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DOES FACTOR-BIASED TECHNOLOGICAL CHANGE STIFLE INTERNATIONAL CONVERGENCE? EVIDENCE FROM MANUFACTURING

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Abstract

Factor-biased technological change implies divergent productivity growth across countries with different amounts of skill and capital per worker. I estimate the extent of factor bias within industries and countries in a 19-country panel of manufacturing data covering the 1980s. Estimates using both production functions and total factor productivity functions show that technological change is strongly biased against less-skilled workers and toward both skilled workers and capital. An industry or country with twice the capital and skill per less-skilled worker enjoys 1.4%-1.8% faster total factor productivity growth annually due to the effects of factor-bias. These results are consistent with the empirical literature on skill-biased technological change. They may well explain why “conditional convergence” of per capita income across countries is so slow.

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1. INTRODUCTION

Why do some countries remain so much poorer than others? The two basic approaches to income convergence yield quite hopeful conclusions. The factor accumulation approach [Solow 1956] explains that low productivity is the result of low ratios of skill and capital to labor. In the presence of diminishing returns, countries with low skill and capital intensity have highly productive skill and capital. That implies relatively rapid accumulation of capital and skill per worker in poor countries, eventual convergence in factor intensities and thus in convergence in labor productivity. A second approach argues that low labor productivity is the result of using inferior technologies.[1] Replicating technology must be less costly than inventing new technologies, so technology use should converge, leading to eventual convergence of total factor productivity.

The evidence, on the other hand, is not hopeful at all. Growth rates of GDP/capita are not generally higher in countries with low GDP/capita (at least since the early 1960s) [Barro 1991]. Most studies find that only after conditioning on the slow accumulation of skill and capital in poorer countries is there convergence [Mankiw, Romer and Weil 1992]. Even then, this "conditional convergence" is quite slow.

This paper suggests an explanation for slow productivity convergence: Factor-biased technological change. That mechanism has been quite successful in explaining the increased return to schooling in the U.S. and the shift in labor demand away from less educated workers and toward more educated workers in the OECD. Substantial evidence exists demonstrating that technological change has favored skilled (more educated) workers over less skilled (less educated)

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[1] Solow [1957] measures the extent of total factor productivity growth in the U.S. Eaton and Kortum [1996,1999] offer evidence of international technology transfer using R&D and patent statistics. Technology transfer models fall into two broad categories. The "appropriate" technology model (Schumacher [1973]; Basu & Weil [1998]) posits that new technologies are not absorbed immediately in developing countries because of a lack of human or physical capital, differences in production technologies in use, or differences in factor prices. In contrast, the conventional assumption in growth theory is of *pervasive* technology in use everywhere. A weaker assumption is that technologies differ, but recent innovations are so efficient that they are adopted across a wide range of industries, factor price combinations and local technological capabilities. That concept is related to recent work on "General Purpose Technologies" [Bresnahan and Trajchtenberg, 1995; Helpman 1998], such as electrification and information technology which increase productivity in a wide range of industries.

workers at least for the past few decades in many parts of the world.[2] Table 1 provides a sampling of that evidence, showing the declining wagebill shares of production workers in the manufacturing industries of both high and middle income countries.

The connection between factor bias and slow productivity growth is intuitive. If technology favors the skilled over the unskilled, then we would expect industries with more skilled workers to have faster total factor productivity (TFP) growth rates [Klenow 1998; Kahn and Lim 1998]. Similarly, it would not be surprising if countries with a high proportion of less-skilled workers had slower growth rates of income per capita. That basic insight is not new. It formed the motivation for previous work investigating skill-bias in developing countries [Berman and Machin 2000] and is developed quite fully in the induced technological change model of Acemoglu and Zilibotti [2000] to explain productivity differences across countries.[3] The contribution of this paper is in developing that argument in a very general setting and in estimating the extent to which factor bias can slow productivity convergence.

This paper estimates the factor bias of technological change and applies the estimates to the puzzle of slow productivity convergence. The data are a three dimensional panel of industries over time for 19 countries in the 1980s. The factor-bias parameters are estimated twice: in both a production function and a TFP function. Both approaches yield consistent, strong evidence that technological change was labor saving. That conclusion is robust to a number of alternative approaches and specifications. Factor bias estimates indicate that an industry or a country with

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[2] For evidence of recent skill-biased technological change in the *U.S.* see: Bound and Johnson, [1992]; Katz and Murphy, [1992]; Lawrence and Slaughter, [1993]; Berman, Bound, and Griliches, [1994]. Historical evidence is offered by Goldin and Katz [1996, 1998]. Evidence from *other OECD countries* is available in Freeman [1988], Freeman and Katz [1994], Katz and Revenga [1989], Katz, Loveman and Blanchflower [1995], Davis [1992], Berman, Bound and Machin [1998]. Several studies have found *increased* relative wages of skilled labor in several *developing* countries despite widespread trade liberalization in the 1980s which would predict the opposite through the Stolper-Samuelson mechanism [Feliciano, 1995; Hanson and Harrison, 1995; Robbins, 1995; Berman, Bound and Machin, 1998; Berman and Machin, 2000.].

[3] That paper develops a theory of endogenous skill-bias in technological change. Their assumptions imply that the difference in measured TFP levels between developed and developing countries will be greater for unskill-intensive industries than for the skill-intensive. Their estimates, which draw on the same dataset as this paper does, find that pattern, but data limitations cannot allow them to tell if that is evidence of skill-bias or of some change in preferences.

twice the ratio of skills and capital to less-skilled labor enjoys a 1.5%-1.8% faster annual rate of TFP growth.

The next section of this paper provides background about the lack of productivity convergence in the world, in the sampled countries and in their manufacturing industries. Section 3 develops a production function framework for estimation. Section 4 describes the data, deals with potential estimation problems and presents estimates. The fifth section examines the implications of estimated factor-bias for productivity convergence. Section 6 concludes.

2. TFP GROWTH AND FACTOR ACCUMULATION IN MANUFACTURING

Figure 1 looks at the manufacturing sample in the context of global nonconvergence, to check the representativeness of the data. The top panel, 1A, reproduces the standard finding that income per capita growth rates between 1960 and 1990 are uncorrelated with income levels [Barro 1991]. (Data are drawn from the Penn World Tables, version 5.6). The developing world shows higher variance in growth rates, but the same mean.

That international pattern of nonconvergence is quite stable. Figure 1B plots the same relationship for 1980-90, revealing that the 1980s show the same pattern of nonconvergence, - a triangle pointing right.

The sample of manufacturing data used in this paper is drawn from the nineteen countries labeled in Figure 1B. They are a subsample of middle and high income countries used in previous work, further selected on having usable measures of capital at the beginning and end of the 1980s. Selection on data quality results in a disproportionate number of high income countries. Nevertheless, the relationship in the sample between growth and levels of GDP/capita roughly mimics the pattern in the larger sample: the cross-country variance of growth rates declines with income and the average growth rate shows a slight reduction as income increases. National growth rates are quite persistent. The correlation between the 1960-90 growth rate and the 1980-90 growth rate is 0.88 (α=0.00) for these nineteen countries.

Figure 1C plots growth rates in manufacturing value added/worker against levels of GDP/capita for the nineteen country sample. This relationship shows the same triangle. Growth rates do not decline with income and have higher variance at lower income levels. Countries with high growth rates in GDP/capita generally have high growth rates in manufacturing value added per worker, though Portugal and Chile are exceptions. The correlation between the 30 year GDP/capita growth rate and the value added per worker rate in the 1980s is 0.22 (α=0.38), but rises to 0.42 (α=0.08) without Chile. Overall manufacturing value added per worker in this sample mimics the pattern of nonconvergence in international GDP/capita. This is consistent with the conventional view that successful NICS, such as Korea, have grown by rapidly expanding manufacturing.

Is it factor accumulation or TFP that is not converging in manufacturing? Within the nineteen countries a careful decomposition of growth rates is possible into TFP growth on the one hand and factor accumulation (skill and capital intensity) on the other. Assume a production function Y = AF(L,S,K) using unskilled labor, skilled labor and capital respectively. Assume constant returns and competitive markets to develop a standard definition of TFP growth:

$$\Delta TFP = \Delta y - (\psi_l \Delta l + \psi_s \Delta s + (1- \psi_l - \psi_s) \Delta k),$$

where lowercase letters are logarithms and ψ's are factor shares. Now let E (= L + S) denote employment and develop the decomposition for the growth rate of value added per worker,

$$\Delta y\text{-}\Delta e = \psi_l(\Delta l\text{-}\Delta e) + \psi_s(\Delta s - \Delta e) + (1- \psi_l - \psi_s)(\Delta k - \Delta e) + \Delta TFP$$

$$= \text{“factor accumulation”} + \Delta TFP .$$

Figure 2 illustrates that decomposition, with the left figure plotting factor accumulation against GDP/capita, and the right panel plotting TFP growth against GDP/capita. The left panel makes it clear that little Solow convergence occurred in the form of capital or skill accumulation. That pattern is analogous to the results of Mankiw, Romer and Weil (1992), who found convergence only once they conditioned on accumulation rates.

The right panel illustrates quite clearly that most of the variance in growth of manufacturing value added per worker (86%) is in TFP growth. It is worth stressing that TFP growth rates are calculated as a residual, and that improved measurement might reallocate growth from TFP to factor accumulation. That was the case in the study by Griliches and Jorgenson [1967] of U.S. TFP growth, and in Young's [1995] study of TFP growth Hong Kong, Singapore, South Korea and Taiwan.[4] On the other hand, these measured TFP growth rates in manufacturing are not simply measurement error. The correlation between the 1960-1990 GDP/capita growth rate and the manufacturing TFP growth rate in the 1980s is 0.17 (α=0.50), but rises to 0.42 (α=0.095) without Chile. That is a remarkably tight correlation considering the difference in data sources and fact that the two growth rates have only ten of thirty years in common. It's safe to conclude that a large component of growth in manufacturing output per worker is TFP growth. Furthermore, factor accumulation would have to be understated by an order of magnitude, and disproportionately so in the low income economies, for the basic picture in Figures 2A and 2B to be reversed.

Manufacturing TFP growth is not contributing to convergence either: it shows the same triangular pattern that observed in Figure 1 for manufacturing value added per worker and for GDP per capita.

To sum up, the manufacturing data are consistent with the pattern in GDP. They reveal that most of the nonconvergence is in TFP growth rates. So if replication is less costly than invention, why is TFP growth not contributing to convergence in value added per worker?

[4] Young [1995] addresses a debate as to whether the rapid growth of several East Asian economies is due to TFP growth or to factor accumulation. One of the messages of this paper is that the dichotomy is false, since factor bias translates current factor accumulation into future TFP growth.

3. FACTOR-BIASED TECHNOLOGICAL CHANGE IN PRODUCTION: A FRAMEWORK FOR ESTIMATION

An augmented Cobb-Douglas production function allows the possibility of factor-biased technological change,

(1) $$Y = e^{(\alpha + \rho t)} K^{(\beta_k + \gamma_k t)} S^{(\beta_s + \gamma_s t)} L^{(\beta_l + \gamma_l t)}.$$

Here Y is product, K capital, S skilled labor and L unskilled labor. Technological level is indexed by t.

The logarithmic form is convenient for discussing factor bias. Rewritten using lowercase letters to indicate logarithms, the production function is

(2) $$y = \alpha + \beta_k k + \beta_s s + \beta_l l + \rho t + (\gamma_k k + \gamma_s s + \gamma_l l)t.$$

For those returns to be constant, the β's must sum to one. For returns to scale to remain unchanged by technological progress, the γ terms must sum to zero. Call that assumption "unchanging returns to scale" (URS). I will discuss its implications below.

The output elasticities of factors are given by

$$\frac{\partial y}{\partial f} = \beta_f + \gamma_f t \qquad for\ f \in (k,s,l).$$

The γ terms represent the factor bias of technological change, the rate at which output elasticities change over time, $\frac{\partial^2 y}{\partial f \partial t} = \gamma_f$.

Defining some terms will be useful.

(3) Technological change is *relatively skill biased* if $\gamma_s > \gamma_l$.

To justify that usage, take a look at the implications of relative skill-bias. Assuming perfectly competitive labor markets, (3) implies that, holding relative wages constant, the relative demand for skilled workers increases, since

$$\frac{w_s}{w_l} = \frac{MP_s}{MP_l} = \frac{(\beta_s + \gamma_s t)(Y/S)}{(\beta_l + \gamma_l t)(Y/L)} = \frac{(\beta_s + \gamma_s t)}{(\beta_l + \gamma_l t)} \frac{L}{S} ,$$

so that

$$\frac{S}{L} = \frac{(\beta_s + \gamma_s t)}{(\beta_l + \gamma_l t)} \frac{w_l}{w_s} \quad .$$

Conversely, holding relative quantities fixed, relative skill-bias implies that the relative demand wage of skilled workers increases. For this production function, relative skill-bias also implies that the wagebill share of skilled workers increases over time.

This framework allows estimation of the absolute (rather than the relative) sizes of the factor bias terms. Define technological change as

$$\begin{aligned} &\textit{absolutely f - biased} \quad \text{if } \gamma_f > 0, \text{ and} \\ (4) \quad &\textit{absolutely f - saving} \quad \text{if } \gamma_f < 0, \\ &\text{for } f \in (l, s, k). \end{aligned}$$

In the two factor model with unchanging returns to scale $\gamma_s = -\gamma_l$, so absolute and relative skill bias are equivalent, and skill-biased technological change is equivalent to labor saving technological change.

The three factor model, even with unchanging returns to scale, is more flexible. For instance, technology could be absolutely biased against both *s* and *l*, but relatively biased toward *s*. Assuming unchanging returns, absolute skill-bias and absolute capital bias imply absolute labor-saving technological change, since $\gamma_l = -\gamma_k - \gamma_s$.

Factor Bias and Productivity Growth

To study the effect of factor bias on productivity change, note that the γ terms also reflect the effect of factor quantities on changes in total factor productivity. To see this, note that

$$(5) \qquad \frac{dTFP}{dt} \equiv \frac{\partial y}{\partial t} = \rho + (\gamma_k k + \gamma_s s + \gamma_l l) \quad \textit{and} \quad \frac{\partial^2 y}{\partial t \partial f} = \gamma_f \quad .$$

Here the partial derivative of y with respect to time is a change in total factor productivity, since inputs are held constant. The cross partial of product with respect to time and input *f* is the factor-bias term. For example, if technological change is absolutely skill biased, then TFP growth must be faster the greater the level of skilled labor in production. That property is not particular to the

Cobb-Douglas form. It follows from the symmetry of cross-partial derivatives for any production function.

Figure 3 illustrates a relatively skill-biased technological change as the shift of an isoquant in S, L space, holding K constant. For a country or an industry at point B, with the relatively skill-intensive S/L ratio given by the slope of the vector OB, the productivity gain is given by length of the segment BC --the decrease in required inputs to produce a unit of output. The technological change is relatively skill-biased since, at the relative wage illustrated by the slope of the line tangent to the isoquant at B, the new isoquant requires a higher S/L ratio (at point D). In contrast, a country or industry with the S/L ratio given by the vector OA experiences no productivity gain. The size of the differential productivity gain between A and B is given by the factor bias coefficients (the γ's), which will be estimated below.

Assuming unchanging returns to scale, γ_1 has the following convenient interpretation: If one industry has twice the K/L ratio and twice the S/L ratio as another, the TFP growth rate of the former will be $-\gamma_1$ faster. Anticipating the results, γ_1 will be negative, so the former will grow faster.

Is the unchanging returns assumption reasonable? The data will insist that the factor bias terms sum to a negative number, implying that returns to scale decline over time. Yet there is a replication argument for unchanging returns, like that for constant returns. Without URS, scale would affect the TFP growth rate of an industry (see equation (5)). If declining returns were true at the firm level, large firms would split into smaller pieces to achieve optimal scale. If it were true at the industry level, large industries would send production abroad to achieve optimal scale. Either way, in equilibrium we should not observe a decline in returns to scale. The plausibility of URS will come up again in discussing the results and their implications.

Measurement Issues and Estimating Equations

The data available to estimate the parameters of the production function (equation (1)) are a three-dimensional panel of manufacturing industries within countries observed in two periods. Measurement issues complicate estimation since the definitions of skilled and unskilled labor are likely to differ across countries. The quality of all three inputs may also differ across industries.

For instance, middle income countries are more likely to undersample small firms, which tend to have lower proportions of skilled workers, leading them to overestimate the proportion of skilled workers.[5] More generally, we know from the work of Griliches and Jorgenson [1967], that mismeasurement of input quality can lead to substantial mistakes in TFP accounting. Assume that capital, skilled labor and unskilled labor are measured with a country-specific error of proportionality. In logarithms, the measured quantity is then the sum of the true quantity and a country-factor specific error:

(6) $$f^{m}_{ict} = f_{ict} + u^{f}_{c} \quad \text{for } f \in (k, s, l)\,.$$

Besides inconsistent measurement of factor qualities, value added is also likely to be measured using misleading price comparisons across countries and industries. National price indexes (from the Penn World Tables) are not completely corrected for quality, which is likely to differ disproportionately across industries because of market power, particularly for nontraded goods. For that reason it is important to add a country-industry specific level effect, α_{ic} . This absorbs productivity differences but also measurement error in output and any industry-country specific measurement error in prices or quantities. These may be substantial considering that the data are collected from disparate sources without the intention of making them comparable. We also include a country-period specific productivity level δ_{ct}, and an industry specific productivity trend in output growth ρ_{i}. With these additions, substituting (6) into (2) yields

(7) $$\begin{aligned} y_{ict} = {} & \alpha_{ic} + \delta_{ct} + \beta_k(k_{ict} + u_c^k) + \beta_s(s_{ict} + u_c^s) + \beta_l(l_{ict} + u_c^l) \\ & + \rho_i t + (\gamma_k(k_{ict} + u_c^k) + \gamma_s(s_{ict} + u_c^s) + \gamma_l(l_{ict} + u_c^l))t + \epsilon_{ict}\,. \end{aligned}$$

Differencing (7) over time removes the time-invariant measurement error from β coefficients but not from γ coefficients. Labeling the periods t=0 and t=1 and defining $\Delta x_{ict} = x_{ic1} - x_{ic0}$, (for a generic variable x)

[5] For example, the measured proportion of skilled workers in Japanese manufacturing jumped from 46 to 53 percent between the 1975 and 1978 surveys when the minimum firm size which got the "long form" with the skilled worker question changed.

(8) $$\Delta y_{ic} = \beta_k \Delta k_{ic} + \beta_s \Delta s_{ic} + \beta_l \Delta l_{ic} + \gamma_k k_{ic} + \gamma_s s_{ic} + \gamma_l l_{ic} + \rho_i + [\Delta \delta_c + \gamma_k u_c^k + \gamma_s u_c^s + \gamma_l u_c^l] + \Delta \epsilon_{ic} \quad .$$

Under these assumptions the elasticity coefficients β and the factor-bias coefficients γ are identified despite the measurement error. The estimated country effect includes all the bracketed terms: the country-specific change in productivity $\Delta\delta_c$ and terms involving country-specific measurement error in factors. We could make a symmetric argument for industry-factor specific measurement error, u_i^f, which can be accommodated in the same way, compromising identification of industry specific changes in productivity, ρ_i, but not affecting identification of the elasticities and factor bias terms.

One final measurement problem is that physical units of value added are not actually observed. What I can measure is PY (sales net of intermediate inputs), or $p + y$ in logarithms. This is a familiar problem in production function estimation anytime the price deflator is suspect, but the ability to estimate industry effects adds a novel element to the solution. Consider the reduced form regression of Δp on Δy (which cannot be run for lack of data),

(9) $$\Delta p_{ic} = a_i + b_c + m\, \Delta y_{ic} + v_{ic} \, .$$

Here a_i and b_c are industry and country fixed effects in price changes. The coefficient m cannot be signed. Using the textbook simultaneity bias calculation, it is an average of the (inverse) demand and supply elasticities of industry output, weighted by the variance of demand and supply shifts. Since those variances are conditional on common industry effects across countries, they can be interpreted as local supply and demand shifts. For instance, m will be positive if the variance of local demand shifts exceeds that of local supply shifts and the price elasticity of demand exceeds that of supply (in absolute value). Conditional on industry effects, m would be quite small if trade makes product demand quite elastic. In the estimates reported below, m will in fact be quite small.

Adding Δp to both sides of (8) and substituting for Δp on the right hand side from (9) yields

$$\begin{aligned}(10)\qquad \Delta p_{ic} + \Delta y_{ic} &= \Delta p_{ic} + \beta_k \Delta k_{ic} + \beta_s \Delta s_{ic} + \beta_l \Delta l_{ic} + \gamma_k k_{ic} + \gamma_s s_{ic} + \gamma_l l_{ic} \\ &\quad + \rho_i + [\Delta\delta_c + \gamma_k u_c^k + \gamma_s u_c^s + \gamma_l u_c^l] + \Delta\epsilon_{ic} \\ &= (1 + m)\,(\beta_k \Delta k_{ic} + \beta_s \Delta s_{ic} + \beta_l \Delta l_{ic} + \gamma_k k_{ic} + \gamma_s s_{ic} + \gamma_l l_{ic} \\ &\qquad + \rho_i + [\Delta\delta_c + \gamma_k u_c^k + \gamma_s u_c^s + \gamma_l u_c^l] + \Delta\epsilon_{ic}\,) \\ &\quad + a_i + b_c + v_{ic} \ .\end{aligned}$$

Unmeasured price changes introduce the ambiguity that the coefficients of (8) are identified only up to a proportion (1+*m*): (1+*m*) β_f, (1+*m*)γ_f for factors $f \in (l,s,k)$. The extent of that distortion m can be estimated if constant returns are assumed. Then the sum of estimated β coefficients is, $\sum_f (1+m)\beta_f = (1+m)$. Note that industry and country effects in price changes from (9) will also be loaded onto the estimated industry and country effects.

TFP Specification

An alternative approach to estimating the factor-bias terms is to use the relationship in (4), regressing dTFP on input levels.[6] This approach requires making standard assumptions in order to calculate factor weights in TFP - constant returns and competitive markets. On the other hand, it allows much more flexibility in the production function. The time invariant part is not restricted to have a Cobb-Douglas form, to have a constant elasticity of substitution between factors or to have common parameters in different industries and countries.

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[6] This approach is similar to that taken by Kahn and Lim [1998] in their study of skill-augmenting technological change in the U.S. In their estimating equation the shares appear as covariates and they are forced to impose an adding up constraint on these, similar to URS.

Assuming constant returns to scale and competitive markets, the value-added shares of each factor, ψ, provide factor weights in calculating the rate of TFP change,

$$(11)\qquad \frac{dTFP}{dt} = \Delta y_{ic} - \psi^{k}_{ic}\Delta k_{ic} - \psi^{s}_{ic}\Delta s_{ic} - \psi^{l}_{ic}\Delta l_{ic}$$
$$= \gamma_k k_{ic} + \gamma_s s_{ic} + \gamma_l l_{ic} + \rho_i + [\Delta\delta_c + \gamma_k u^k_c + \gamma_s u^s_c + \gamma_l u^l_c] + \Delta\epsilon_{ic} \quad .$$

The factor-bias portion of the remainder of the equation is specified as in (8), allowing separate trends of biased technological change for each factor. As in (10) , factor bias coefficients are identified up to a multiplicative constant (1+*m*). Similarly, estimated country and industry effects in productivity change capture country and industry-specific price changes as well as country and industry-specific measurement error in factors (though the equation only illustrates this point for the country effect).

Factor bias terms are estimated in the following section using both Cobb-Douglas and TFP specifications.

4. RESULTS

A rich three-dimensional panel of industries across countries over time is available to estimate the factor bias terms. Since it covers countries with industries at different levels of development, it contains unusually rich variation over time, industries and countries. This section describes the data, discusses potential biases in estimation and presents results.

Data

To investigate factor bias this paper uses the United Nations General Industrial Statistics Database [United Nations 1992] (later administered by UNIDO). It includes manufacturing employment, wagebill, investment and output data for many countries. This rich data set reflects the unique capability of the United Nations to compile data by soliciting contributions from the statistical agencies of member countries.[7] It covers 28 manufacturing industries at (broadly) the two to three digit level, consistently defined across countries and years using the ISIC classification. Countries were selected that provide data of consistent quality over time.

Table 2 reports descriptive statistics for the 19 countries used. They are ranked by income, (all figures reported in constant 1985 dollars, using the GDP deflators and 1985 exchange rates from the Penn World Tables [Summers and Heston, 1991]. Following a classification used in previous work [Berman and Machin, 2000], countries are arranged into two income groups: a high income group with GDP per capita exceeding $10,000 (1985 US$) in 1980; and a middle income group with GDP per capita between $2,000 and $10,000 in 1980.

The 10 middle income countries are from Asia, Europe and South America. This group includes several countries with large manufacturing sectors: (the former) Czechoslovakia, Korea, and Spain. The high income group includes 9 countries ranging in income from Japan to the U.S. The choice of 1985 exchange rates favors the U.S., but note that U.S. value added per worker is twice as high in 1980 as that of West Germany, the second-ranked country in this group. The U.S. is also the largest manufacturing employer, with 19m workers, followed by Japan with 10.5m, the UK with 6.5m and West Germany with 6.3m.

Our measure of skill in these data is the classification into nonproduction and production workers (operatives and nonoperatives in UN terminology). The term production worker usually refers to employees directly engaged in production or related activities of the establishment. That includes clerks or working supervisors whose function is to record or expedite any step in the production process. Employees of a similar type engaged in activities ancillary to the main activity of the establishment and those engaged in truck driving, repair and maintenance and so on, are also considered to be production workers.

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[7] The main purpose of these data is to facilitate international comparisons relating to the manufacturing sector. Concepts and definitions are drawn from the International Recommendations for Industrial Statistics [Statistical Papers, Series M, No 48/Rev 1, United Nations Publication] and the classification by industry is taken from the International Standard Industrial Classification (ISIC) of All Economic Activities [Statistical Papers, Series M, No 4/Rev 2, United Nations]. For details see the Data Appendix in Berman, Bound and Machin [1998].

This is a far cry from the ideal measure of “skill,” which would include elements of education and training.[8] Clearly the educational level of each of these categories of worker differs across countries. Two sources of evidence indicate that nonproduction workers have higher educational attainment than production workers: 1) cross-tabulations of matched worker and employer surveys at the plant in the U.S. in 1990 reveal a fairly tight relationship between years of schooling, occupation and nonproduction categories[9] [Berman, Bound and Machin, 1997]. An analogous effort at the industry level in the UK reveals a similar mapping [Machin, Ryan and Van Reenen, 1996]. Harris [1999] reports the results of a similar exercise at the plant level, which also reveal that nonproduction workers have a higher educational level;
2) Nonproduction workers are uniformly better paid. Quality indices based on a comparison of CPS and ASM data in the U.S. suggest that about ½ of skill upgrading in U.S. manufacturing took place within nonproduction and production categories over the 1980s [Berman, Bound and Griliches, 1994]. We conclude that while the aggregation problems are worse than usual for these categories, within country comparisons are probably reasonable measures over periods as long as a decade, while between country comparisons, especially across income ranges, should be viewed with caution.

Capital stock is calculated by summing and discounting lagged investment. These are discounted using the Penn World Tables investment price index. Discount factors and coefficients on lagged investment are fitted from the Gray-Bartelsman [1995] data on U.S. manufacturing, which reports both investment and capital stock. For details see Berman and Machin [2000].

Table 3 provides descriptive statistics for estimating equations. Total factor productivity growth is only slightly higher in our sample among middle income countries than among the developed countries. (The calculation of TFP growth is described in the next subsection.) The standard deviation is almost three times as high among middle income countries, reproducing the

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[8] The term “skill” in skill-bias is an unfortunately vague expression we inherit from the literature. In our discussion “skill”can be interpreted as education.

[9] 75 percent of nonproduction workers are in white collar occupations, while 81 percent of production workers are in blue collar occupations. 76 percent of nonproduction workers have at least some college education, while 61% of production workers have a high school education or less.

pattern in Figure 2 of selective convergence. Note also that manufacturing industries in high income countries have a much faster decline in production worker employment.

Potential Pitfalls in Estimation

Estimation of (10) and (9) is complicated by several potential sources of bias familiar from the literature on the estimation of production functions [Griliches and Mairesse, 1995]. Before we get distracted by the estimates and the economics, let's turn to the dirty work of discussing potential biases and how they are treated.

First, *measurement error* is likely in the levels of factors, which is both transitory and industry-country specific, so that industry and country effects will not absorb it. This could be anything from fluctuations in unmeasured quality, to price changes in capital to coding error.

One implication of transitory measurement error is that it appears on both sides of equation (11), creating the potential for spurious correlation between factor levels and ΔTFP. To illustrate, let f_t be a vector of measured factors in period t. Now

$$f_t = f_t^* + u_t ,$$

where f_t^* is the true level and u_t is classical measurement error, uncorrelated with f or y. The change in TFP would then be calculated as

$$\Delta TFP = \Delta y - \psi` \Delta f = \Delta y - \psi` \Delta f^* - \psi`(u_t - u_{t-1}) = \Delta TFP^* - \psi`(u_t - u_{t-1}) .$$

That measurement error would create a spurious negative correlation with f_t and a spurious positive correlation with f_{t-1} .

A convenient solution is to use the average level of factors over time as a regressor (consistent with the approximation of the derivative with respect to time in equation (11)). Let $f = (f_t + f_{t-1}) /2 = f^* + (u_t + u_{t-1}) /2$. Let Σ_t denote the variance of u_t . The spurious covariance $\psi`Cov(u_t - u_{t-1}, u_t - u_{t-1})\psi/2 = \psi`(\Sigma_t - \Sigma_{t-1})\psi/2$, which will be zero if the variance of the measurement error is unchanged over time.

A related problem arises with the shares $\psi^f = w^f F/Y$ (where $w^f F$ is the wagebill of factor f, and capital's share is calculated as a residual). These include the level of factor F on the left-hand side of (11). So transitory measurement error appears in levels on the left-hand side and in logarithm on the right-hand side, inducing a spurious correlation. That spurious correlation is prevented by predicting ψ_{ic} using a regression of shares on industry and country indicators and use the predicted values to calculate TFP. These predicted values will be purged of industry-country specific measurement error.

A second, more standard, implication of measurement error in factors of production is that bias due to measurement error is attenuated by differencing, because of the reduction in the signal to noise ratio (the ratio of the true variance to the variance of the measurement error). This problem is relevant to estimation of the elasticities (the β's) in equation (10). This is a common problem in estimating production functions in differences. The estimated capital coefficient in firm data is often near zero [Griliches and Mairesse 1995].

The potentially biased β estimates are incidental in this case, but their bias would be transmitted to the estimated γ terms through the covariance of estimated coefficients. To see this, consider the least squares regression estimating vectors β and γ, where $X_1 = \Delta f$, and $X_2 = f$, assuming that Δf is correlated with the error term, but f is not. The least squares estimator is then

$$\begin{aligned}
&\begin{bmatrix} b \\ g \end{bmatrix} = (X'X)^{-1}X'[X_1\beta + X_2\gamma + \epsilon] \\
&\textit{so} \quad \begin{bmatrix} b-\beta \\ g-\gamma \end{bmatrix} = (X'X)^{-1}\begin{bmatrix} X_1'\epsilon \\ X_2'\epsilon \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix}\begin{bmatrix} X_1'\epsilon \\ X_2'\epsilon \end{bmatrix} \\
&\textit{Assume} \quad E(X_1'\epsilon\,|X) = a\,, \quad \textit{and} \quad E(X_2'\epsilon\,|X) = 0\,. \\
&\textit{Then} \quad E(b-\beta\,|X) = Aa \\
&\textit{and} \quad E(g-\gamma\,|X) = Ca = CA^{-1}E(b-\beta\,|X) \\
&\qquad = Cov(g,b')\;V(b)^{-1}E(b-\beta|X) \quad \textit{under homoskedastic errors.}
\end{aligned}$$

Aggregation to the industry level helps in this respect, as measurement error between firms tends to cancel, raising the ratio of signal to noise. The developing country data also seem to be rich in signal, as we shall see below. Defining f as an average over time also helps. It reduces the spurious negative covariance of Δf with f due to measurement error, thus reducing the spurious covariance between estimated β and γ coefficients. A third treatment to this problem is to use prior beliefs about the range of values that the β can take on to bound the possible bias on γ.

Those priors suggest ways to restrict the estimated β and see how that affects the estimated γ. This last idea will probably be clearer when it is demonstrated below.

A third potential source of bias is an *endogenous response* of factor use Δf, to an industry-country specific change in productivity or prices. That would induce a positive covariance with the error term, $Cov(\Delta f, \Delta\epsilon) > 0$, and a generally upward bias in the estimated β in equation (10). As before, experimenting with restrictions on the estimated β can help gauge the extent of bias transmitted to the estimated γ .

A related concern is that endogenous response will induce a positive correlation between the measured level of f and the error term, $Cov(f, \Delta\epsilon) > 0$, since f_t appears in f. That problem can be treated by using f_{t-1} as an instrument, since it is determined before $\Delta\epsilon_t$ is observed. Strictly speaking, that instrument will be invalid in the production function specification, since $Cov(u_{t-1,} [u_t + u_{t-1}] /2) > 0$. Nevertheless, the induced bias may be no worse than the standard least squares attenuation bias (which involves the covariance of $(u_t + u_{t-1}) /2$ with itself, but also a larger denominator). A more serious problem arises in estimating the TFP specification. There, in the presence of transitory measurement error, the error term will include $- \psi`(u_t - u_{t-1})$. Thus, the instrument f_{t-1}, which includes the lagged measurement error u_{t-1}, will tend bias the estimated γ upwards (in addition to any bias toward zero due to standard attenuation bias).

In summary, identifying the factor-bias terms in the production function specification appears to be feasible, since as the major sources of bias can be controlled. In the TFP change specification, there is a potential for bias due to endogenous response that does not have a convincing solution, in principle. In practice, comparing the results of the two approaches will turn out to be informative.

Results

Table 4 reports the result of estimating the translog specification in equation (10). The first three rows report the factor bias coefficients (γ) on log levels of inputs, while the next three report the elasticities (β) on changes in logarithms. As noted in the last section, bias in the estimated β might be transmitted to the estimated γ. Looking first at the β coefficients in the leftmost row, note that they are large, with an estimated β_k of .774 and returns to scale of 1.39.

This is not an unusual result in cross-country regressions with developing countries. It may be due to endogenous adjustment of inputs, especially capital, to price and productivity shocks. It may also be due to a positive correlation of prices and quantities of product, reflected in a positive *m* coefficient in (9). Those excessive returns to scale recede when we include country effects. The estimated β_k declines to a more reasonable 0.448. That change indicates that the high coefficient on Δk in the leftmost column of results may have been due to country-specific, cyclical increases in measured productivity [Basu and Fernald ??]. The β's sum to 1.09, indicating that if constant returns hold, the effect of not measuring prices is rather small - they are 9% too high in absolute value. The reasonable size of the estimated β's from the "country effects" column on also provides some reassurance about bias in the estimated β that may be transmitted to the estimated γ coefficients.

The third column adds industry effects in productivity growth, as specified in equation (10). That does not much change the estimated β's. Under constant returns, *m* is estimated at 8%. The addition of industry effects corrects a positive omitted variable bias on the estimate of γ_1 in the previous column, changing it from -1.24% to -2.15%. Conditional on country effects, industries with high production worker employment tended to have high measured TFP growth, implying a sector bias [Haskell and Slaughter 1998] *toward* unskilled workers[10] (or at least industry-specific time-invariant measurement error in inputs).

Before turning to robustness checks, consider the economic interpretation of the factor-bias coefficients. The estimated coefficient on production workers, γ_1, is -2.15%. Subtracting 0.16 due to *m* , this implies that annual productivity growth is almost 2% slower in industries with twice as many production workers. The estimated standard error is (0.51), indicating strong evidence of absolute labor saving technological change.

The estimated coefficient on skilled labor, γ_s, is positive, at 0.69, but not statistically significant, providing weak evidence of absolute skill bias. The evidence for relative skill-bias is strong, as the estimated value of γ_s - γ_1 is 2.41% (s.e.=1.05%) (not shown in the Table). The

[10] In the analysis that follows that sector bias will be allowed to differ by income group.

estimated coefficient on capital, γ_k is 0.87% (0.41%), providing strong evidence of absolute capital bias in technological change.

The second to last row reports the change in returns to scale $\gamma_s + \gamma_k + \gamma_1$, which would be zero under unchanging returns to scale (URS). The estimated sum is -0.59%, indicating that declining productivity of unskilled labor is not fully compensated by increased productivity of skilled labor and capital. (This does not imply a productivity decline, since the equation allows Hicks-neutral productivity change.) Changing returns to scale are an uncomfortable finding. They conflict with the replication argument offered in the previous section, since they imply that industries of different sizes have systematically different TFP growth rates. (In this case smaller industries have higher growth rates.) Those objections, and the clear interpretation that URS allows, argue for exploring what happens if URS is imposed. I will return to discuss the cost of the URS assumption in the next section.

To put these results in context (ignore the data's objections and) impose URS. That raises the estimated skill and capital bias coefficients, yielding an implied γ_1 estimate of -1.80% (which is less negative than the unrestricted estimate), or -1.67% corrected for *m*. In other words, conditional on industry and country effects, an industry with twice the capital/unskilled labor ratio and twice the skilled/unskilled labor ratio has an annual TFP growth advantage of 1.67% !

Are these results driven by some outlier, rogue industry or misbehaving country? Figure 4 illustrates a leverage plot of the estimated γ_1 . It graphs the growth rate of value added against the log of production employment, once both have been conditioned on all the other covariates (in the linear regression sense). The Frisch-Waugh theorem implies that this slope is the same as that in the weighted, multivariate regression. The upper left panel is a simple scatterplot. The upper right panel is drawn with circles proportional to the weights used in the regression (value-added shares within country). The lower two panels are labeled by country and industry. Combined, the four panels make it clear that estimated labor-saving technological change is not driven by outliers. As a separate robustness check the regression was run dropping a single country each time. That had no substantial effect on the factor bias coefficients.

What about other potential pitfalls? Table 5 examines these. One potential source of bias is the endogenous reaction of factors (l, s, k) to industry-country specific productivity or price changes, which would appear in the residual, $\Delta\epsilon$. Since factors are measured at their average level between the beginning and end of the period, this may bias estimated coefficients, probably towards one. That problem can be treated by using lagged levels (l_{t-1} , s_{t-1} , k_{t-1}) as instrumental variables, since these will be determined before the productivity or price shock. The column labeled "lagged levels as instruments" reports those instrumental variable estimates. These are essentially identical to the least squares estimates in the previous table. A Hausman test reveals that we cannot reject the hypothesis of identical coefficients, indicating that endogenous reaction of factors to productivity or price shocks is not a source of discernible bias.

Another potential source of bias discussed above is a bias transmitted from the β coefficients to the γ coefficients. (The β coefficients are estimated without an instrument in all specifications so they are vulnerable to bias due to endogenous response to productivity or price shocks, for instance.) Regardless of the source of that bias, the most suspicious estimated β coefficient is that on log change in nonproduction workers. At 0.49, it is much higher than the nonproduction wagebill share in value added. One way to approach the potential transmitted bias is to force that coefficient to take a lower value and observe the change in γ estimates, (as suggested by the bias formula in the subsection above). A possible restriction would be constant returns to scale, which are imposed in the next column to the right. That exercise has little effect on the β's so it is not surprising that the γ's are not much changed. A more drastic step is to force the estimated β_s coefficient to be zero, in order to provide an upper bound on the possible transmitted bias. That reduces the estimated γ_s coefficient from 0.69 to 0.47 but has little effect on the other factor-bias coefficients. The URS-restricted γ_l estimate rises to -1.64 (as compared to -1.80), which can be thought of as an upper bound for the rate of absolute labor saving technological change.

The main conclusions of Table 4 are robust to corrections for endogeneity and measurement error biases: very strong evidence that technological change had an absolute labor saving bias, weaker but statistically significant evidence of an absolute capital-bias, and evidence of absolute skill-bias on the borderline of statistical significance. Evidence of relative skill-bias is quite strong, which is consistent with the literature discussed in the introduction.

TFP Function Estimates

The total factor productivity specification is more flexible in many ways than the production function. It requires no functional form assumptions except on the factor bias terms. In particular, it does not impose unitary elasticity of substitution between factors. It does require the standard assumptions of constant returns to scale and competitive markets to define TFP. (Note that constant returns were not rejected in the specifications estimated in Table 3, except in the first, -which did not include country effects).

Table 6 reports estimated factor-bias terms as specified in equation (11) of section II. Despite the difference in specification, the γ estimates are quite similar to those obtained from a production function, though a little smaller. Begin with the preferred specification (in the middle row), which includes country and industry effects. The estimated coefficient on production workers is large and negative at -1.83% (s.e.=0.49%), showing absolute labor saving technological change. The coefficients on nonproduction workers and capital are positive at 0.53% and 0.71% but not significantly different from zero, providing weak evidence of absolute skill-bias and absolute capital bias.

The sum of factor bias terms is -0.59% (0.33), indicating weak evidence for a decline in returns to scale. If we assume unchanging returns, the implied estimate of γ_1 from the restricted regression is -1.49% (0.43). That estimate is only slightly smaller in absolute value than the restricted estimate of γ_1 (-1.80%) in the production function specification. Like the production function estimates, these estimates imply substantially faster TFP growth for skill and capital intensive industries.

Omitting industry effects cuts the size of the estimated γ_1 coefficient to -0.98, indicating TFP growth disproportionately concentrated in industries with high levels of production employment, conditional on country (as in the production function specification). Omitting country effects as well tends to lower the estimated γ_1 and γ_s coefficients while raising the coefficients on capital. I.e., countries with high levels of capital and low levels of employment tended to have faster measured TFP growth.

Recalling the discussion of potential biases above, the TFP specification is vulnerable to endogeneity bias. Country-industry specific productivity or price shocks could cause an endogenous adjustment of factor levels (*l*, *s*, and *k*), which are measured by averaging the first and last measurements of the decade. In the production function estimates endogeneity bias was not a discernible problem, as indicated by the similarity of instrumental variable and least squares results. So it's hard to see how they would be a major problem in this specification. If the major form of adjustment is through unskilled labor (which has the lowest adjustment costs), then endogeneity bias could explain why the TFP estimates have a less negative γ_1 estimate. Unfortunately, the instrument available in the production function specification, the lagged factor levels, f_{t-1}, are not valid here, - they are spuriously correlated with any measurement error in Δf, which appear in the calculation of ΔTFP on the left-hand side of (11). (Those would tend to bias estimated coefficients upwards as they induce a positive spurious correlation with the error term. Thus, they are not helpful in establishing a lower bound for a bias that is probably upwards.)

Summarizing the three tables, both approaches show the same pattern: statistically significant evidence of absolute labor-saving technological change, weaker evidence of absolute skill-biased technological change and evidence of capital-biased technological change that is statistically insignificant in the TFP specification but significant in the production function specification. The restricted γ_1 estimate summarizes the results neatly (though the sum of factor bias terms rejects that restriction, the unrestricted estimates would make the following a slight *understatement*): conditional on industry and country effects, and allowing for fixed country and industry specific measurement error, a manufacturing industry in the 1980s with double the *K/L* ratio and double the *S/L* ratio is predicted to have an annual TFP growth rate 1.4 to 1.8 percent higher. That is a remarkable level of labor saving technological change, compared to the sample average TFP growth rate of 1.6 percent

Middle vs. High Income Countries

In an analysis of labor productivity convergence the real concern is with low and middle income countries. So before interpreting applying the results to productivity convergence, it would be prudent to check if the conclusion of factor bias applies to the middle income subsample. Table 7 reports separate regression estimates for the nine high income countries and the ten middle income countries. Cutting the sample in half reduces precision. To make the interpretation easier I report only the URS-restricted results.

The high income countries provide a surprise. While the estimates without industry effects are similar to those reported for the sample as a whole, the preferred specification (with country and industry effects) reports labor-biased technological change which is capital-saving! These coefficients are statistically insignificant, so they should not be interpreted as overturning the large body of evidence in the literature suggesting skill-bias in the U.S. and other high income countries. It is more likely that at the level of resolution this method has, we cannot find skill-bias in these countries. More interesting is the contrast between estimates with and without industry effects. Apparently, industry-specific measured productivity growth worked against production workers in the high income countries. This is consistent with the finding of Haskell and Slaughter [1998] on sector-bias. It also suggests that the ambiguity expressed by Kahn and Lim [1998] about the interpretation of their own estimates as evidence of skill augmenting technological change was well founded. They could not include industry effects in the same way as they had only one country to work with.

The ten middle income countries actually drive the key results of this paper. In the country and industry effects specification they show strong evidence of capital-bias and of labor savings in technological change, while the coefficient indicating skill-bias is positive but imprecisely estimated. The implied γ_1 estimate is -2.71% (0.84), indicating very strong evidence of substantial labor-saving technological change.

Here too, the treatment of industry effects matters. The contrast between the results with and without industry effects indicates that industry effects in measured productivity favored *production* workers in developing countries. Overall the pattern in both subsamples of countries is consistent with the prediction of Heckscher-Ohlin trade theory in a period of declining trade restrictions: price changes favored capital and skill intensive industries in countries with high skill and high capital intensity, while price changes favored industries intensive in unskilled labor in countries with low skill and low capital intensity.[11] Once these industry effects in productivity

[11] The pattern of these price effects is inconsistent with the argument that demand for skills increased in middle income countries because of foreign outsourcing to low income countries [Feenstra and

growth are accounted for, the full extent of labor saving technological change in middle income countries is evident.

Can the disparity between high and middle income γ_1 coefficients be that large? Previous research suggests that in the 1980s middle income countries absorbed several vintages of technology from high income countries [Berman and Machin, 2000]. One possible explanation is that accelerated technological catchup induces factor bias at a rate much faster than that experienced at the technological frontier. (E.g., if technological convergence is 4 times as fast in middle income countries as the rate of advance at the frontier, then the labor-saving rate would be $4\gamma_1$ in middle income countries.)

Tables 4-7 all report extremely high rates of labor saving technological change. Are these estimates too large to be believed? In the Cobb-Douglas specification the γ_1 coefficient also represents the shift in value-added share of production workers. Using that approach, the shifts reported in Table 1 suggest values of γ_1 between -0.2% and -0.5%, which are only a fraction of the estimated values in Tables 4-7 in the -1.4% to -1.8% range. Part of the difference may be due to reallocation of production between industries. Table 7 suggests that these reallocations favor production workers in middle income countries but work against them in high income countries. Yet reallocation between industries is too small to provide most of the answer. A more likely explanation is that the assumptions about supply and demand in labor market, which underly that calculation, are too restrictive. In particular, the Cobb-Douglas implies a unitary elasticity of factor demand. If manufacturing demand for unskilled labor is elastic, then a decline in demand for less skilled workers could result in a very small decline in their wagebill share.

Hanson??], as that would predict industry effects in the opposite direction.

5. IMPLICATIONS

The estimates assuming unchanging returns lend themselves to straightforward interpretation. The U.S. has about twice the measured K/L and S/L ratios as Cyprus and Portugal. The estimated rates of labor-saving bias, between 1.4% and 1.8% annually, imply TFP growth rates 1.4 to 1.8 percent higher in U.S. manufacturing than in the manufacturing sectors of those countries. Thus, all other things equal, manufacturing value added per worker will diverge quite quickly, with the labor productivity gap doubling every 39-50 years.

So why don't we observe divergence? Capital intensity in middle income countries is about half that of high income countries, and skill intensity is about 2/3 (though correcting for measurement error would lower that figure). For lower income countries the factor intensity gap is even larger.

One possible mechanism that accounts for the lack of divergence is that suggested at the outset: replication is faster than invention, so that technological catchup compensates for factor bias. Another possibility is that URS does not hold, despite the replication argument offered: smaller industries have higher TFP growth rates, a force which favors convergence and compensates to some extent for the factor bias effect. This is the pattern suggested by the data when the sum of estimated γ coefficients is negative. Note that those estimates cannot be interpreted as evidence for technological catchup across countries (or industries), as they are present in specifications that already include country effects.

The extent of compensation for factor bias (through these or some other mechanisms) can be roughly estimated by seeing how much of the cross-country variance in TFP growth rates is explained by country effects in a (URS restricted) regression which allows factor-bias. This calculation is not completely accurate, -estimated country effects include not only the true country effect in TFP growth but also an estimation bias due to measurement error in factor levels (as shown in equation (10)). For instance, if a country miscodes less-skilled labor as skilled, and $\gamma_s + \gamma_l$ is negative, the estimated country effect will be biased downwards.

Figure 5 reports the result of that exercise in a plot of TFP growth rates against GDP/capita. Points labeled are the country effects in the industry and country effects specification for the pooled sample, reported in the rightmost column of Table 4.[12] Squares represent TFP growth rates for the same countries, as in the right panel of Figure 2. Estimated country effects exceed TFP growth in all but one middle income country (Columbia) and are lower than the TFP growth rate in all high income countries. While the TFP growth rates are uncorrelated with GDP/capita, the country effects show a slight negative correlation, illustrated by the regression line. That negative correlation should not be overemphasized, as t=-0.9 in that regression. On the other hand, if middle incomes did not tend to overstate measured skill intensity the slope would be more negative. Thus, this exercise underestimates both the extent of factor bias and the extent to which it is compensated by some other (more hopeful) mechanism, such as technological replication or declining returns, to prevent TFP divergence between countries.

6. CONCLUSIONS

Factor-biased technological change provides a plausible explanation for the lack of convergence between countries in TFP per worker. Factor bias is now a familiar finding for developed countries in the labor economics literature. In the countries sampled, most of the cross-national variation in growth rates of manufacturing value added per worker is TFP growth. Thus the factor-bias explanation for lack of convergence in TFP growth rates provides most of the explanation for lack of convergence in value added per worker. These, in turn, are highly correlated with (nonconvergent) growth rates in GDP/capita.

The data yield strong evidence that technological change is absolutely labor-saving, absolutely capital-biased and relatively skill-biased. These estimates are large, suggesting that a country or industry with twice the capital and skill intensity will have a total factor productivity growth rate 1.4% - 1.8% higher annually. The data are unusually rich, allowing estimation of factor-bias coefficients for the first time which allow for country and industry specific effects in TFP growth. Estimated factor bias coefficients are driven for the most part by the 10 middle

[12] A constant has been added to estimated country effects so that their mean is the same as that of the TFP growth rate. Otherwise they would reflect the conditional mean TFP growth rate with S/L and K/L set equal to unity, which would be an unusual country indeed.

income countries in the sample, the relevant subsample for a discussion of international income per capita convergence.

These results are based on manufacturing data from a single decade, so extrapolation to entire economies over longer periods should be done with caution. On the other hand, these data show considerable similarity to the Baumol-Barro-style 1960-90 nonconvergence diagram (see the triangles and correlations of Section 2). So let's hazard the extrapolation anyway.

The good news inherent in these results is that a country accumulating skill and capital intensity has a twofold benefit: there is both an immediate increase in labor productivity and a repositioning which increases the benefit from future (absolute) skill and (absolute) capital bias in technological change. In this second sense current savings increases future growth. If a Solow growth model were augmented with labor saving technological change there might initially be periods of divergence, during which the factor bias effect on TFP growth more than compensated for convergence through factor accumulation. In that sense, factor bias stifles convergence in labor productivity. Nevertheless, in the long run, GDP per worker (and its growth rate) would converge, because skill and capital intensity would converge.

The bad news inherent in these results is this: Since evidence of Solow convergence through factor accumulation is absent (in these data or in Mankiw, Romer and Weil 1992, for example), *neither* of those benefits of accumulation is being achieved.[13] These combined findings underscore the need to understand the answer to a basic, classic question of development economics: Why is the accumulation of skill and capital intensity not faster in developing economies?

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[13] That is the prediction of several models, including those with open economies and factor price equalization and those with constant returns to skill and capital combined [Barro1991]. Interestingly enough, these data cannot reject that second possibility, especially for the middle income countries for which the point estimate indicates slightly increasing returns.

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Table 1. Factor Shares in Value Added

	Middle Income			High Income		
	~1980	~1990	**change**	~1980	~1990	**change**
production	25.5	23.1	**-2.4**	30.3	25.7	**-4.6**
nonproduction	10.1	10.2	**+0.1**	18.4	18.0	**-0.4**
capital	64.4	66.7	**+2.3**	51.3	56.3	**+5.0**

Notes: The wagebill shares of production and nonproduction workers are wagebill/value added. The capital share is the complement so that the three shares sum to one. These figures are calculated from the UN GIS database, using the same sample as regression results in the other Tables, which is restricted to countries for which capital can be calculated both near the beginning and near the end of the 1980s. Middle Income countries have GDP per capita between $2,000 and $10,000 US in 1980. They are: Turkey, Columbia, Czechoslovakia, Malta, Portugal, Chile, Cyprus, South Korea, Ireland and Spain. High Income countries (those with GDP per capital above $10,000 US) are: Japan, UK, Austria, Finland, Denmark, West Germany, Sweden, Australia, US.

Table 2. Sample Descriptive Statistics - 1980

Country	GDP/capita (1985 $)	Manuf. Value Added / Worker ($)	Manufactur Value Added as % of GDP	Manufactu Employme nt (1000s)	Annual Production Wage ($)	Annual Non-Production Wage ($)	Proportion Non-production	Years of education /adult
A. Middle Income Group								
Turkey	2872	5780	14	795	3290	4312	0.22	2.6
Colombia	2948	4662	23	508	2660	5139	0.27	4.2
S. Korea	3093	6764	28	2015	3346	4772	0.21	6.8
Czecho-slovakia.	3731	5651	-	2472	2780	3064	0.27	
Chile	3898	7472	21	206	4711	14496	0.27	5.9
Malta	4488	7790	-	25	5826	11584	0.15	6.3
Portugal	4982	2390	-	663	4157	6766	0.14	3.2
Cyprus	5289	6990	-	36	4884	7252	0.16	7.2
Ireland	6828	11894	-	212	12929	18383	0.19	7.6
Spain	7391	8835	-	1159	11842	16478	0.23	5.2
B. High Income Group								
Japan	10068	18467	29	10500	10506	11908	0.46	8.2
UK	10161	13988	27	6462	14559	19045	0.30	8.3
Austria	10499	15657	25	679	11602	19309	0.30	6.2
Finland	10843	16256	28	531	13645	20597	0.24	9.6
Denmark	11333	15664	20	381	22356	29948	0.28	10.1
W. Germany	11916	20262	-	6302	20810	31450	0.28	8.5
Norway	12141	14360	15	354	18619	25869	0.26	10.3
Sweden	12447	17813	23	853	17520	27207	0.29	9.5
Australia	12518	15702	19	1138	16380	19517	0.26	10.1
US	15311	40078	22	19200	18357	28145	0.28	11.9

Notes: All manufacturing figures are author's calculations from the United Nations General Industrial Statistics Database. These apply to 1980, except where otherwise noted. GDP/capita, is from the Penn World Tables. Percent of GDP in manufacturing is from World Development Indicators, 1999. Years of education/adult (aged 25 or more) are from the Barro-Lee data. All pecuniary figures reported in 1985$ deflated by the implicit Laspeyres GDP deflator in the Penn World Tables.

[1] Employment reflects the sample rather than the population. Samples typically include only plants with ten or more employees.

Table 3. Descriptive Statistics for Estimation

	All 19 countries		10 middle income countries		9 high income countries	
Growth rate (x100):						
total factor productivity	1.62	(3.47)	1.72	(4.59)	1.52	(1.82)
value added	3.11	(5.30)	4.16	(6.90)	2.10	(2.71)
production	-0.73	(3.16)	-0.02	(3.65)	-1.42	(2.42)
nonproduction	0.62	(3.36)	1.44	(3.91)	-0.18	(2.49)
capital	2.64	(3.47)	3.70	(4.24)	1.62	(2.07)
Log level of:						
production	10.44	(1.83)	9.64	(1.73)	11.20	(1.59)
nonproduction	9.46	(2.05)	8.44	(1.82)	10.45	(1.76)
capital	21.53	(2.09)	20.40	(1.90)	22.62	(1.63)
Observations	422		197		225	

Notes: Standard deviations in parentheses. Observations are weighted by their value-added share within each country. Total factor productivity is calculated using wagebill shares in value added as weights. Those weights are predicted by regression using a full set of country and industry indicators. Production worker weights are predicted with an R^2 of 0.84 and nonproduction worker weights are predicted with an R^2 of 0.77. Capital weights are calculated as the complement so that the weights sum to one.

Table 4: Factor Bias Estimates from a Production Function

Dependent variable: Annualized change in log value added (x100)

		country effects	..& industry effects	.. & impose unchanging returns
production	**-1.46**	**-1.24**	**-2.15**	
	(0.72)	(0.44)	(0.51)	
nonproduction	-0.17	0.77	0.69	**0.89**
	(0.69)	(0.29)	(0.43)	(0.44)
capital	1.51	0.58	0.87	**0.91**
	(0.61)	(0.45)	(0.41)	(0.42)
Δ production	34.9	22.5	21.5	19.3
	(12.9)	(14.5)	(13.8)	(14.2)
Δ nonproduction	27.1	41.7	48.6	49.9
	(9.9)	(9.4)	(9.2)	(9.5)
Δ capital	77.4	44.8	37.9	37.3
	(8.3)	(8.5)	(6.6)	(7.0)
19 country effects		x	x	x
28 industry effects			x	x
R^2	0.65	0.84	0.87	0.87
Sum of elasticities (β's)	139 (10)	109 (09)	108 (11)	107 (11)
sum of factor bias coefficients (γ's)	-0.11 (0.20)	0.10 (0.13)	-0.59 (0.24)	0 -
γ_1 assuming unchanged r.t.s.				**-1.80** (0.51)

Notes: All specifications include 422 observations of industries within countries. Standard errors (in parentheses) are heteroskedasticity-consistent, allowing a country specific grouped error term. Observations are weighted by value added share within each country. The sum of factor bias coefficients sums estimated coefficients of production workers, nonproduction workers and capital. The coefficient γ_1 assuming unchanged returns to scale is the estimated coefficient on production workers, using the same specification but restricting the three factor bias coefficients to sum to zero. The "constant returns" specification imposes constant returns to scale. The dependent variable in that case is Δlog(value added)-Δlog(production). For descriptive statistics see Table 3. Estimating equation is (10) in text.

Table 5: Factor Bias Estimates from a Production Function - Specification Checks

Dependent variable: Annualized change in log value added (x100)

	lag level instru-ments	..& un-changing returns	impose constant returns	..& un-changing returns	impose $\beta_s = 0$	..& un-changing returns
production	**-2.10**		**-2.07**		**-2.07**	
	(0.55)		(0.53)		(0.58)	
nonproduction	0.63	0.82	0.70	0.89	0.47	0.71
	(0.42)	(0.44)	(0.42)	(0.43)	(0.52)	(0.52)
capital	0.89	0.93	0.82	0.87	0.87	0.93
	(0.42)	(0.43)	(0.38)	(0.41)	(0.43)	(0.45)
Δ production	21.5	19.4	17.1	15.8	58.2	56.7
	(13.9)	(14.2)	-	-	(10.4)	(10.9)
Δ nonproduction	48.6	49.8	48.4	49.6	0	0
	(9.2)	(9.5)	(9.1)	(9.5)	-	-
Δ capital	37.9	37.3	34.5	34.6	48.5	48.1
	(6.6)	(7.0)	(5.4)	(5.5)	(7.4)	(7.9)
19 country effects & 28 industry effects	x	x	x	x	x	x
R^2	0.87	0.87	0.78	0.77	0.84	0.84
Sum of elasticities (β's)	108 (11)	107 (11)	-	-	107 (12)	105 (12)
sum of factor bias coefficients (γ's)	-0.57 (0.24)	0 -	-0.55 (0.26)	0 -	-0.72 (0.30)	0 -
γ_1 assuming unchanged r.t.s.	**-1.76** (0.57)	**-1.76** (0.57)	**-1.76** (0.52)	**-1.76** (0.52)	**-1.64** (0.55)	**-1.64** (0.54)

Notes: All specifications include 422 observations of industries within countries. Standard errors (in parentheses) are heteroskedasticity-consistent, allowing a country specific grouped error term. Observations are weighted by value added share within each country. The sum of factor bias coefficients sums estimated coefficients of production workers, nonproduction workers and capital. The coefficient γ_1 assuming unchanged returns to scale is the estimated coefficient on production workers, using the same specification but restricting the three factor bias coefficients to sum to zero. The "constant returns" specification imposes constant returns to scale. The dependent variable in that case is Δlog(value added)-Δlog(production). For descriptive statistics see Table 3. Estimating equation is (10) in text.

Table 6. Factor Bias Estimates using a TFP specification

Dependent variable: Annualized change in TFP (x100)

		country effects	..& industry effects	..& un-changing returns
production	**-1.34**	**-0.98**	**-1.83**	
	(0.77)	(0.46)	(0.49)	
nonproduction	0.13	0.78	0.53	0.73
	(0.73)	(0.36)	(0.40)	(0.38)
capital	1.11	0.41	0.71	0.76
	(0.59)	(0.47)	(0.44)	(0.46)
country effects		x	x	x
industry effects			x	x
R^2	0.09	0.59	0.65	0.65
sum of factor bias terms (γ's)	-0.10 (0.21)	0.22 (0.13)	-0.59 (0.33)	0 -
γ_1 assuming unchanged r.t.s.	**-1.17** (0.54)	**-1.04** (0.45)	**-1.49** (0.43)	**-1.49** (0.43)

Notes: All specifications include 422 observations of industries within countries. Standard errors (reported in parentheses) are heteroskedasticity-consistent and allow a country specific grouped error term. Observations are weighted by their value added share within each country. Total factor productivity is calculated using wagebill shares in value added as weights. In all but the rightmost column those weights are predicted using country and industry effects (see text and Table 3 for details). In the rightmost column the TFP weights are calculated by averaging across all industries and countries. The sum of factor bias coefficients sums estimated coefficients of production workers, nonproduction workers and capital. The coefficient γ_1 assuming unchanged returns to scale is the estimated coefficient on unskilled labor, calculated using the same specification but restricting the three factor bias coefficients to sum to zero. For descriptive statistics see Table 3. Estimating equation is (11) in text.

Table 7. Factor Bias Estimates: High vs. Middle Income Countries
Unchanged Returns Assumed

Dependent variable: Annualized change in log value added (x100)

	High Income			Middle Income		
		country effects	..& industry effects		country effects	..& industry effects
nonproduction	1.47	0.67	0.23	-1.25	1.05	1.28
	(0.52)	(0.45)	(0.33)	(1.33)	(0.67)	(1.28)
capital	0.12	0.27	-0.70	2.48	0.62	1.42
	(0.35)	(0.25)	(0.63)	(0.89)	(0.89)	(0.62)
Δ production	61.7	49.8	55.6	21.8	12.4	6.1
	(14.8)	(6.6)	(7.4)	(16.4)	(20.8)	(19.0)
Δ nonproduction	-0.1	21.8	30.9	43.6	51.7	60.6
	(10.4)	(6.7)	(5.2)	(13.0)	(14.1)	(11.1)
Δ capital	23.0	19.2	11.2	84.2	50.5	41.7
	(11.8)	(4.4)	(5.4)	(10.0)	(9.9)	(10.4)
country effects		x	x		x	x
28 industry effects			x			x
R^2	0.65	0.76	0.83	0.70	0.85	0.89
sum of elasticities (β's)	85 (10)	91 (6)	98 (8)	149 (11)	114 (13)	108 (16)
γ_1 assuming unchanged r.t.s.	**-1.60** (0.20)	**-0.94** (0.23)	**+ 0.46** (0.41)	**-1.23** (1.00)	**-1.67** (0.45)	**-2.71** (0.84)
Observations		225			197	

Notes: Standard errors (in parentheses) are heteroskedasticity-consistent, allowing a country specific grouped error term. Observations are weighted by value added share within each country. The sum of factor bias coefficients sums estimated coefficients of production workers, nonproduction workers and capital. The coefficient γ_1 assuming unchanged returns to scale is the estimated coefficient on production workers, using the same specification but restricting the three factor bias coefficients to sum to zero. The "constant returns" specification imposes constant returns to scale. The dependent variable in that case is Δlog(value added)-Δlog(production). For descriptive statistics see Table 3 . Estimating equation is (10) in text.

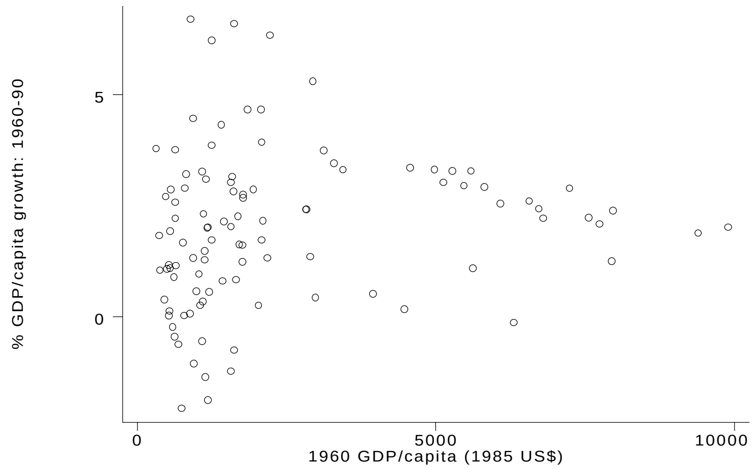

Figure 1A: Nonconvergence 1960-90

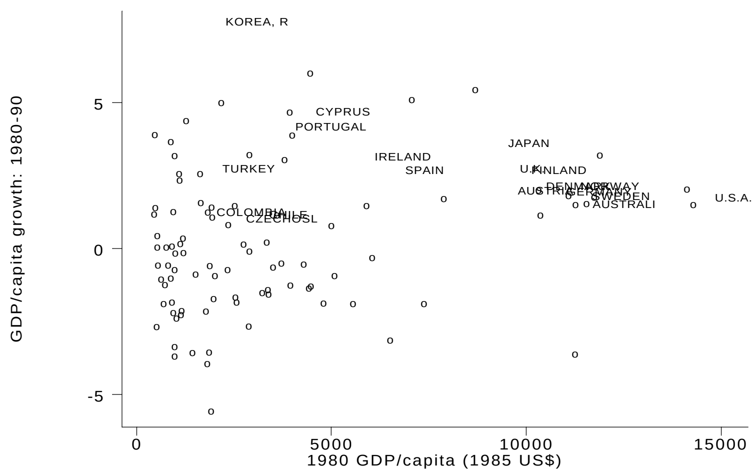

Figure 1B: Nonconvergence 1980-90

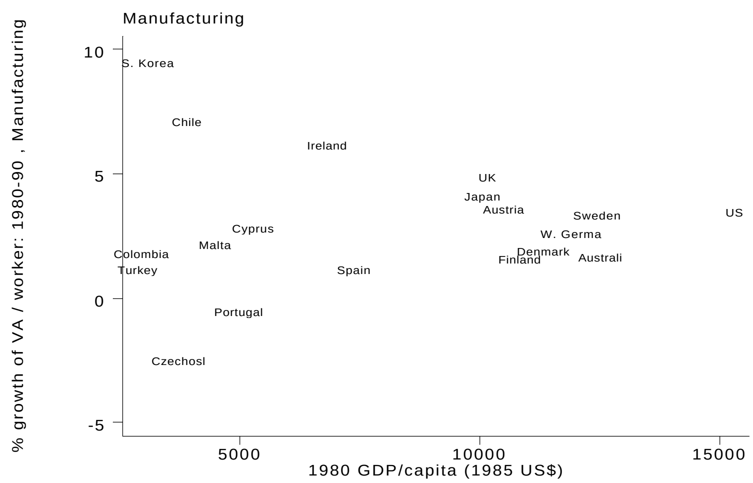

Figure 1C: Nonconvergence in Manufacturing Sample (product/worker)

Figure 2A: Factor Accumulation Growth

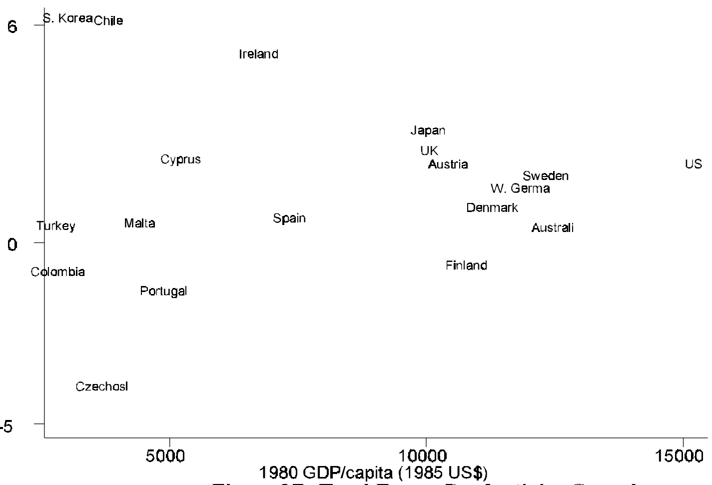

Figure 2B: Total Factor Productivity Growth

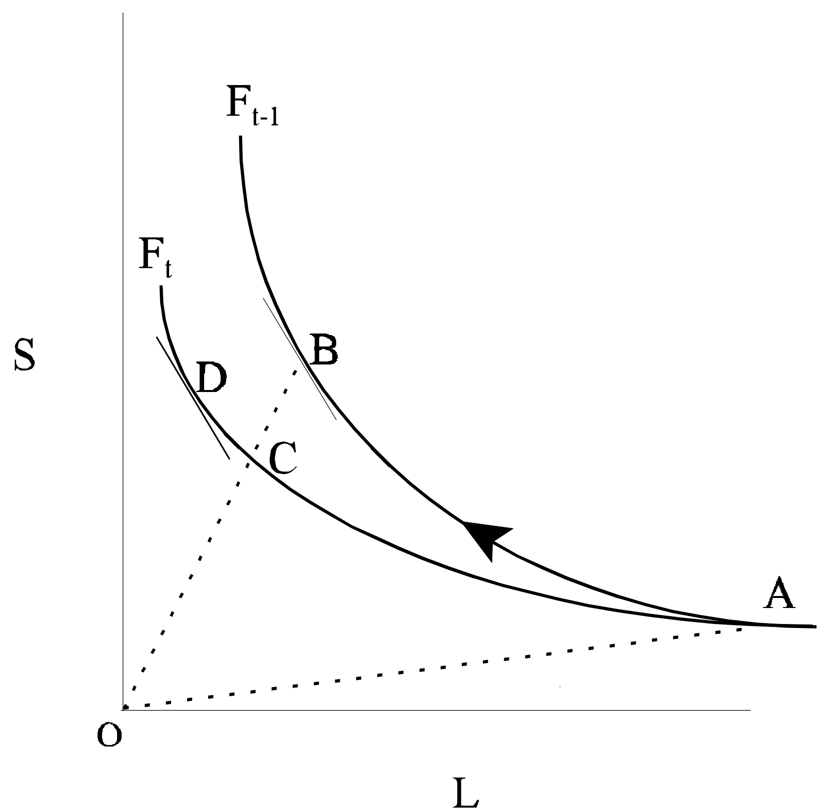

Figure 3: Technological Change with a Relative Skill Bias

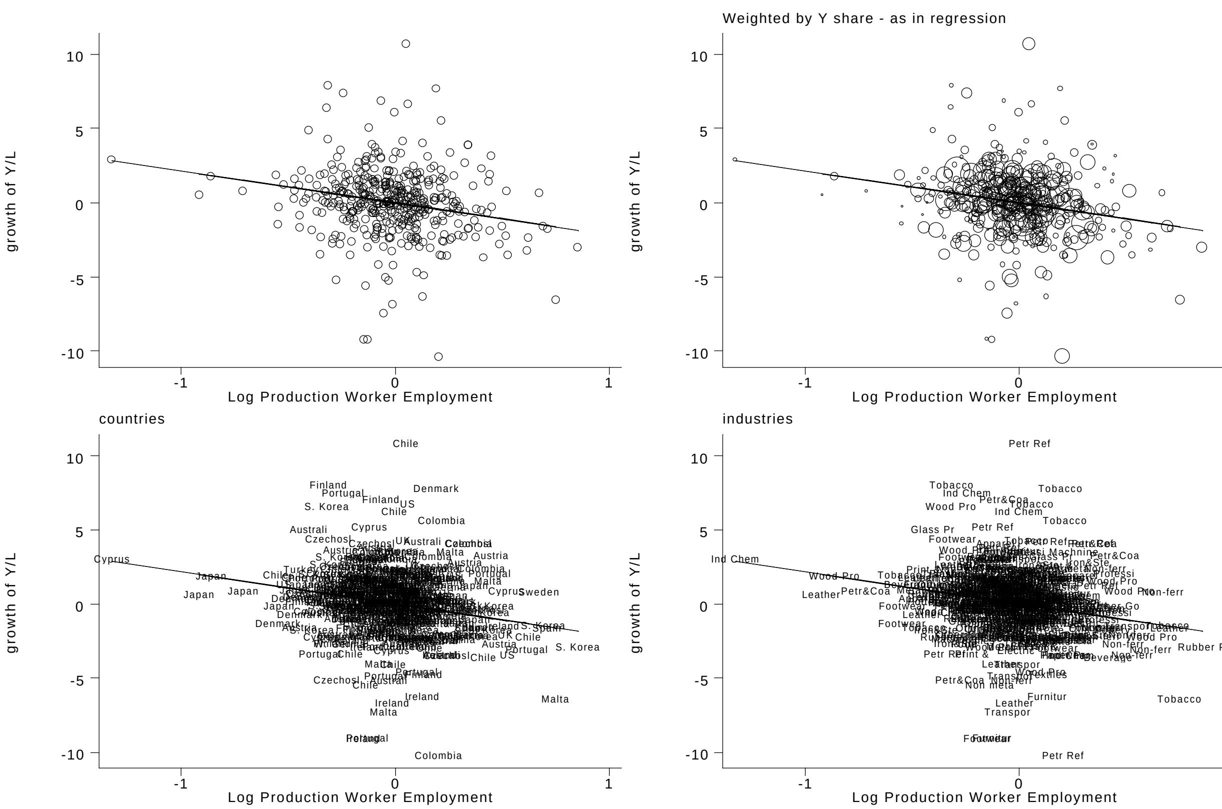

Figure 4: Leverage Plot of Labor-Saving Coefficient

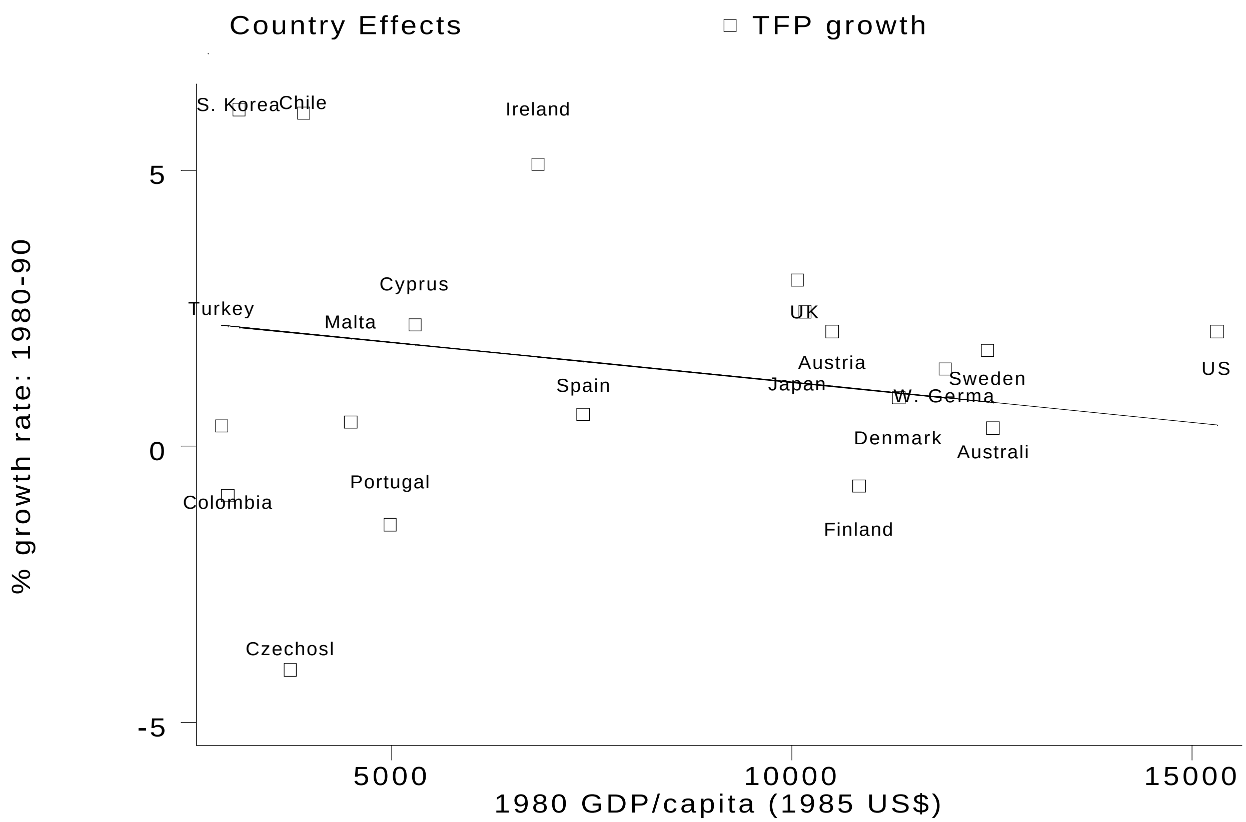

Figure 5: TFP Convergence Conditional on Factor Bias?