Does Promoting High Tech Products Spur Development?

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I. OVERVIEW

In the past decade, contributors to the endogenous growth literature have identified a variety of ways that learning might sustain long run growth. Among these, Lucas (1993) has argued that the mechanisms emphasized by Krugman (1987), Stokey (1988 and 1991) and Young (1991) provide an especially appealing characterization of developing countries: growth is accomplished by concentrating resources in those goods whose production processes induce learning and knowledge spillovers. Hence trade policy, by influencing the mix of production, can affect long run growth rates.

Despite its appeal, the Lucas/Krugman/Stokey/Young (hereafter LKSY) view remains largely untested. To distinguish it convincingly from other theories that relate trade to growth requires information on product-specific market shares and their evolution, as well as the technological sophistication and productivity growth rates associated with each product. Comprehensive product-level data of this kind are rarely available, and they are certainly missing in the relatively aggregated data sets that the empirical growth literature has focussed upon.[1]

Nonetheless, by exploiting plant-level panel data, it may be possible to get much closer to testing the LSKY view than the existing empirical growth literature has done. If particular products may be associated with particular plants, and if technological sophistication may be associated with the plant-specific engineer- and technician-intensity of production, these data should provide a reasonable basis for inference. This paper begins from the premise that they do.

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[1] Recent contributions to the empirical literature include Barro and Sali-Martin, 1994; Coe and Helpman, 1995; Keller, 1995; and Sali-Martin 1997.

After reviewing the theoretical models of interest (section II), we devote considerable time to rendering the concept of a "learning industry" empirically meaningful (section III). We then use plant- and industry-level data from Colombia and Morocco to characterize rates of movement up the continuum of products from low-end (little learning potential) to high-end goods (section IV). Finally, we look for evidence that relatively rapid productivity gains accompany relatively rapid movement up the goods continuum.

II. THE MODELS OF INTEREST

Most of the models that motivate our empirical work involve learning by doing. That is, in the process of manufacturing output, managers and workers acquire experience that makes them more productive. This well-documented phenomenon is typically summarized by a "learning curve" relating process-specific production costs to cumulative units produced.[2] For new processes the learning curve is downward sloping, but it eventually flattens out as the potential for learning is exhausted.

If each process is associated with a given product, knowledge accumulation is a non-decreasing, concave and bounded function of that product's cumulative output. Hence, when the set of goods produced is fixed, growth associated with learning is limited by the scope for refinement of the associated production techniques, and steady- state growth cannot be sustained by learning by doing. But if there are infinitely *many* goods subject to learning by doing, some not yet manufactured, then a shift of production away

[2] See, for example, early work by Alchian (1936) on airframe construction. Since then, many studies have found corroborating evidence that production experience decreases unit costs. Benkard (1997) provides an excellent recent contribution and documents partial spillovers from experience producing one generation of wide-body aircraft to the next generation's efficiency. Malerba (1992) provides a recent review of the literature and some evidence of his own.

from goods where learning by doing has been exhausted toward new goods where no learning has yet occurred induces growth. So long as new goods are introduced, growth persists.

Lucas (1988), elaborating on Krugman (1987), provides some structure to this line of thinking. He supposes that goods exist in infinitely-lived families. Each generation of good requires more human capital than the foregoing generation because it inherits the foregoing generation's human capital requirements and has some additional needs of its own. Because new generations of goods are continually introduced, learning by doing within each family is never exhausted. Some families of goods hold more potential for learning than others, so at any point in time, the aggregate rate of productivity growth in an economy is a weighted average of the learning rates in different families, the weights being measures of sector-specific production.

This framework provides one formalization of the infant industry argument: trade protection drives up the relative demand for industrial goods, accelerating learning there. Once industrial productivity is sufficiently high relative to productivity in other sectors, the economy has a comparative advantage in industrial goods, and opening to trade will cement in place specialization in the high growth sector.

The Krugman (1987) and Lucas (1988) models do not formally describe the process by which the goods within each family are introduced, refined, and eventually abandoned. But Stokey (1988) does precisely this. Focusing on a single family of products, she begins by positing an infinite continuum of produced or potentially producable goods, indexed in ascending order of technological sophistication. The higher the value of the index, the larger the number of Lancaster's (1966) characteristics the good possesses. For example, 133 megahertz laptop computers with CD ROM are more sophisticated than first generation PCs because they deliver all the useful characteristics supplied by early PCs, and much more.

As production occurs, all producers become more efficient through knowledge spillovers, but the effect of these spillovers on efficiency is strongest among relatively sophisticated goods. So over time these high-end goods drift into the set of goods produced, and eventually drive low-end goods from the market. Efficiency gains create income growth, which expands the relative demand for high-end products through Engel effects. Hence sustained growth is possible, and is accompanied by the introduction of increasingly sophisticated goods and the discontinuation of relatively primitive goods.

The model is general enough that growth rates may increase, decrease, or remain constant in the long run, depending upon one's assumptions regarding tastes, technology and knowledge accumulation. Further, when a "traditional" sector without learning effects is added to the model, it is possible that the economy will be trapped in a no-growth equilibrium, producing only the traditional good. However, if demand shocks induce at least some manufactured production, sustained growth begins. In this context, it is possible that trade could drive a country to specialize in goods without learning potential, thereby preventing growth. So results qualitatively similar to Krugman's (1987) and Lucas's (1988) are attainable with a more complete representation of the evolving product mix and associated learning processes.[3]

[3] As Lucas (1993) notes, however, trade becomes *intra*-industry when one moves to heterogeneous products and technologies.

Focusing more directly on trade, Young (1991) also posits a model where learning by doing in high-end goods is the source of growth. (Details are provided in Appendix I.) As in Stokey (1988), learning is bounded on each individual good and has positive spillovers across goods because learning contributes to aggregate human capital. However, instead of indexing goods by the number of their characteristics, Young ranks goods in terms of the "sophistication of the technical processes used" in their production. Experience producing one good reduces the unit cost of producing all goods with learning potential, and production costs are monotonically increasing in the level of sophistication. So, goods are introduced in the order of increasing technological sophistication.

Consumers have a strong, but bounded, preference for variety. As more and more technologically sophisticated goods are produced, consumers purchase a greater variety of them, but the price to marginal utility ratio for low-tech goods eventually sufficiently high that consumers drop them. Equilibrium here, as in Stokey's model, is characterized by unbounded growth and a gradual shift in the product mix toward high-end goods.

To explore the consequences of North/South trade, Young assumes that North is initially endowed with more human capital than South. This implies that in autarky the most sophisticated products are produced only in the North, and the most primitive products are produced only in the South. Moving to free trade generates the usual static gains, but there are also some dynamic effects that depend upon the relative populations and the initial difference in human capital.

To illustrate, suppose North has a greater labor force than South, and initial levels of human capital imply that there is some overlap in the range of goods produced by the two regions. Then North's low-end goods, where learning by doing for North has been exhausted, compete with South's high-end goods, where much of South's learning potential lies. (Simple electronic goods, like no-frill telephones and radios, might fall in this category.) Trade discourages both regions from producing this range of middle goods by making cheaper high-end substitutes available in South, and cheaper low-end substitutes available in North. Consequently, North diverts its workers toward higher-end goods, where more learning potential is, and South toward lower-end goods, where learning has been exhausted. North grows faster than in autarky and South grows slower.[4]

Of course, not all learning is a by-product of experience producing particular goods. Individuals typically devote some effort to skill acquisition because the returns from doing so can be partly internalized. Although Young (1991) rules out this type of activity, Stokey (1991) shows in a second model that schooling can be substituted for learning by doing without changing Young's (1991) conclusions much. In this model, high-end products are human-capital intensive, so a shift of demand toward these goods spurs investment in education, and accelerates the rate of knowledge accumulation.[5] Thus growth acceleration is still associated with shifts in the product mix toward high-end goods, and trade liberalization still has the potential to slow growth in developing countries, which have a comparative advantage in low-end products. One distinguishing

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4 Other outcomes are possible but less plausible. If South is sufficiently larger than North and the human capital gap sufficiently small, South may overtake North. In this example, South is so large and its technological handicap so small that before trade it produces all goods produced by North and some lower-end goods. Trade causes both to divert resources away from these goods toward higher-end goods, with greater learning potential. But because South has more workers to employ in high-end production, South grows faster than North and faster than in autarky.

5 Externalities in schooling are necessary to make the rate of knowledge accumulation a positive function of the *level* of schooling chosen by each generation.

feature of Stokey's (1991) schooling model is that production technologies themselves do not evolve with learning.

To summarize, Young (1991), Stokey (1988, 1991) and Lucas (1993) each attribute productivity growth to learning processes that make feasible the production of increasingly sophisticated products, and to the associated knowledge spillovers. The more rapidly learning takes place—either through schooling or through learning by doing—the higher the rate at which new high-end products are introduced, and the higher the rate of productivity growth. (Similarly, the productivity growth rate is monotonically related to the rate at which low-end products are discontinued.) Trade policy influences the relative demand for high-end products, and thus affects all three of these endogenous variables. A likely, but not necessary, consequence of trade liberalization in LDCs is that demand for high-end goods is dampened, thereby limiting the amount of learning and spillovers taking place.

These models capture a fundamental, albeit second best, rationale for infant industry protection in developing countries. They are distinct from other endogenous growth models because they link learning directly with product sophistication rather than with product variety (as, for example, in Romer, 1990, and Keller, 1995), with general improvements in the quality of a fixed set of goods (as, for example, in quality ladder models like Grossman and Helpman's, 1991b), or with the general quality of labor (as, for example, in Lucas's, 1988, human capital model). Accordingly they are unique in predicting that productivity growth is associated with continual movement up the spectrum of product sophistication, and that high-end goods should exhibit more productivity growth than low-end goods.[6] We now look for evidence that they are empirically relevant.

III. What is a Good with Learning Potential?

A. How theorists sort goods

The definition of a high-end good varies from model to model. Krugman (1987) and Lucas (1988) simply assume that in the high-end sectors, productivity is relatively sensitive to the amount of output they have produced. Since the scope for learning in the production of any particular product is eventually exhausted, the implicit notion is that sectors are composed of families of goods, and the family composition is continually shifting toward goods with unexhausted potential for learning by doing.

More elaborate models explicitly describe the shifting process. This means distinguishing individual products according to their unexploited learning potential rather than sorting broadly defined sectors. In Young's (1991) formulation high-end goods are those introduced recently enough that some refinements in the production process are still undeveloped. These goods are also characterized by learning spillovers that help other producers near the high-end of the product sophistication spectrum to become efficient more quickly. Stokey's (1988) formulation is similar, except in that efficiency gains among high-end goods are relatively rapid for any given increment to the stock of general knowledge.

[6] Stokey's (1991) model does not carry the implication that productivity growth should be more rapid among the more sophisticated goods.

Knowledge accumulation in both Young's (1991) and Stokey's (1988) first model is a purely external byproduct of production. In contrast, Stokey's (1991) second model treats knowledge accumulation as the result of privately optimal schooling decisions on the part of households. High-end goods in this formulation are simply those that require relatively high levels of schooling inputs per unit output. They are goods with learning potential only in the sense that they induce demand for schooling, which improves the quality of current generation workers and makes human capital acquisition easier for future generations through positive externalities. Unlike in the learning-by-doing models, the production technologies for these goods exhibits no more tendency toward efficiency gains than those for goods at the low end of the spectrum.

B. Feasible Empirical Sortings

The unexploited learning potential of a good cannot be directly observed; nor can the effects of any good's production on the general stock of knowledge. Thus, to examine empirically the growth mechanisms embodied in the models of interest, our first task is to characterize the learning potential associated with different products using observable data.

We will base our characterizations on comprehensive plant-level panel data sets from Colombia (1977 through 1991) and Morocco (1986 through 1990). In addition to annual information on inputs and outputs at each plant, these data include information on the composition of each producer's work force, distinguishing technical personnel from others. [7]

Unfortunately R&D intensity is not directly observable for either of the sample countries. However, our data bases do include a number of other variables that should proxy for the amount of learning going on. The number of technicians and their total wage bill is reported annually for plants in the Colombian panel, and in two years for plants in the Moroccan panel. When information on technicians is provided, the Moroccan data further disaggregate them into three categories: upper management, middle management and skilled workers. From these variables we construct *techwork*, *upmaemp*, *mimaemp*, and *skilemp*, which measure the share of technicians, upper management technicians, middle management technicians, and skilled workers, respectively, in total employment (Table 1). We also construct *techwage*, *techprod*, and *techexpe*, which measure the cost of technicians relative to the total wage bill, the total value of output, and total expenditures, respectively.[8]

Do our various measure of sophistication correspond to the theoretical notions described by Stokey (1988, 1991) and Young (1991)? Each measures the intensity of technical worker use, which is directly related to the notion of a high-end producer in Stokey's (1991) schooling model, and should proxy Young's (1991) and Stokey's (1988)

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7 The first version of this paper also treated Chilean data, which did not provide information on technicians, but did report expenditures related to patents. These data proved to be poor proxies for technological sophistication (in the sense that will be discussed shortly) so we have dropped Chile from the analysis.

8 In the Moroccan surveys, the categories of employees changed somewhat between 1986 and 1990. Further, consistency checks revealed that the labelling of certain worker types in Morocco was inconsistent between these two years. Appendix II discusses the measures we took to recover the correct labels.

earlier notion of a good with learning potential as well, so long as the production of products that involve learning requires relatively educated workers. Shortly we will look at correlations of product and firm rankings across proxies and countries.

Table 1: Technological Sophistication Indicators

Country/Years	***Variable***	***Definition***
Colombia, 1977-1991	*techwork*	number of technicians/total employees
	techwage	technicians' wage bill/total wage bill
	techprod	technicians' wage bill/total output
	techexpe	technicians' wage bill/total expenditures
Morocco, 1986 and 1990	*upmaemp*	upper management technicians/total employees
	mimaemp	middle management technicians/total employees
	skilemp	skilled workers/total employees

C. Correlations across indicators, countries, time

Before using our proxies for technological sophistication to rank industries and firms, it is worth exploring their empirical properties. We would like to know if they are stable through time at the industry level, as the Lucas and Krugman theories presume. (At the firm level, rankings may change if the potential for learning is exhausted among some producers.) Further, if our sectoral rankings are to provide a basis for generalization, we require that they be stable across countries. Finally, it would be comforting to find that our rankings are consistent with earlier work on product sophistication in the literature, which has focussed on R&D.

relation to R&D

Addressing the last issue first, we compare the industry rankings implied by our various measures in Table 1 to industry rankings based on R&D expenditure data from the

United States.[9] The United States data are reported at a level comparable to the 2 digit ISIC level, so we aggregate our plant-level data from Colombia and Morocco up to that level, and take averages of all variables in Table 1 over time.

Our findings are reported in Table 2. Even if technician intensity were an excellent proxy for R&D activity, we would expect imperfect correlations because of cross-country differences in product mixes within each industry, and variations in production techniques for given products. Nonetheless, a strong (greater than 0.75) correlation between both *techwage*, *mimaemp* and U.S. R&D expenditures appears to exist. There is also a high (greater than 0.65) correlation between both *techwork* and *upmaemp* and US R&D. Clearly, the high-end sectors in terms of R&D intensity in the U.S. appear to also be the high-end sectors in terms of technician-intensity in Colombia and Morocco. If R&D reflects learning, this is support for our use of the technician-intensity variables to rank products.

9 The U.S. data describe the period 1981-91. The R&D data are from *Science & Engineering Indicators–1993.*, p. 368.

Table 2: Correlation Coefficients Between Technological Sophistication Indicators and R&D Expenditures

Colombia		*Morocco*	
Technological Sophistication Measure	Correlation Coefficient (p-value)	Technological Sophistication Measure	Correlation Coefficient (p-value)
techwork	0.6500	*upmaemp*	0.6833
	(0.1476)		(0.1802)
techwage	0.7667	*mimaemp*	0.8500
	(0.0791)		(0.0351)
techprod	0.4000	*skilemp*	-0.2333
	(0.2909)		(0.3801)
techexpe	0.3833		
	(0.3000)		

Stability of rankings

Next, we wish to know whether product rankings based on the variables in Table 1 are stable over time. If we cannot associate a given *class* of products with a given position in the ranking, a basic premise of the LKSY framework is wrong, and it makes little sense to proceed. Individual firms, however, can be expected to drift up or down in the ranking as the nature of their products changes and goods enter or exit the population.

Table 3: Cross-Time Rank Correlations of Firms'Technological Sophistication

	Colombia (inital year 1977)				Morocco (inital year 1986)		
Correlation after:	*techwork*	*techwage*	*techprod*	*techexpe*	*upmaemp*	*mimaemp*	*skilemp*
4 years	0.5030	0.5128	0.5010	0.5020	0.4130	0.3153	0.1618
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
7 years	0.4642	0.4737	0.4645	0.4531	n.a.	n.a.	n.a.
	(0.0001)	(0.0001)	(0.0001)	(0.0001)			
10 years	0.4245	0.4339	0.4233	0.4143	n.a.	n.a.	n.a.
	(0.0001)	(0.0001)	(0.0001)	(0.0001)			
13 years	0.4002	0.4127	0.3994	0.3971	n.a.	n.a.	n.a.
	(0.0001)	(0.0001)	(0.0001)	(0.0001)			

Table 3 reports cross-time Spearman correlations of firms' sophistication rankings, for each of the technological sophistication indicators we consider. The results suggest that most of our technological sophication rankings are stable from period to period. As expected, the persistence of the rankings weakens over time; nonetheless it remains positive and significant for most sophistication measures. For example, the correlation coefficient for *techwork* is 0.50 for 1977 and 1981, but declines to 0.40 for 1977 and 1990 (the full time span). The same pattern emerges for the other indicators of technological sophistication, excepting *skilemp* in Morocco.

Cross-country stability

Finally, are the rankings stable across countries? If so, this suggests that technological factors, rather than local conditions, dictate the nature of production processes. If not, the results are unlikely to provide a basis for generalization to other countries.

Given that both the Moroccan and the Colombian rankings correlate strongly with U.S. R&D-based rankings, it is not surprising that they correlate well with each other (Table 4).[10] At the two digit level, the Colombian indicators *techwork* and *techwage* are highly correlated (i.e., $\rho > 0.675$) with the Moroccan indicators *upmaemp* and *mimaemp*. And in 1986 all are significant at the 5% level or below.

Disaggregating introduces more scope for country-specific products and technologies. Nonetheless, correlations remain strong at the three digit level (refer to the middle panel of table 4). Note that *techwage* and *techwork* are significantly correlated with

[10] Table 4 is based on 1986 data. Patterns in the 1990 data are similar, but somewhat weaker. Figures are available upon request.

all of the Moroccan indicators of technician intensity. And *skilemp* is significantly correlated with all of the Colombian indicators of technician intensity.

At the four-digit level, all indicators of Colombian technician intensity and Moroccan technician intensity are significantly correlated (bottom panel, table 4). The strongest correlations are between i) *techwork* and both *upmaemp* and *mimaemp* and ii) *techwage* and both *upmaemp* and *mimaemp*.

Table 4: Cross-Country Correlation Coefficients, 1986

	upmaemp	*mimaemp*	*skilemp*
	2-digit rankings		
techwage	0.7167	0.6333	0.0500
	(0.0298)	(0.0671)	(0.8984)
techwork	0.7667	0.4167	0.2333
	(0.0159)	(0.2646)	(0.5457)
techprod	0.0833	0.0667	0.3833
	(0.8312)	(0.8647)	(0.3085)
techexpe	0.2333	0.3167	0.2333
	(0.5457)	(0.4064)	(0.5457)
	3-digit rankings		
techwage	0.6254	0.5562	0.0677
	(0.0008)	(0.0039)	(0.7478)
techwork	0.6408	0.5423	0.0300
	(0.0006)	(0.0051)	(0.8868)
techprod	0.3546	0.1969	0.1800
	(0.0820)	(0.3454)	(0.3892)
techexpe	0.5223	0.2446	0.1777
	(0.0074)	(0.2386)	(0.3955)
	4-digit rankings		
techwage	0.4394	0.4116	-0.0304
	(0.0002)	(0.0005)	(0.8059)
techwork	0.4691	0.4195	0.0127
	(0.0001)	(0.0004)	(0.9181)
techprod	0.1752	0.2693	0.1508
	(0.1530)	(0.0264)	(0.2198)
techexpe	0.1855	0.2705	0.1314
	(0.1298)	(0.0257)	(0.2856)

summary

In sum, two Colombian technician intensity indicators, *techwork* and *techwage* , and two Moroccan indicators, *upmaemp* and *mimaemp* , are strongly correlated across countries. Moreover, these indicators yield industry rankings closely related to those based on U.S. R&D intensity, and are quite stable over time. For all of these reasons we will hereafter focus on *techwork, techwage, upmaemp* and *mimaemp* in our analysis.

IV. EVOLUTION OF THE SECTOR-LEVEL TECHNOLOGICAL SOPHISTICATION

With a means to describe the learning potential associated with each industry—indeed, each firm—we can now proceed to ask whether the manufacturing sectors in our sample countries have been getting increasingly sophisticated. There are two senses in which this might occur. One, which is predicted by the LKSY product spectrum models, is by continually shifting resources toward high-end products. The other is through a *general* increase in the intensity of skilled input use among all types of products. This is the kind of human capital deepening that provides an engine for growth in models that do not distinguish a spectrum of products in terms of their potential to generate learning (e.g., Barro and Sali-Martin, 1995, Chapter 5; Lucas, 1988).

A. Inter-industry shifts

To distinguish these two types of increases in the sophistication of production, we begin by writing the growth rate of manufacturing-wide technological sophistication, *e*, between *t-1* and *t* as the sum of two components:

(1) $$\frac{\Delta e_t}{e_{t-1}} = \frac{\sum_{j=1}^{J} \Delta e_{jt}\, \bar{\theta}_j + \sum_{j=1}^{J} \Delta \theta_{jt}\, \bar{e}_j}{e_{t-1}} \;.$$

Here e is the total number of technicians in manufacturing, expressed as a share of total manufacturing employment. Subscripts j and t indicate the industry and time period, respectively, θ_j is the j^{th} industry's share in manufacturing-wide employment, an overbar indicates the simple average over the two time periods, and Δ is the difference operator for the period t-1 to t. The same expression can be used, *mutatis mutandis*, to decompose changes in manufacturing-wide technician wages as a share of some manufacturing-wide normalizing variable (either total wages, expenditures, or production).

The first term in the numerator on the right hand side captures the change in manufacturing-wide technological sophistication due to *within*-industry deepening of technician intensity, and the second term represents the reallocation of workers across industries. If the second term is positive, then the technician-intensive industries are growing relatively rapidly, indicating the type of resource reallocation consistent with LKSY-type productivity growth. In contrast, if all of the change in aggregate technician intensity comes from intra-industry deepening, there is no evidence of this type of broad resource reallocation. Nonetheless, it may still be case the case that *within* particular 3-digit or 4-digit industries, resources are being shifted toward high-end products, in which case further disaggregation is needed to detect the LKSY growth mechanism.

Table 5: Change in Technological Sophistication: Decomposition

Country	Period	Measure of Technological Sophistication	Total Growth		Deepening Effect		Share Shifting Effect
	(t-1)–t		$\Delta e/e_{t-1}$	=	$\Sigma\Delta e\ \bar{\theta}/e_{t-1}$	+	$\Sigma\Delta\theta\ \bar{e}/e_{t-1}$
Colombia	77–91	*techwork*	0.6159		0.6253		-0.0094
	78–86		0.1765		0.1780		-0.0146
	82–89		0.2054		0.2154		-0.0099
	77–91	*techwage*	0.0543		0.0338		0.0206
	78–86		-0.0241		-0.0593		0.0353
	82–89		0.0720		0.0759		-0.0039
Morocco	86–90	*upmaemp*	0.8846		0.9581		-0.0735
	86–90	*mimaemp*	0.3895		0.4835		0.0940
	86–90	*skilemp*	2.4135		2.3113		0.1022

Table 5 implements equation (1) for each of the sophistication measures in Table 1, distinguishing industries at the **3**-digit level. For Colombia we report three sub-periods to control for business cycle effects: the entire sample period (1977-91), the trough-to-trough period (1978-1986), and the peak-to-peak period (1982-1989). Moroccan manufacturing output expanded during the entire sample period so this exercise was not feasible. Note also that in Morocco the definition of a skilled worker changed somehow between 1986 and 1990, rendering *skilemp* useless as a measure of the total increase in technological sophistication.

The message conveyed by table 5 is striking. Clearly, although technological sophistication generally increased from period to period, this was almost entirely attributable to upgrading within industries, rather than a reallocation of market share toward more technologically sophisticated industries. So, at this very broad level, aggregate technological sophistication appears to increase because of a deepening of technological sophistication in all industries, not because high-end sectors grew relative to other industries.

It is somewhat surprising that inter-sectoral shifts are not more important. Other studies have documented a systematic shift of production away from simple manufactured products as the development process unfolds (e.g., Chenery and Syrquin, 1986). One interpretation is that our time periods are relatively short, and much of the temporal variation is due to the major contractions and recoveries associated with the debt crisis and its aftermath. Nonetheless, we find evidence that production became more technician-intensive in the aggregate during *all* subperiods, so the data do reflect long-term forces.

Interestingly, similar decompositions have been done for a wide range of developed countries to address the issue of whether pervasive skill-biased technical change explains the globally rising wage gap between skilled and unskilled labor. The findings, summarized in Behrman, Machin and Bound (1996), suggest that most of the rise in the skill intensity of production is due to skill deepening *within* industries, rather than shifts in the product mix toward skill-intensive sectors. However, with a few exceptions, they also find a role for product mix shifts toward skill-intensive industries.[11] So, assuming that the level of disaggregation is sufficient, one might argue that during the 1980s, whatever movement toward high-end products took place was concentrated in the industrialized economies.

[11] Between 1980 and 1990, Behrman, Machin and Bound (1996) report that 73 percent of the skill deepening in the U.S. was due to within-industry effects, 143 percent in Luxembourg, 59 percent in Sweden, 99 percent in Australia, 121 percent in Japan, 87 percent in Denmark, 79 percent in Finland, 73 percent in Austria, 94 percent in the U.K., and 49 percent in Belgium. The level of disaggregation they use is roughly comparable to our 3-digit ISIC results.

B. Intra-Industry Shifts

We now look at changes within industries and ask whether sector-level technological sophistication increased because all firms became more sophisticated, or because of intra-industry market share reallocations toward more sophisticated firms. To do this we decompose each Δe_{jt} term in equation (1) into the effect of intra-plant changes in technician intensity, and the effect of changes in the allocation of workers across plants. This exercise is basically the same as our sectoral decomposition, however it is complicated by extra terms to deal with the entry and exit of producers over the sample period. Our expression becomes:

$$(2) \quad \frac{\Delta e_{jt}}{e_{jt-1}} = \frac{\overline{\alpha_j}\left[\sum_{i=1}^{I} \Delta e_{ijt}^{c}\, \overline{\theta}_{ij} + \sum_{i=1}^{I} \Delta \theta_{ij}^{c}\, \overline{e}_{ij}\right]}{e_{jt-1}} + \frac{\Delta \alpha_j \left[\overline{e_j^{c}} - \frac{e_j^{b} + e_j^{d}}{2}\right]}{e_{jt-1}} + \frac{(e_j^{b} - e_j^{d})(1 - \overline{\alpha_j})}{e_{jt-1}}$$

Here *c*, *b* and *d* indicate continuing, entering (beginning) and exiting (dying) firms, respectively and *i* subscripts refer to individual producers. α_j is the share of continuing plants in total employment within industry *j*. (The other symbols are as before.) The first ratio on the right-hand side resembles equation (1). Its numerator disaggregates changes in technician intensity among incumbent producers into two subcomponents: one is *incumbent upgrading*, and the other is *shifts in market share among incumbents.* The second ratio measures the effect of changes in the market share of incumbent firms, or equivalently, *changes in the turnover rate*. This term indicates that when incumbents are more intensive in technicians than entering and exiting plants, then reductions in the amount of turnover (increases in α_j) will increase industry-wide technology intensity. Finally, if entering plants are more technician-intensive than the exiting plants they replace, ongoing producer turnover will also increase industry-wide technology intensity. This *replacement effect* is described by the third ratio.

Note that a positive value for any of these four effects except *incumbent upgrading* corresponds to resource reallocation toward high-end producers. To the extent that individual firms manufacture the same product or products over time, these cross-firm resource reallocations can be interpreted as cross-*product* shifts, reflecting the LKSY growth mechanism. Of course, if the movement toward higher-end products takes place mainly *within* plants, rather than by high-tech plants displacing more primitive plants, the associated increase in technician intensity will show up as incumbent upgrading and we will fail to isolate it with our decomposition.

We summarize the findings using weighted-averages of the industry-specific findings in Table 6.[12] Interestingly, unlike in the cross-industry results (Table 5), here we do find evidence of systematic cross-product resource reallocation toward high-end plants. It is not due to market share reallocations toward incumbents who are technician-intensive; rather it reflects the ongoing replacement of dying, low-end plants by entering higher-end plants. Although the magnitudes of these figures vary with the country, time period, and measure of sophistication, the general pattern is remarkably stable. Finally, it is worth noting that there is tremendous cross-industry variation in the change in total technological sophistication and its components. (Industrry-by-industry figures are available upon request.)

[12] The weights are the shares of each industry in total employment.

Of course, even these figures the miss the market share shifting that goes on *within* plants as older products are dropped or scaled back and new products are added. If this is the dominant kind of product shifting, the LSKY growth mechanism will be consistent with stable market shares for high-tech plants, but these plants will consistently log the highest productivity growth rates. We will explore this possibility in section IV below.

Table 6: Sources of Intra-Industry Change in Technological Sophistication (Weighted Averages of Industry-specific Results)

Country	*Period*	*Measure of Technological Sophistication*	***Total Change***	***Incum-bent Effect***	*Market Share Shifts among Incumbents*	*Incumbent Upgrading*	***Changes in firm Turnover Rate***	***Replacing Exiters with Entrants***
			(1)	(2)	(2a)	(2b)	(3)	(4)
Colombia	77–91	*techwork*	0.8153	0.5197	0.0171	0.5026	-0.0099	0.3054
	78–86		0.2936	0.2159	0.0221	0.1938	0.0096	0.0681
	82–89		0.3370	0.2631	-0.0103	0.2734	-0.0034	0.0773
	77–91	*techwage*	0.1944	0.1638	0.0092	0.1546	-0.0057	0.0363
	78–86		0.0870	0.0937	0.0326	0.0611	0.0071	-0.0138
	82–89		0.2147	0.1722	-0.0054	0.1776	0.0042	0.0385
Morocco	86–90	*upmaemp*	1.0684	0.8781	0.0278	0.8503	0.0462	0.1476
	86–90	*mimaemp*	0.6568	0.4849	-0.0008	0.4857	0.0179	0.1582
	86–90	*skilemp*	2.4539	2.0838	0.0014	2.0824	-0.0138	0.3764

IV. IS PRODUCTIVITY GROWTH CONCENTRATED AMONG HIGH-END GOODS?

Thus far we have seen evidence that our sample countries have increased the intensity with which they use technicians, and that this is partly (although not mainly) due to intra-industry shifts in their product mixes toward high-end producers. If the these producers manufacture goods that hold the most potential for learning and productivity growth, then the LKSY growth mechanism is present. In this section we empirically address this key final link.

A. R&D & Productivity: The Literature

Not surprisingly, the notion that invention and technical change are central to productivity growth has attracted considerable attention from applied researchers. Several basic findings have emerged. First, firm-level data suggest that the elasticity of output with respect to the stock of firm R&D capital is sizable and significant.[13] Second, a number of studies find evidence of significant R&D spillovers. In his literature survey, Griliches (1992) concludes that, "taken individually, many of the studies are flawed and subject to a variety of reservations, but the overall impression remains that R&D spillovers are both prevalent and important."

These studies simply suggest that the return to R&D is positive. But the LKSY mechanism requires a link between product sophistication and rates of learning-based productivity *growth*. Given that R&D-intensive firms produce relatively sophisticated products, there is some evidence to support this phenomenon as well. For example, Clark and Griliches (1984) regress total factor productivity growth on R&D intensity and find a positive, significant relationship.

B. What we find in our data

Does the link between product sophistication and productivity carry over to the developing world? If so, is there evidence that productivity growth is accomplished there by shifting the product mix toward high-end goods? Are spillovers in evidence?

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13 Griliches and Jacques Mariesse (1984) find this relationship in the cross-sectional dimension of a sample of more than 100 U.S. manufacturing firms. In the time dimension, however, the collinearity of key variables makes it difficult to isolate a positive relationship. Using a panel of French firms, Cuneo and Mariesse (1984) find that the elasticity of value added with respect to the stock of firm

We approach these questions at two levels. First, at the level of the firm, we investigate whether technician-intensive firms are relatively productive and/or exhibit relatively high productivity growth. Then, at the level of the industry, we ask whether technologically sophisticated industries exhibit relatively rapid productivity growth, and whether they accomplish this by shifting market shares toward high-end firms and/or exploiting spillover effects.

Our productivity measure is based on estimates of a constant returns Cobb-Douglas production function relating gross output to primary factor inputs:

(3) $$\bar{y}_i = \alpha + \beta * \bar{k}_i + (1-\beta) * \bar{l}_i + \varepsilon_i$$

Here overbars denote cross-year averages of the associated variables, *i* indexes plants, and *y*, *k* and *l* are the log of output, capital stock and labor, respectively.[14] We measure labor in efficiency units, so l is a relative wage-weighted-sum of the different types of labor. This ensures that productivity will *not* appear to improve when a high-skilled worker is employed unless that worker's employment increases real output more than it increases the cost of labor inputs to the firm. Using the estimates from (3), we obtain firm level primary factor productivity estimates residually from:

(4) $$PFP_{it} = y_{it} - \hat{\alpha} - \hat{\beta} \cdot k_{it} - (1-\hat{\beta}) \cdot l_{it}$$

Appendix III provides further details.

R&D capital in both the cross-sectional and time dimensions is large and significant. Similarly, Fikkert (1996) finds large and significant effects of R&D on productivity in a panel of Indian firms.

14 The data sets are unbalanced panels; so estimate (3) using weighted least squares. The weight for the ith observation is the number of years for which the *i*th firm reports data.

Firm-level correlations Table 7 reports our findings at the firm level. The first column reveals a strong relationship between contemporaneous technician intensity and productivity levels in both countries, and the second column reveals a weaker but still significant correlation between lagged technician intensity and productivity levels. These results are similar to the finding that high-R&D firms are more productive in industrialized countries. But here it does not simply mean that there is a positive return to replacing unskilled workers with highly paid technicians. Since we have used a wage-weighted average of worker types to construct our measure of the labor input, the implication is that technicians generate more in revenue than they add to cost (see Appendix III). That is, conditioning upon capital stocks, gross revenue per unit cost is higher among technician-intensive producers.

Table 7: Firm Level Productivity and Technological Sophistication

	Firm Level Correlations				
Country Year	(PFP_t, TS_t)	(PFP_t, TS_{t-1})	$(\Delta\ln(PFP), \ln(TS_t))$	$(\Delta\ln(PFP), \ln(TS_{t-1}))$	$(\Delta\ln PFP, \Delta\ln TS)$
Morocco 86-90	0.2067* (0.0000)	0.0725* (0.0004)	0.0338 (0.3030)	0.0015 (0.9691)	0..0465 (0.4488)
Colombia 77-91	0.0858* (0.0003)	0.0094 (0.6948)	-0.0029 (0.9324)	0.0205 (0.5564)	-0.0058 (0.3353)
Colombia 78-86	0.1671* (0.0000)	0.0709* (0.0011)	-0.0477 (0.1328)	0.0618 (0.0513)	-0.0267 (0.5374)
Colombia 82-89	0.1380* (0.0000)	0.0552* (0.0177)	-0.0582 (0.0798)	0.0511 (0.1242)	-0.1608 (0.0002)
Colombia Average	0.1802* (0.0000)				

For Morocco, TS = upmaemp; for Colombia, TS = techwage.
** Significant at the 95% level of confidence.*

This pattern is encouraging, and consistent with previous work. But it does not speak directly to the LKSY hypothesis, which posits that productivity *growth* is relatively rapid among high-end goods. To look for evidence of this phenomenon, we examine the correlation between firm productivity growth rates and technician intensity levels (columns 3 and 4). Neither initial technician intensity (TS_{t-1}) nor ending technician intensity (Ts_t) correlates significantly productivity growth rates. Hence, although technician intensity is clearly related to the *level* of productivity, there is no evidence that the firms with high-skilled workers generate rapid productivity *growth*.

More puzzling is the lack of association between *growth* in technician intensity ($\Delta\ln TS$) and growth in productivity ($\Delta\ln PFP$). This is simply a growth form of the relationship described by column 1. One interpretation is that the association between technological sophistication and efficiency gains is a loose one. Productivity growth does not immediately kick in when new technicians are hired, nor is it automatic after a gestation period. Hence timing lags and uncertainty make the number of technicians a noisy measure of the flow of efficiency-enhancing services, and the bias due to this noise is most severe when we identify the correlation parameter using only temporal variation in the data.[15]

Industry-level correlations: Presuming that we may associate products with plants, the absence of a plant-level correlation between technological sophistication and productivity growth is inconsistent with models in which high-end goods exhibit relatively rapid efficiency gains. But it does not rule out all growth models based on product

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[15] Panel data estimators that rely on temporal variation for identification are well known to exacerbate measurement error bias (Griliches and Hausman, 1986).

shifting. For example, if the gains from learning quickly diffuse throughout a sector, then the technician-intensive plants at which learning originates may not exhibit unusual productivity growth, even when the LKSY growth mechanism is present.[16] Also, if all of the shifting toward high-end goods takes place by low-end plants shutting down and high-end plants replacing them (as Table 6 suggests), turnover can sustain productivity growth even if individual plants exhibit constant productivity during their lifetime.

To address these possibilities, we must look at industry-level patterns of technician use and performance. Specifically, using our industry-specific decomposition of growth in technician intensity (equation 2), we distinguish intra-plant upgrading from inter-plant share reallocation effects. Then we regress our industry-level productivity growth rates on these two sources of technician intensity growth to determine if share reallocations are associated with productivity growth spurts (columns 1 and 2). Also, we regress productivity growth on the sum of these components, that is, the industry-wide rate of technological sophistication.

16 Although this would mean that producers did not internalize all of the returns to hiring technicians, we have seen that technicians pay off in a static sense by generating higher output levels.

Table 8: Sector Level Productivity and Technological Sophistication

(Dependent Variable = %ΔPFP)

	Equation 1		Equation 2
	Within-Plant Deepening	With-Industry Share shifting	Total Increase in Technological Sophistication
Morocco	-0.4422	0.8804	-0.0520
86-90	(0.3027)	(0.6440)	(0.1090)
Colombia	0.1097	-0.1240	0.0015
77-91	(0.0683)	(0.1952)	(0.0133)
Colombia	0.3202*	-0.4860	0.0609
78-86	(0.1409)	(0.4025)	(0.0722)
Colombia	0.2819*	-0.0512	-0.0316
82-89	(0.0850)	(0.2429)	(0.0547)

Standard errors are in parentheses.

* Significant at the 95% level of confidence.

The results of this exercise are reported in table 8.[17] Notably, there is still no evidence that changes in technician intensity are related to productivity growth in Morocco. However in Colombia, there is a fairly strong relationship between productivity growth and increases in technician intensity due to *intra*-plant upgrading (column 1). That is, the sectors that become increasingly reliant on technicians are also the ones that exhibit the most rapid productivity growth. On the other hand, increases in technician intensity due to market share reallocations are *not* significantly associated with productivity gains (column 2). Finally, simple regressions of TFP growth on the rate of growth in technician intensity reveal no significant associations (column 3).

This Colombian pattern is intriguing. It suggests, first, that industries do not typically sustain productivity by shifting market shares toward plants that produce high-end products. This is evidence against the LKSY vision of successful development,

[17] The results are similar across the various measures of technological sophistication so, for Morocco, we report only the results for *upmaemp* and, for Colombia, *techwage*.

although shifts toward high end goods may take place *within* multi-product plants rather than across plants, remaining invisible to the measure of reallocation effects described by equation (2).

There is a second message in the Colombian results. We have already seen in Table 7 (column 5) that there is no tendency for plants that increase their technician intensity relatively quickly to exhibit relatively rapid productivity growth. Yet Table 8 tells us that this link between growth in technician intensity and productivity growth exists at the *industry* level for the same plants and time periods. One interpretation is that spillovers are indeed important, and that the returns to learning at the plant of origin are less than the industry-wide returns. Such spillovers are central to endogenous growth models with learning, not just of the LKSY variety.[18] So if this interpretation is correct, it constitutes an important piece of evidence in favor of these models' relevance.

Are other interpretations plausible? We initially thought our results might imply that the link between technician intensity and productivity growth is only present among large producers. This would explain why simple cross-plant correlations don't pick much up, but weighted averages at the industry level do. But limiting the sample to producers with at least 50 workers and repeating the correlations in table 7, we still found no evidence that productivity growth was related to growth in technological sophistication. (The results are available upon request.) A third view is that the measurement error bias one encounters when using firm level data is reduced when the noise is "averaged out" by aggregating across firms. This remains a possibility.

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[18] Jones (1995) provides an illuminating summary of the role of knowledge spillovers in endogenous growth models.

A final message of Table 8 is that the relation between technician intensity varies across countries. None of the industry-level correlations we find in Colombia appear in Morocco. An important, yet unanswered question is why the correlation patterns are unstable.

V. SUMMARY AND CONCLUSIONS

Many policy makers know in their hearts that they can induce learning-based productivity growth by promoting technologically sophisticated products. They have cited this article of faith for at least 40 years as a justification for infant industry protection, and the growth models to back them up have been belatedly contributed by Krugman (1987), Lucas (1993), Stokey (1988, 1991) and Young (1991). This paper looks for evidence of its empirical relevance using plant-level panel data from Colombia and Morocco.

To link productivity growth with product sophistication, it was necessary to develop an observable proxy for the latter. We used the share of technicians in total employment because this measure yielded stable plant rankings across time, and stable industry rankings across time and countries. Further, it proved highly correlated with industry rankings from U.S. data based on R&D intensity. (R&D was not observable in our panels.)

Next, using this product sophistication measure, we documented the extent and nature of shifting going on in our sample countries. We found that Colombia and Morocco both became significantly more technician-intensive over their respective sample periods, but most of this was due to increases in technician intensity within plants rather than increases in the market share of technician-intensive producers. To the extent that the latter took place, it was mainly due to the exit of low-tech plants and their replacement by more sophisticated entrants.

Although our sample countries did not rapidly shift market shares toward high-end producers, it seemed quite possible that the shifts which did take place were generating productivity growth. To investigate this possibility, we constructed plant-specific productivity trajectories for the firms in our sample and looked at the patterns of correlation between technician intensity and efficiency gains. As in other studies based on data from industrialized countries, we found that high-tech plants were more productive; so much so that the productivity gains more than offset the extra cost of hiring technicians. However, there was no evidence in the data that productivity *growth* rates were above average in the high-end plants. Hence a key link in the argument that promoting high-end goods increases productivity growth was not supported by the data.

Interestingly, however, we also found that in Colombia the *industries* undergoing rapid intra-firm growth in technician intensity were also improving their productivity relatively rapidly. Since the individual plants that were acquiring more technicians were not experiencing unusually rapid growth, it appears that they may have been generating positive spillovers for their competitors by increase the general knowledge stock. If this interpretation holds up to closer scrutiny, the Colombian data appear to confirm one key link in learning-based endogenous growth models. Further work is needed to pursue this important possibility, but the preliminary evidence is quite strong.

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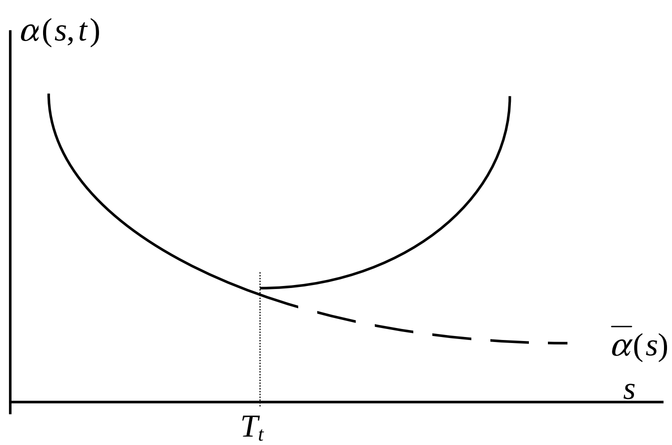
Appendix I: Young's (1991) model

Young (1991) begins by sorting potentially producable goods according to their technological sophistication. Positions in the ranking are indexed by $s\in [B,\infty]$, with higher s indicating greater sophistication. Also, at time t, all goods for which learning possibilities have been exhausted have indicies $s < T_t$, and all goods with further learning potentional have indicies, $s > T_t$.

Producing a unit of good s at time t requires $\alpha(s,t)$ units of labor and nothing else. For closed form solutions, Young assumes:

$$\alpha(s,t) = \begin{cases} \overline{\alpha}(s) \ if \ \ s \leq T_t \\ \overline{\alpha}(T)e^{s-T} \ \ if \ \ s \geq T_t \end{cases}$$

where $\overline{\alpha}(s) = \overline{\alpha}e^{-s}$. This ensures that the greater the sophistication of the good, the greater potential efficiency, once learning effects are exhausted. Further, among goods with unexhausted learning possibilities, labor requirements are positively related to their sophistication, as depicted below.

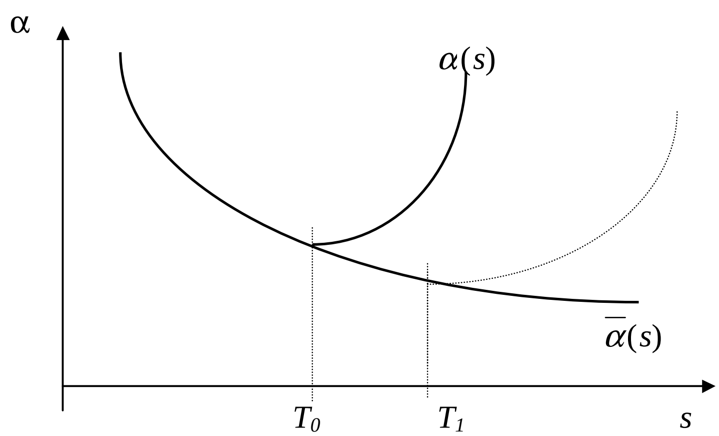


Finally, among goods with learning, Young assumes that efficiency improves at the common rate: $\frac{\partial \ln \alpha}{\partial t} = -2\frac{dT}{dt}$ The rate of efficiency growth among goods with unexhausted learning potential is then directly related to the amount of labor employed in the learning sectors:

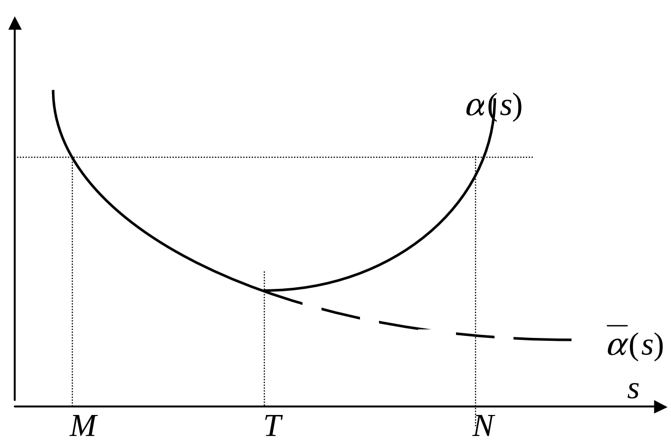
$$\frac{dT}{dt} = \int_T^\infty L(s,t)ds, \quad \text{so}$$

$$\frac{\partial \ln \alpha(s,t)}{\partial t} = \begin{cases} -2\frac{dT}{dt} = -2\int_T^\infty L(v,t)dv & \forall\ s > t \\ 0 & \forall\ s \le t \end{cases}$$

where $L(s,t)$ is the amount of labor being used to produce good s at time t. These expressions imply that the locus of production costs drifts rightward as experience producing the high-end goods accumulates. Hence, for any $T_0 < T_1$:



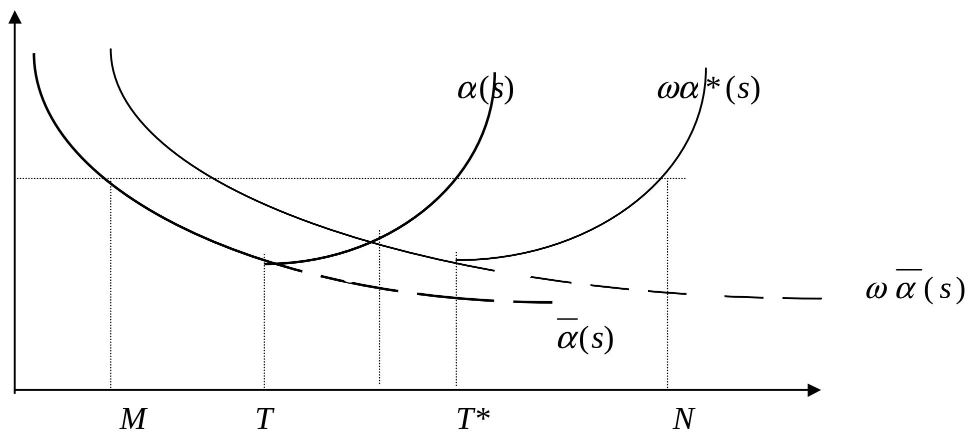
The returns to knowledge creation through learning cannot be internalized, so given the constant returns technology, pricing is competitive: $P_s = w\alpha(s,t)$. Given perfect foresight regarding these prices and economy-wide income, consumers maximize the present value of their instantaneous utility, $V = \int_B^{\infty} \ln[C(s)+1]ds$, where *C(s)* denotes instantaneous consumption of good *s*. There is no storage, so at each point in time consumers spend all their income and the conditions for static utility maximization apply. Among all goods consumed, the usual condition holds, $\frac{MU_S}{MU_{S'}} = \frac{C_{S'}+1}{C_S+1} = \frac{P_S}{P_{S'}} = \frac{\alpha(s)}{\alpha(s')}$, but some goods are so expensive relative to the utility they generate that they aren't consumed at all. Call the low-tech good on the margin between zero and positive consumption good *M*, and the high-tech good on this margin good *N*. Then, $\frac{1}{C_S+1} = \frac{P_S}{P_M} = \frac{\alpha(s)}{\alpha(M)}$, or $\alpha(s)C_s = \alpha(M) - \alpha(s)$. In autarky, this means that labor devoted to the production of each good consumed is the vertical distance to the horizontal line at height $\alpha(M)$:



The rate of change in T is *L/2*, and this is also the rate of growth in GDP per capita.

Now suppose that trade is opened up with a country that is further along (larger *T*) and has a higher wage $w^* = \omega w$. Then the menu of alternative goods available in the

South will be as diagrammed below. (Other configurations are possible, depending upon relative size and tech. gap.)



Note that the LDC high-end goods are undercut by the more advanced DCs, so trade shifts the LDC labor force toward goods with no learning potential, and less spillovers take place. Growth slows in the LDCs. In the DC s, production of the low end goods is undercut by the low-wage LDC. So there, labor is shifted toward goods with high learning potential and spillovers.

APPENDIX II: MOROCCAN WORKER TYPES

The worker types distinguished by the 1986 and 1990 Moroccan surveys are summarized in table AII.1 below. Because their were some changes in the category names, and because there was apparently a coding error in the data base for one of those years, it was necessary to experiment with mapping of 1986 categories onto 1990 categories.

Two criteria were used. First the average share of employment accounted for by each category was expected to remain fairly stable over the four 4 year period, so mappings in which this changed dramatically were considered suspect. Second, the correlation of 1986 values with 1990 values for a given category was expected to be high. That is, plants that relied relatively heavily on a given worker type in 1986 were expected, on average, to continue relying on that worker type in 1990. Mappings that did not exhibit high correlations were considered suspect.

The table below describes the two mappings that worked the best by these criteria. Our first and second choice are labeled primary and alternative mappings, respectively. The primary mapping was used throughout this chapter. Many unreported results were also obtained under the alternative mapping and were nearly identical to those obtained under the primary mapping.

Table AII.1: Mapping of 1986 and 1990 Moroccan Worker Types

1986	1990	
	Primary Mapping	Alternative Mapping
Non-paid workers	n.a.	n.a.
Administrative upper management	High level administrative staff	High level administrative staff
Technical upper management	Technical staff	Technical staff
Middle management (technical)	Intermediate technical staff	Intermediate level administrative staff
Mastership agents and similar positions	Skilled and specialized workers	Skilled and specialized workers
Skilled workers and specialists	Intermediate level administrative staff & Office workers	Office workers
Office employees	Unskilled workers	Unskilled workers
Manual and unskilled labors	Other workers	Other workers
Total	Total workers	Total workers
n.a.	n.a.	Intermediate technical staff

APPENDIX III: MEASURING PLANT-SPECIFIC PRODUCTIVITY

Productivity Concepts

In an earlier study, experimentation with the Chilean and Colombian panels revealed that total factor productivity (TFP) measures are quite sensitive to the exchange rate (Liu and Tybout, 1996). This is because the cost of imported inputs increases dramatically when major devaluations take place, and the effects are concentrated at plants that use imported inputs intensively. (Since plant-specific price deflators are unavailable, we cannot construct pure measures of input quantities.) Measures of *primary* factor productivity (hereafter PFP), which describe output per unit bundle of capital and labor, do not suffer from this shortcoming and are much more stable (Liu and Tybout, 1996). Further, under the assumption that intermediate inputs are used in fixed proportion to output, they are equivalent to total factor productivity. For these reasons, we base our productivity analysis on PFP.

Estimation techniques

To construct PFP measures, one must somehow aggregate capital and labor usage into a scalar measure of primary input usage. We did this by estimating a constant-returns-to-scale Cobb-Douglas production function relating gross output to capital and labor. This appendix provides the details of how the estimates were constructed and how both capital and labor were measured.

Because large plant-level panel data sets, were available, a number of estimation techniques were feasible. Some, like the "within" or dummy variable estimator and the "difference" estimators, are based solely on temporal variation in the data.[19] The advantage of these estimators is that they sweep out serial correlation due to unobserved plant characteristics that persist over time. They also eliminate simultaneity bias due to correlation of these unobserved effects with the explanatory variables.[20] However, when one of the explanatory variables exhibits transitory measurement error, estimators based on temporal variation can be biased, and evidence suggests the problem is quite important when panel data are used to estimate production functions (Westbrook and Tybout, 1994). Between estimators are much less sensitive to measurement error bias; further, since they are based purely on cross sectional variation, serial correlation is not an issue.[21] Hence, so long as simultaneity bias is not a serious problem, between estimators are an attractive way to estimate production technologies.

Previous work suggests that the bias is indeed minor, so we use between estimators here (Tybout and Westbrook, 1996). Specifically, letting overbars denote

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[19] A simple within estimator is computed by using firm-specific dummy variables to capture unobserved firm specific effects. The number of observations will be equal to the number of firms times the number of time periods. Simple difference estimators are constructed by performing ordinary least squares on the data after all variables have been converted to changes.

[20] In the current context, this correlation might be present because high-productivity firms tend to have relatively large market shares, and therefore employ relatively large amounts of capital and labor.

[21] The simple between estimator is obtained by averaging all of the years of data on each variable, plant by plant, then using the resulting plant-specific mean values in an ordinary least squares regression. The number of observations will be equal to the number of firms in the sample.

cross-year averages of the associated variables, we fit the following constant-returns-to-scale Cobb-Douglas production function:

(AIII.1) $$\bar{y}_i = \alpha + \beta * \bar{k}_i + (1-\beta) * \bar{l}_i + \varepsilon_i$$

where *i* indexes plants, *y*, *k* and *l* are the log of output, capital stock and labor efficiency units. The data sets are unbalanced panels; we account for this in our estimation by weighing each observation by the number of years for which we have firm data.

Finally, using the estimates from (A1), we obtain firm level primary factor productivity estimates residually from:

(AIII.2) $$PFP_{it} = y_{it} - \hat{\alpha} - \hat{\beta} * k_{it} - (1-\hat{\beta}) * l_{it}$$

Aggregating up from the plant-level using weighted averages, we obtain the industry specific productivity levels and productivity growth rates reported in Table 3.A.2 at the end of this appendix.

The capital stock series for all three countries were constructed using the perpetual inventory method with a five percent depreciation rate. For a precise description of how the Colombian series was constructed see Roberts (1996), and for the Chilean series see Liu and Tybout (1996). The Moroccan series were constructed by essentially following the method described in Sullivan (1996). However, to maximize the number of observations and to allow for firm entry, the base year was allowed to vary across plants. Recall we focus our attention on 1986 and 1990, the years for which data on technician intensity are reported; using 1985 and only 1985 as our base year. This means that in order for a firm to be included in our sample, it must have reported data in both 1985 and 1986, or in both 1985 and 1990. Thus with 1985 as the base year, firms entering between 1985 and 1990 are excluded from our sample. By using other base years, we introduce some of the error we hoped to reduce by using the perpetual inventory method, but we do not exclude entering firms from our sample.

To take into consideration cross-plant variation in the quality of workers, we measure labor's contribution to output using labor efficiency units. The following equation documents how the labor efficiency units (LEUs) were calculated.

(AIII.3) $$LEU_i = E_{iu} + \sum_{l=1}^{L} E_{il} * W_{il} / W_{iu}$$

where i denotes firm, u unskilled or blue collar labor, l the category of labor, E the number of workers, W average wage paid to workers in its sector. (Under the assumption that workers are paid the value of their marginal products, relative wages provide the correct aggregation weights.) The labor categories for each country are:

Table AIII.1: Worker Types

	Morocco	Colombia	Chile
u =	Unskilled Workers	Unskilled Workers	Blue Collar Workers
l =	Administrative Upper Management	Management	White Collar Workers
	Technical Upper Management	Skilled Workers	
	Technical Middle Management	Local Technicians	
	Mastership Agents and Similar Positions	Foreign Technicians	
	Skilled Workers and Specialists	Apprentices	