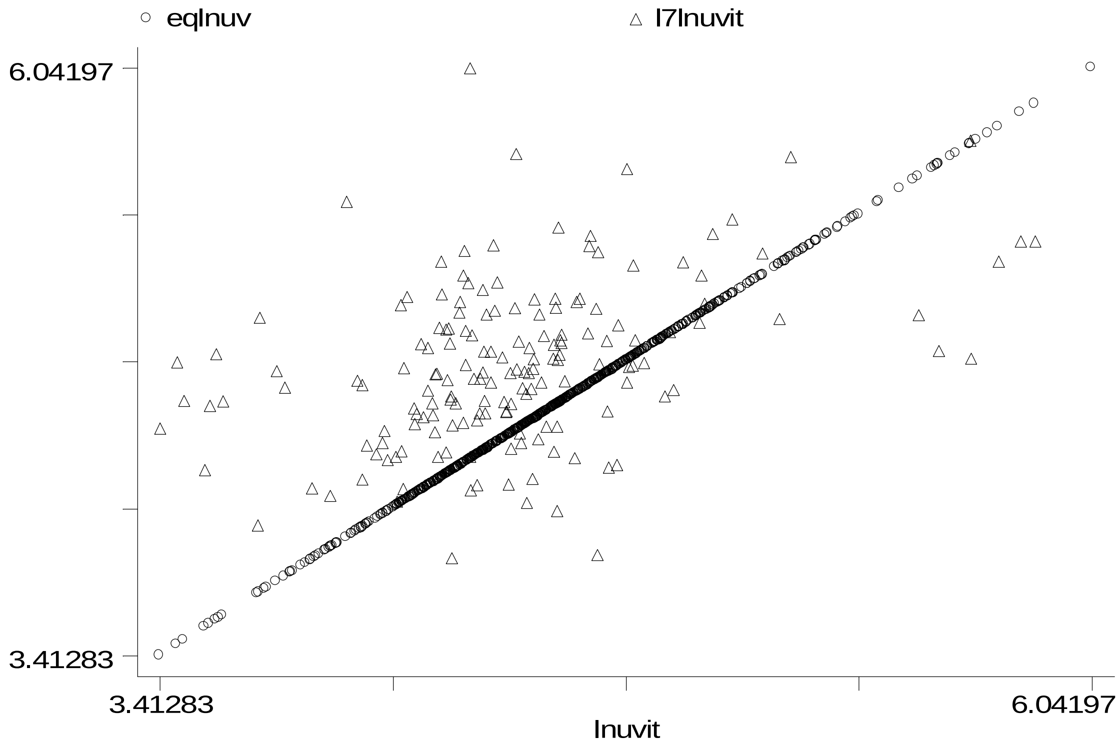


Figure3 c
Persistency of the technology gap
7 year lags



It is not clear why we observe a sudden decline in the unit values of the machines in Eastern European countries. A possible explanation of this factual evidence, which is consistent with earlier findings based on the skill index (Barba Navaretti, Galeotti and Mattozzi, 2000) runs as follows. Eastern European countries used to buy most of their machines within the Soviet Block. They would only import top technology machines from Europe. The first years observed in our data may capture this earlier distortion. Once trade was liberalised with the EU a huge geographical re-orientation of imports took place and later most machines were imported from Europe. Consequently the average quality of the machines imported now is lower than it used to be.

4. Do embodied imported technologies boost productivity? Econometric analysis

We have shown some descriptive evidence that developing countries import machines embodying simpler technologies than industrialized ones. Does this matter for productivity and income growth? As discussed in the introduction, earlier papers found that imports have a favorable impact on growth because they act as a channel for R&D spillovers. (Coe and Helpman, 1995, Coe Helpman and Hoffmaister, 1997, Keller, 2000). The larger the R&D stock in the exporting country, the larger the spillovers induced by imports and the larger the effect on productivity.

The descriptive evidence above shows that even if we consider one homogeneous exporter, the EU, the quality of the machines exported vary with the importing country. Thus, the same total expenditure on machines imported from the same exporter (the EU) may comprise very different bundles of technologies. In this paper, we estimate the impact of the technologies embodied in imported machines on total factor productivity. To single out the effect of embodied technologies, we also control for the total expenditure on imported machines.

Given that machines are sector specific, we will examine their impact on total factor productivity in the industries using them as factors of production. Appendix 2 reports industry matching. Appendix 3 describes the methodology we have followed to construct

TFP. Our estimations are therefore carried out at the industry level (j), assuming that industry values represent the behavior of the average firm in the industry. We have a panel comprising 13 industries, six countries and 8 years (1989 to 1996).

As discussed in appendix 1, we assume that total factor productivity at time t depends on lagged productivity and on a vector of technologies imported in the past. The empirical version of the productivity function (A3), discussed in appendix 1, for sector j, country c at time t can be represented as follows:

$$Ln(\gamma_{cjt}) = \alpha_1 + \alpha_2 (\sum_{\tau=1}^{n} Ln\gamma_{cjt-\tau}) + \alpha_3 LnIMP_{cjt-1} + \alpha_4 LnUVI_{cjt-1} + \alpha_5 LnGDP_{ct} + \alpha_6 Dj + \alpha_7 Dc + \alpha_8 Dt + \varepsilon_{cjt} \quad (2)$$

where γ_{cjt} is total factor productivity for industry j in the importing country c at time t, the second term on the RHS is lagged TFP, the third term, IMP is the share of imported machines on total investments in industry j, UVI is the unit value index as defined in (1) which proxies the complexity of the machines imported, GDP measures the overall level of development of country c at time t and D are industry country and time dummies respectively.

The theoretical model assumes that firms are only facing the choice between two alternative machines. Given that the unit value index is a continuous variable, in the empirical analysis we assume that firms are facing an infinite number of options for technologies embodied in a given machine. However, as discussed in the appendix, productivity and imported technologies are simultaneously determined. On the one hand, the use of more advanced technologies is expected to have a positive effect on productivity. On the other hand, firms will buy advanced technologies if the expected effect on productivity is positive. We consequently also need to analyze the choice of the embodied technology, as a function, among other things, of expected productivity. In the appendix we develop a model for the choice of technology. We learn from the theory that this choice is affected by past choices, relative factor prices, and the ability of importers to use high tech technologies efficiently. This latter terms is composed of the level of productivity firms manage to achieve immediately and the level of productivity they manage to achieve in the future by learning to use a given technology. From equation (A8) in the appendix we can derive an empirically implementable equation of the choice of technology:

$$LnUVI_{cjt} = \beta_0 + \beta_1 \Big(\sum_{\tau=1}^{n} \ln UVI_{cjt-\tau} \Big) + \beta_{21} Ln \frac{w_{cjt}}{P_{USjt}(1 + r_{ct} + \delta)} + \beta_3 Ln\gamma_{cjt} + \beta_4 Ln\phi_{cjAV} +$$
$$+ \beta_5 GDP_{ct} + \beta_6 Dj + \beta_7 DC + \beta_8 Dt + v_{cj} \qquad (3)$$

where UVI is the unit value index for the machines imported by sector j in country c at time t. The first RHS term is the lagged unit value index which captures the hysteresis effect of lagged machines choices. The second term is a wage rental ratio which captures the effect of relative prices: w is the average sectoral wage, r is the real inters rate δ a fixed yearly depreciation rate of 10% and P_{Usjt} is 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). The third term is TFP at time t for industry j in country c. The fourth term is average yearly productivity growth (the learning ability of the firm) which can be measured either directly or indirectly by looking at factors that may affect the learning ability, like foreign investments. The fifth variable is GDP per capita of country c at time t, which is a broad indicator of the level of development of country c. We then have sector, country or time dummies.

Equation (2) and equation (3) jointly define the system of equations to be empirically estimated to analyze the link between imported technologies and productivity. However, 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 to high tech machines. Third, there is an endogeneity problem arising from this simultaneity between productivity and the choice of technology.

To eliminate the effect of time-invariant unobservable factors we carry out our 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 could in principle sort it out by running a system of simultaneous equations, where productivity and technology are jointly determined. However, given that we work in first differences, endogeneity also applies to lagged variables and we would be left with a non sufficient number of exogenous variables to run the system. A simpler alternative is to run two independent regressions, using the appropriate lagged variables as instruments. The GMM-Instrumental Variable - GMM-IV - method developed by Arellano and Bond (1991) for dynamic panels is the right alternative to the estimation of a simultaneous system of equations by three-stage least squares. The endogeneity problem can be sorted out by using the appropriate lagged variables as instruments.

We consequently transform equations (2) as follows:

$$\Delta Ln(\gamma_{cjt}) = a_1 \Delta Ln(\gamma_{cjt-1}) + a_2 \Delta LnUVI_{cjt-1} + a_3 \Delta LnIMP_{cjt-1} + a_4 \Delta LnGDP_{ct-1} + a_5 Dt + \Delta \varepsilon_{cjt} \tag{4}$$

and equation (3):

$$\Delta LnUVI_{cjt} = b_1 \Delta LnUVI_{cjt-1} + b_2 \Delta Ln[\frac{w_{cjt}}{P_{USjt}(1 + r_{ct} + \delta)}] + b_3 \Delta Ln\gamma_{cjt} + b_4 \Delta LnOPT_{cjt} + b_5 \Delta LnGDP_{ct} + $$
$$+ b_6 Dt + \Delta \nu_{cjt} \qquad (5)$$

Besides for transforming (2) and (3) in first differences, we have only included one lag for both productivity and UVI. In the technology choice equation we also substitute the variable measuring the learning capacity of industry j with a variable measuring the involvement of foreign firms in the industry, under the assumption that foreign investors indirectly speed up the learning process with new technologies. As we do not have consistent sector specific data on FDI, we measure them indirectly by looking at the share of exports of sector j from country c which is classified as outward processing trade (OPT). OPT captures flows of temporary trade between subcontractors and between parent companies and subsidiaries.

The results of our estimations are reported in table 1 for productivity and 2 for the choice of technology. A detailed description of the variables used and their sources is found in appendix 4. In general terms all regression perform well. The non significant Sargan tests tell us that there is no over-identification in the instrument matrix used. Disturbances are serially uncorrelated given that we find evidence of first order-auto-correlation and no second order auto-correlation.

Table 1: Determinants of TFP Growth

Dependent variable: Diff Ln Total Factor Productivity

	R1	*R2*
Lag Diff Ln Total Factor Productivity	-0.32*** (-3.64)	-0.45*** (-4.53)
Lag Diff Ln Unit Value Index	0.77*** (5.44)	0.80*** (4.99)
Lag Diff Ln Import Shares	0.06** (2.19)	0.06*** (1.74)
Lag Diff Ln Gross Domestic Product		1.74 (1.68)
N observations	90	90
Wald (joint)	29.98***	33.05***
Wald (dummy)	76.85***	23.95***
Sargan test:	16.13	15.42
AR (1) test	-2.32**	-2.46**
AR (2) test	0.91	0.74

The table includes only results from the second step of two-stage GMM-Instrumental Variables estimates.
"Diff" indicates first-order differencing.
Time dummies are included in all the equations.
t values into brackets. ***99% significance, **95% significance, *90% significance
Transformed instruments are the second lags of all the explanatory variables. Level instruments include time dummies and the dependent variable at time 0 and time t-1.

We first focus on the determinants of TFP growth. Regression 2 includes gross domestic product as an explanatory variable. We find that the share of imported machines on total investments in the industry has a positive impact on TFP. This result is in line with findings in Coe and Helpman, 1995, Coe Helpman and Hoffmaister, 1997, Keller, 2000. However, we find that embodied technologies, as measured by the unit value index of the machines imported have a larger effect on TFP and this variable is more robust to different specifications of the model. If we look at regression 1 and we interpret the coefficients as elasticities, we have that an increase in 10% in the rate of growth of the unit value index generates an increase of 7.7% in the rate of TFP growth; in contrast the same increase in the rate of growth of the import share generates an increase of 0.6% in the rate of TFP growth. We also find, as expected, that GDP growth has a positive effect on sectoral TFP.

Table 2: Choice of Technology

Dependent variable: Diff Ln Unit Value Index

	R3	*R4*
Lag Diff Ln Unit Value Index	-0.44**** (-13.3)	-0.45**** (-14.1)
Diff Ln Wage Rental	1.76**** (5.47)	0.77* (1.82)
Squared Diff Ln Wage Rental	-0.17**** (-5.52)	-0.08** (-2.03)
Diff Ln Outward Processing Trade		-6.75**** (-9.89)
Squared Diff Ln Outward Processing Trade		6.27**** (6.89)
Diff Ln Total Factor Productivity	0.61**** (6.60)	0.66**** (6.84)
Diff Ln Gross Domestic Product	2.51** (3.00)	1.47 (1.48)
N observations	333	333
Wald (joint)	364.4****	462.8****
Wald (dummy)	308.5****	295.6****
Sargan test:	33.2	30.4
AR (1) test	-2.01**	-1.78*
AR (2) test	-0.18	-1.05

The table includes only results from the second step of two-stage GMM-Instrumental Variables estimates.
"Diff" indicates first-order differencing.
Time dummies are included in all the equations.
t values into brackets.
****100% significance, ***99% significance, **95% significance, *90% significance
Transformed instruments are the first lags of all the explanatory variables. Level instruments include time dummies and the dependent variable from lag 1 up to all the possible lags.

We now move to the choice of technology. We find that TFP has a positive and significant effect on the Unit Value index, confirming our hypothesis of simultaneity between the two variables. Firms buy high tech machines if they have enough skills to use them in a sufficiently productive way. Factor prices have the expected effects, although we find some non-linearity. The negative sign on the coefficient of the squared variable, shows that growing wages induce firm to move to more capital intensive machines, embodying more advanced technologies only when wages are relatively low. When wages are high, any further increase has little effect on the decision to change the technology of the machines used.

In regression 4 we include the variable OPT, capturing the involvement of foreign firms. Also in this case we have a non-linear relationship. The share of high tech machines increases only if the involvement of foreign firms in the industry is relatively large. If foreign involvement is low, an increase in the role of foreign firms has a negative impact on the level of the technologies purchased. The reason for this result could be that foreign firms may have a double effect in the choice of the technology. On the one hand they may help locals to choose appropriate technologies. If foreign firms are only marginally involved, this means that they also have limited requirements for high quality. So, simpler machines could be more appropriate. When foreigners get more involved, their demand for high quality increases and they consequently help locals in using more complex machines. In any case to reach firm conclusions on the role of foreign investors, we would need better data than OPT on FDI.

Finally, GDP growth has a positive impact on the choice of technology, confirming the descriptive evidence reported in the previous section.

5. Conclusions

In this paper we explore 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, which have recently deeply integrated their economies with the European Union.

This paper departs from earlier studies of international technology diffusion as it focuses on the technology embodied in the machines imported. The technological level of the machines imported 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. Moreover, 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. This reflects two inherent characteristics of technological progress in the last decade. On the one hand, the price of machines is stable, independently of technological progress. On the other hand, at any point in time, the prices of machines differ according to productivity. Therefore, although with time developing countries import machines which are increasingly more advanced, the gap *vis a vis* the technological leaders is constant. We show that this gap is significantly persistent, and that it is higher the lower the level of GDP of the importing country.

We also show that although the choice of developing countries to buy cheaper and less sophisticated machines is optimal, given relative factor prices and their endowments of technology, this choice has a negative effect on TFP growth at the industry level. In other words productivity growth in manufacturing depends positively on the type of machines imported in a given industry. The effect of embodied technologies on growth is found to be much more important than the effect of the share of imported machines on total investments in the industry.

Our results partly confirm earlier findings that importing machinery is a fundamental channel for productivity growth. Fundamental, but not sufficient. If, as the evidence clearly shows, developing countries keep buying low tech machines, they get captured in a poor technology low growth trap. If their productivity is low, they buy low tech machines. But if they buy low tech machines, they grow less. Thus the persistency of the technological gap is worrying, even when the share of imported machines on total investments grows.

Appendix 1. The Analytical Framework

We develop a simple framework to analyze the choice of the imported technology at the firm level and to estimate the impact of imported technologies on total factor productivity which provides a useful background to the empirical analysis.

Define total factor productivity

We assume the following Cobb-Douglas production function with constant elasticity to scale for a generic firm i at time t:

$$Q_{i,t} = \gamma K_{i,t}^{1-\alpha} L_{i,t}^{\alpha} \qquad (A1)$$

Total factor productivity is therefore given by:

$$\gamma_{i,t} = \frac{Q_{i,t}}{K_{i,t}^{1-\alpha} L_{i,t}^{\alpha}} \qquad (A2)$$

We assume that total factor productivity at time t depends on a vector of technologies imported at t and in the past Mit=(m_{it}, m_{it-1},..... m_{it-n}), on exogenous shocks x_{it} and on lagged productivity[6]:

$$\gamma_{i,t} = f(\gamma_{i,t-1},....\gamma_{i,t-n,} M_{it}, x_{it}) \qquad (A3)$$

Mit includes all different activities that allow i to acquire foreign knowledge, like importing foreign machines, exporting and developing relationships with foreign partners as buyers, suppliers, subcontractors or shareholders. As argued in various recent studies (Hoekman and Tybout, 1999, Djankov and Hoekman, 2000, Clerdies Lach and Tybout, 1998, Kraay, 1996), the main problem with the empirical specification of this productivity function is that the choice of the foreign activity is endogenous, in that it depends on expected productivity. We therefore need to jointly analyze and explicitly model the choice of the foreign activities. In this paper we focus on the choice of imported machines, under the assumption that the other foreign channels of learning affect productivity only indirectly, by reducing the cost of acquiring more complex foreign machines.

Machines

There are two types of machines: low technology (L) and high technology (H) ones. When machines are used at full capacity, productivity is higher for high tech than for low tech machines, i.e. $\gamma_H > \gamma_L$.

[6] This general specification of productivity is derived from Hoekman and Tybout, 1998

Full capacity output, q, is invariant with the type of the machine. TFP is higher when high tech machines are used as the amount of labour employed per unit of output q and capital k is lower, i.e. $L_H < L_L$. Thus, TFP when only one machine (unit of capital) is employed, is given by:

$$\gamma_{j,i,t} = \frac{q_{i,t}}{L^{\alpha}_{j,i,t}} \qquad for\ j = H, L \qquad \text{(A4)}$$

Machines last for one period and every period firm i decides whether to buy high tech or low tech machines. The choice is driven by the dynamics of TFP which differs for the two types of machines.

For low tech machines, TFP is time and firm invariant. Any firm is able to use low tech machines at full capacity. Thus:

$$\gamma_{L,i,t} = \gamma_L. \qquad \forall\ i,t$$

For high tech machines, TFP varies across firms and time. We assume a learning by doing process. TFP increases each period at a time-constant rate if i keeps choosing machines of type H. The time constant rate of increase of productivity is different for every firm. Firms are heterogeneous and some are better than other at using high tech machines:

$$\gamma_{H,i,t} = \phi_i \gamma_{H,i,t-i} \qquad where\, \phi_t \geq 1 \qquad \text{(A4)}$$

If $\phi_i = 1$ there is no learning by doing as

$$\gamma_{H,i,t} = \gamma_{H,i,t-1}. \qquad \forall\ i,t$$

If $\phi_i > 1$ there is learning by doing, in that productivity increases at a time constant rate ϕ_i. Thus learning takes place at a faster rate if ϕ_i is large. The ability of i to absorb new technologies (absorptive capacity) may depend on a series of factors, like the average education of the work force, or i's access to other sources of foreign knowledge, like linkages to foreign firms, exports etc.

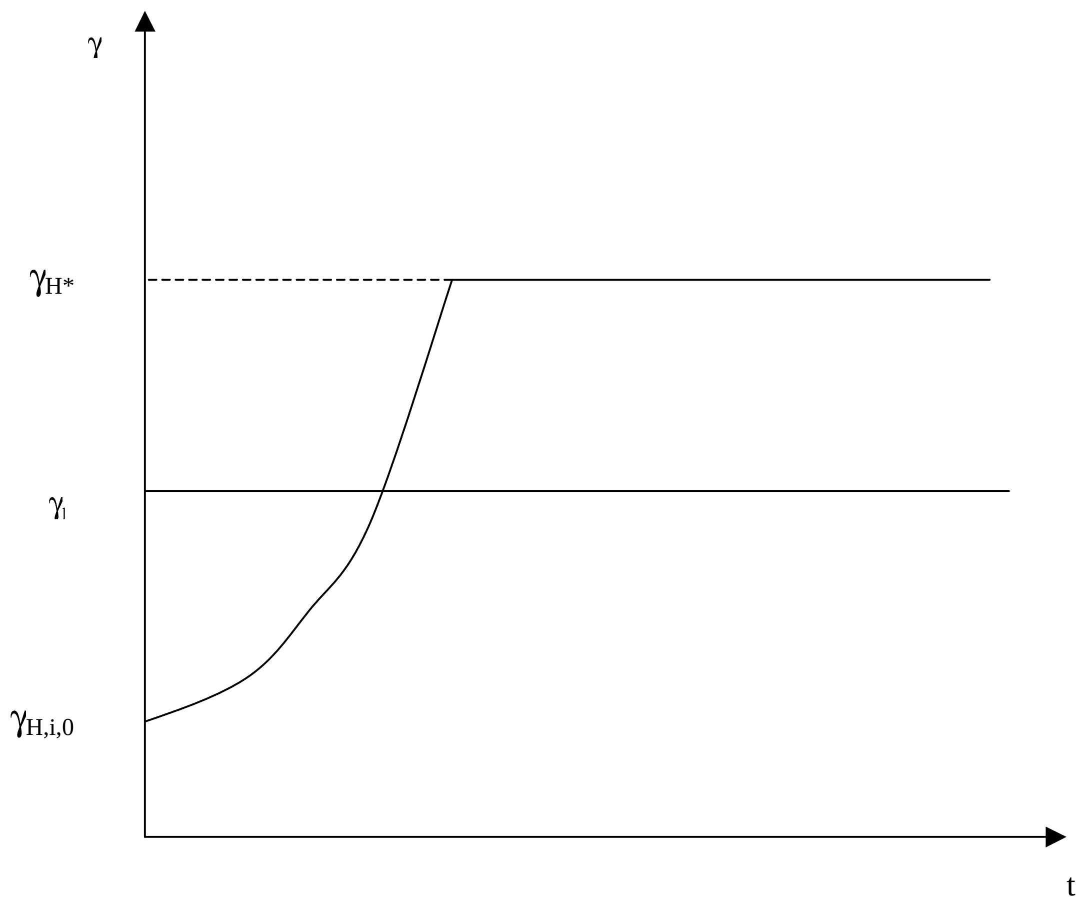
TFP in high tech machines reaches a maximum (full capacity) $\gamma_{H,i,t} = \gamma_{H,*}$, (which is the same across all times and firms) after a number of periods n_i.

$$n_i = \frac{\gamma_{H*}}{\gamma_{H,i,0}} \frac{1}{\phi_i}$$

thus the number of periods required to achieve full capacity TFP depends on the ratio between full capacity TFP and initial TFP when i first decides to use H and on the firm specific learning rate ϕ_i

The dynamics of TFP for high and low tech machines is reported in figure 1

Figure 1
Time path of total factor productivity for high and low tech machines



When i chooses a high tech machine, productivity could initially be even lower than for low tech machines. It then gradually increase with time at a rate that will depend on the firm's ability to absorb the new technology. The larger the absorptive capacity (ϕ_i) the steeper the $\gamma_{H,i,t}$ line and the faster i reaches full productivity capacity.

The choice of the machine

Each firm i will choose machine(s) of type L or H so as to ensure profit maximization. Given that productivity does not affect output per machine but just the labour requirement per unit of machine-output and given constant returns to scale, profit maximization is equivalent to minimizing production costs per unit of capital (machine). End of period production costs with machines L are given by[7]:

$$C_L = P_L(1+r) + w\left(\frac{q}{\gamma_{\mathrm{L}}}\right)^{1/\alpha} \qquad \text{(A6)}$$

where, $L_L = \left(\frac{q}{\gamma_{\mathrm{L}}}\right)^{1/\alpha}$, from (2),

End of period production costs with machine(s) H is instead given by:

$$C_H = P_H(1+r) + w\left(\frac{q}{\gamma_{\mathrm{H,i,t}}}\right)^{1/\alpha} - \delta \sum_{\tau=1}^{\infty} GTFP_{i,t+\tau} \quad \text{(A7)}$$

where, $L_{H,i,t} = \left(\frac{q}{\gamma_{\mathrm{H,i,t}}}\right)^{1/\alpha}$, from (2), and the third term in 6 represents the permanent future reductions in costs (increases in productivity) due to the learning by doing taking place in t. In other words, using machines H at time t generates a learning process that permanently increases productivity and reduces production costs. Explicitly, future costs reduction following the choice of H in t are given by:

$$\delta \sum_{\tau=1}^{\infty} GTFP_{i,t+\tau} = \frac{1}{r} w\left[q\left(\frac{1}{\gamma_{\mathrm{H,i,t-1}}} - \frac{1}{\gamma_{\mathrm{H,i,t}}}\right)\right]^{1/\alpha} = \frac{1}{r} w\left[q\frac{1}{\gamma_{\mathrm{H,i,t}}}(\phi_{\mathrm{i}} - 1)\right]^{1/\alpha}$$

Thus, H's cost function can be rewritten as:

$$C_H = P_H(1+r) + w\left(\frac{q}{\gamma_{\mathrm{H,i,t}}}\right)^{1/\alpha} - \frac{1}{r} w\left[q\frac{1}{\gamma_{\mathrm{H,i,t}}}(\phi_{\mathrm{i}} - 1)\right]^{1/\alpha} \qquad \text{(A7')}$$

The first two RHS terms in six represent the cost per unit of machine of producing with machine H at t. It is lower the higher the level of TFP achieved by i at t. Future costs reductions are larger the larger is the absorptive capacity of firm i (ϕ_i) and the lower the level of productivity attainable at time t. They tend to zero as productivity approaches its full capacity level and learning is completed. At this point production costs at t with H are at their minimum level.

Note that these cost functions may generate a hysteresis process for two reasons. First, because present production costs (the second RHS term in 6 and 6') keep declining with time if firms keep using the same type of machines, until full capacity productivity is reached. Second, because future benefits of choosing H at t (the third RHS term in 6 and 6') can only be accounted for if i keeps buying high tech machines in the future. Therefore, once a firm chooses high tech machines it does never move back to low tech ones.

[7] Under the assumption that machines are paid at the beginning of the period and wages at the end of it

To explicitly analyze the choice between L and H we derive the indifference price of high tech machines (i.e. the price at which i is indifferent between machines of type L or of type H) by equating (5) and (6'):

$$P_{i,t}^{*} = P_L + \frac{w}{1+r}[(\frac{q}{\gamma_{\mathrm{L}}})^{1/\alpha} - (\frac{q}{\gamma_{\mathrm{H,i,t}}})^{1/\alpha}] + \frac{w}{r(1+r)}[\frac{q}{\gamma_{\mathrm{H,i,t}}}(\phi_{\mathrm{i}} - 1)]^{1/\alpha} \qquad \text{(A8)}$$

which can be re-written as:

$$P_{i,t}^{*} = P_L + \frac{w}{1+r}[L_L - L_H] + \frac{w}{r(1+r)}[\frac{q}{\gamma_{\mathrm{H,i,t}}}(\phi_{\mathrm{i}} - 1)]^{1/\alpha} \qquad \text{(A8')}$$

Firm i will buy machines of type H whenever $P_{i,t}^{*} > P_H$. The probability of buying a high tech machine will therefore be larger the higher the indifference price of high tech machines.

The indifference price of H will be equal to the price of L, plus the short term savings in labour cost of using H (second RHS term of (7) and (7')) plus the the long term benefits of using H (third RHS term of (7) and (7')). It will be higher if at t i has already achieved a high productivity level (large short term benefits) or if its high absorptive capacity generates a fast learning process (high long term benefits). Given that H is a labour saving technology with a higher cost per unit of capital (machine) than L, higher wages and lower interest rates make short term savings more valuable. Lower interests also increase the discount factor and make future benefits more valuable. Consequently, the wage/interest ratio has a positive effect on the indifference price.

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Appendix 2

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 3: 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:

$$(1) \qquad Y_{jt} = A_{jt}(0)e^{\lambda_{it}}(K_{jt}{}^{\alpha jt} L_{jt}{}^{1-\alpha jt})$$

where *i* indicates sector, $A_i(0)$ represents initial conditions, λ_i is the rate of technological progress in sector *i*, α_i measures the importance of physical capital in output, and $1-\alpha_i$ the importance of labor. After taking logs and differentiating with respect to time, we have:

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

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:

$$(3) \qquad d\ln(Y_{cjt}) = \lambda_{cjt} + \alpha_j d\ln(K_{cjt}) + (1-\alpha_{ji})d\ln(L_{cjt}) + Dc + Dt + DR_{cjt} + \varepsilon_{cjt}$$

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:

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

Values estimated for α (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 and Turkey. Capital stocks were calculated according to the perpetual inventory method, The data source is UNIDO Industrial Statistics data base.

Appendix 4

	Variables description	**Data Source**
Total Factor Productivity	Total factor productivity (see appendix 3)	Unido Industrial Statistics
Unit Value Index	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	Wage rental ratios.	Unido Industrial Statistics and Comex-Eurostat
Import Share	Average share of imported machines on total investments	Comext, Eurostat and Unido Industrial Statistics
Outward Processing Trade	Shares of outward processed exports on total exports of the sample country.	Comext, Eurostat
Gross Domestic Product	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,

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