UNIL | Université de Lausanne
CREA – Institut de macroéconomie appliquée

HEC Lausanne

Endowments, Specialization and Policy

Yuliya Shakurova, Olivier Cadot, Alessandro Nicita, Claudio Sfreddo

Novembre 2007

Endowments, Specialization, and Policy*

November 2007

Yuliya Shakurova§
Olivier Cadot*
Alessandro Nicita+
Claudio Sfreddo†

Abstract

The paper explores the relationship between industry shares in production and their determinants including factor endowments, technology and government policies, in a GDP-function framework. We use a new international panel data set on production and trade compiled by the World Bank. As an intermediate step we calculate Hicks-neutral productivity indices that vary across industries, time and countries. We find that own-TFP is robustly associated with industry shares across time and countries and that, after correcting for these productivity differences, output shares are related to factor endowments (Rybczynski effects) in a plausible way. Once Rybczynski effects are controlled for, we find little evidence of demand-side policies (import tariffs) affecting the allocation of resources; we find, however, more role for supply-side policies as the relative size of capital-intensive industries is positively associated with infrastructure-capital endowments.

Keywords: GDP function, industrial policy, Rybczynski effects, trade and production
JEL classification codes: F1

---

* This paper is part of a World Bank research project. We are grateful to seminar participants at the University of Lausanne and particularly to Rafael Lalive for useful comments and suggestions.
§ HEC Lausanne.
* HEC Lausanne, CERDI, CEPR and CEPREMAP.
+ The World Bank
† University of Geneva. Sfreddo worked on this paper while at HEC Lausanne's Institute of Applied Economics (Créa).

1. Introduction

What determines a country's production pattern across sectors? Trade theory directly suggests a number of potential determinants: factor endowments, demand-side policies (tariffs and subsidies), and supply-side policies (e.g. the provision of infrastructure and public capital). But then, which of these determinants have proved across time and countries to be robustly associated with cross-sectoral production patterns, and can they be influenced by policy?

In a perfect world, production patterns would surely best be left for markets to determine. However governments typically have preferences over them, be it because of technological externalities, social issues, or loose "strategic" considerations. Indeed, there seems to be a recent revival in interest for industrial policy in a broad sense, albeit not in old-style import-substitution policies. For instance, in Chile, a country that has recently grown on the basis of laissez-faire policies, in spite of a strong consensus for the maintenance of these policies, the question of how to reduce the country's dependence on raw-material exports periodically resurfaces, without much answer from either positive or normative trade theory. Beyond Chile's case, empirical observations such as the "natural resource curse" (see e.g. Gylfason 2004) suggest −although without much theoretical backing− that a country's long-run growth performance may be related to its sectoral specialization, suggesting that the latter may be a legitimate subject of policy concern (see also Wood and Kersti 1997, or Wood and Jordan 2000). Our opening question is thus, from a policy perspective, one of interest.

At a general level, the Heckscher-Ohlin-Vanek (HOV) model suggests that the best way for a government to influence a country's pattern of specialization is to create the right policy environment for the appropriate factors of production to be accumulated. Put differently, under the HOV assumptions, whereas demand-side policies such as trade barriers and sectoral promotion are doomed −because they are unlikely to lead to anything but capture by special interests− supply-side policies can be justified. However, there is currently a gap between this type of loose presumption and the operational policy advice that is typically hoped for by governments.

At a theoretical level, specialization is linked to the "factor content of trade", as an industry that has a large share in GDP is likely to be an export one, unless the economy is severely distorted. So the relationship between production patterns and endowments is not independent of the relationship between trade and endowments. A large body of literature has been devoted to testing the HOV model's basic prediction for the factor content of trade. The results were, at first, a long series of setbacks. Although Leamer (1984) solved Leontief's paradox by showing that the test was not robust to large trade imbalances, Trefler (1995) confirmed that the measured factor content of international trade did not reflect differences in trade endowments, a finding he called "missing trade". Based on his work, the subsequent literature (e.g. Harrigan 1997 or Davis and Weinstein 2001) used unobserved or partially observed technology differences across countries and industries to explain the observed deviations of the factor content of trade from the predictions of the HOV model. Together with other adjustments - e.g. for unobserved trade barriers through the use of gravity-predicted trade flows instead of observed ones, as in Davis and Weinstein (2001) the modifications to the model suggested by the empirical literature, which consisted of assuming various forms of technology differences, turned out to close much of the gap between theory and measurement, so that the debate is by now largely settled.[1]

Surprisingly, the normative side of the question (the policy debate about what type of trade intervention, if any, is appropriate) has evolved in parallel with the positive side but without much interaction between the two. Early conceptions in terms of trade policy involved a basic laissez-faire presumption with exceptions only for infant industries and in other very particular cases. Schools of thought with a more activist stand, such as Latin America's ECLAC, drew on altogether different theoretical premises, and the import-

[1] More recent papers (Schott 2003, 2004) have pushed the literature in a different direction in which the assumption of factor-price equalization is done away with and countries "travel" across different diversification cones as they accumulate capital, resulting in evolving specialization patterns characterized in particular by different positioning along a vertically-differentiated quality ladder.

substitution policies that were based on those premises largely failed to live up to their promises. The idea of proactive trade and industrial policies was briefly revived, under the generic name of “strategic trade policy”, with the advent of intra-industry trade models in the 1980s. Essentially, the argument was that under imperfect competition, beggar-thy-neighbor policies could be welfare-enhancing from a national point of view although welfare-reducing from a global one. The vogue of game-theoretic arguments as guides for strategic trade policy was however short-lived, as many of those arguments proved to be not robust to slight changes in the assumptions (e.g. moving from Cournot to Bertrand competition) and US concerns about low productivity growth and large trade deficits with Japan and Europe, which had contributed to the appeal of proactive policy prescriptions, vanished in the 1990s.

The objective of this paper is to shed light on this issue using a traditional GDP-function approach but applied on a dataset that has only recently been made available and that is arguably very well suited to the question. The data set is the World Bank’s Trade and Production Database (Nicita and Olarreaga 2006), which contains data on production, trade and endowments at the ISIC 3-digit level. We estimate Rybczynski derivatives for the database’s 100 countries and 27 sectors using aggregate capital-labor ratios constructed from investment and employment data contained in the database.

Results are encouraging. The baseline model yields positive and significant share effects for own-TFP parameters and sorts industries by capital intensiveness in a plausible way. Preliminary results on tariff protection suggest, however, very little effects.

2. Background

Let $R(\theta\mathbf{p},\mathbf{v})$ be a representative country’s GDP function, solving

$$R(\boldsymbol{\theta}.\mathbf{p},\mathbf{v}) = \max_{v_j}\left\{\sum_{j=1}^{n}\theta_j p_j f^j\left(v_j\right) \text{ s.t. } \sum_{j=1}^{n} v_j = \mathbf{v}\right\}, \tag{1.1}$$

where $\boldsymbol{\theta}$ is an $n \times n$ diagonal matrix of Hicks-neutral country- and sector-specific technology parameters, **p** is an $n \times 1$ vector of commodity prices, and **v** is an $m \times 1$ vector of factor endowments. Following Kohli (1978) and (*inter alia*) Harrigan (1997), for estimation purposes we assume a translog form (a flexible functional form in which elasticities are not constrained to be constant):

$$\begin{aligned}\ln R = \alpha_0 &+ \sum_j \alpha_j \ln \theta_j p_j + \sum_k \beta_k \ln v_k \\ &+ \frac{1}{2} \sum_i \sum_j \gamma_{ij} \ln \theta_i p_i \ln \theta_j p_j \\ &+ \frac{1}{2} \sum_k \sum_\ell \delta_{kl} \ln v_k \ln v_\ell \\ &+ \sum_i \sum_k \phi_{ik} \ln \theta_i p_i \ln v_k .\end{aligned} \tag{1.2}$$

Like any revenue function (see e.g. Dixit and Norman 1980) the GDP function is homogenous of degree one in prices and endowments, which implies the following homogeneity restrictions:

$$\begin{aligned}&\sum_j \alpha_j = \sum_k \beta_k = 1; \\ &\sum_i \gamma_{ij} = \sum_k \delta_{k\ell} = \sum_i \phi_{ik} = \sum_k \phi_{ik} = 0.\end{aligned} \tag{1.3}$$

Sectoral shares can be obtained by differentiating (1.2) with respect to $\ln p_j$:

$$\frac{\partial \ln R}{\partial \ln p_j} = \alpha_j + \sum_i \gamma_{ij} \ln \theta_i p_i + \sum_k \phi_{jk} \ln v_k . \tag{1.4}$$

Homogeneity restrictions (1.3) imply that $\gamma_{i1} = -\sum_{j=2}^{N} \gamma_{ij}$, so (1.4) can be rewritten as

$$\begin{aligned}
\frac{\partial \ln R}{\partial \ln p_j} &= \alpha_j + \gamma_{j1} \ln \theta_1 p_1 + \sum_{j=2}^{n} \gamma_{ij} \ln \theta_i p_i + \sum_k \phi_{jk} \ln v_k \\
&= \alpha_j - \sum_{i=2}^{n} \gamma_{ij} \ln \theta_1 p_1 + \sum_{i=2}^{n} \gamma_{ij} \ln \theta_i p_i + \sum_k \phi_{jk} \ln v_k \qquad (1.5)\\
&= \alpha_j + \sum_{i=2}^{n} \gamma_{ij} \ln \frac{\theta_i p_i}{\theta_1 p_1} + \sum_k \phi_{jk} \ln v_k .
\end{aligned}$$

Similarly using (1.3) to write $\phi_{j1} = -\sum_{k=2}^{M} \phi_{jk}$ we have

$$\frac{\partial \ln R}{\partial \ln p_j} = \alpha_j + \sum_{i=2}^{n} \gamma_{ij} \ln \frac{p_i}{p_1} + \sum_{i=2}^{n} \gamma_{ij} \ln \frac{\theta_i}{\theta_1} + \sum_k \phi_{jk} \ln \frac{v_k}{v_1}. \qquad (1.6)$$

Finally noting that

$$\frac{\partial \ln R}{\partial \ln p_j} = \frac{p_j}{R} \frac{\partial R}{\partial p_j} = \frac{p_j Y_j}{Y} \equiv s_j , \qquad (1.7)$$

where s_j is sector *j*'s share in GDP, we have

$$s_j = \alpha_j + \sum_{i=2}^{n} \gamma_{ij} \ln \frac{p_i}{p_1} + \sum_{i=2}^{n} \gamma_{ij} \ln \frac{\theta_i}{\theta_1} + \sum_k \phi_{jk} \ln \frac{v_k}{v_1} . \qquad (1.8)$$

3. Estimation

Empirically testing an expression like (1.8) involves substantial prior work to generate proxies for right-hand side variables. This section describes our data-construction strategy. Essential differences between our work and Harrigan's come from the availability of a new dataset compiled by the World Bank and from our use of tariffs to approximate international price differences (whereas he simply assumed free trade). Including tariffs in the equation not only makes it possible to do away with a dubious assumption −universal free trade− but it also makes it possible to assess the extent to which trade protection seems to affect the allocation of productive resources. In order to bring more of a policy flavor to our exercise, we also include measures of public infrastructure capital. If infrastructure is complementary with private capital, an improvement in its provision should shift resources toward capital-intensive sectors.

3.1 Data

3.1.1 Data sources

The primary source of our data is the revised version of the World Bank's Trade and Production Database (TPDB, described in detail in Nicita and Olarreaga 2006). The TPDB covers 100 countries and 28 manufacturing sectors at the ISIC-revision 2 3-digit level and includes data on trade, production and protection. All data is in current US dollars (see Table 1 and Tables 2a and 2b). Two variables must be calculated: capital stocks and total factor productivity (TFP), taken as a proxy for the technology parameter θ.

3.1.2 Constructing the capital stock

Capital stocks for each manufacturing sector and country were calculated from the TPDB's sectoral investment data (GFCF) using the Perpetual Inventory Method (PIM).[2] Several variants of the method exist, depending on how capital consumption is modeled, and are described in detail in OECD (2001). Geometric depreciation over an infinite lifetime, used by Statistics Canada, assumes that capital assets lose value most rapidly in their first years. Hyperbolic depreciation, used, *inter alia*, by the US Bureau of Labor Statistics, assumes instead that capital's productive value is a concave function of time, until a finite end of service life.[3] This assumption is better suited to productivity analysis

[2] Capital stock variables are available from the Penn World Tables Mark 5.6 only up to 1992. Mark 6.1 of the PWT is incomplete precisely for those variables.

[3] The service life of machinery is variable and has been estimated in various ways, e.g. by observing discard decisions over a sample to infer the hazard rate of a distribution of discard times assumed to be of the Weibull type. Other distributions (e.g. lognormal, Winfrey) are also sometimes used. The average service life is then taken as the distribution's mean. A simple average of estimated service lives of machinery in the manufacturing sector from Statistics Canada gives 13.6 years, against 14.4 years using the US's Bureau of Economic Analysis data (see Annex 3 of OECD 2001),); revised data by U.S. Department of Labor gives on average 22 years of service life.

as it reflects the machinery's capacity to deliver productive services (e.g. by not breaking down) rather than its market (or accounting) value (OECD 2001).

Formally, let I_t be the flow of gross investment at time *t* (observed) and K_t the net capital stock at time *t* (to be estimated). Let also *L* be the capital stock's average service life and τ the date of its purchase. The "age-efficiency" adjustment factor, $\delta_{t,\tau}$ is given by

$$\delta_{t,\tau} = \begin{cases} \left[L-(t-\tau-1)\right]/\left[L-\beta(t-\tau-1)\right] & \text{if } t-\tau<L \\ 0 & \text{otherwise} \end{cases} \tag{1.9}$$

where β is the slope coefficient (the US Bureau of Labor Statistics (BLS) assumes $\beta = 0.5$ for machinery and $\beta = 0.75$ for construction; we used $\beta = 0.625$).[4] The efficiency-age value of the capital stock at time *t*, ($t = 0$ in the sample's initial year) is then

$$K_t = \delta_{t,0}K_0 + \sum_{\tau=1}^{t-1}\delta_{t,\tau}I_\tau. \tag{1.10}$$

Practical estimation of (1.10) requires an initial estimate for K_0 whose influence on later values of K_t vanishes over time. We set K_0 at 1.5 times value added[5] and use a service life of 23 years, corresponding to the BLS's average across industries (see also Annex 3 of OECD 2001, which lists estimates of machinery service lives from various national statistical offices). All values in the TPDB are in current dollars, so we deflated them using the US producer price index from NBER-CES Manufacturing Industry Database, assuming that purchasing power parity (PPP) holds in the long run. We benchmarked our estimates by comparing them with NBER estimates for the US. The result of the comparison is shown in Figure 1 and suggests that, although not identical, our estimates are within a reasonable range of the NBER's.

---

4 Bureau of Labor Statistics, *BLS Handbook of Methods*, ch. 11, Industry Productivity Measures; available at www.bls.gov.

5 The simple average across industries and years of the capital-output ratio (capital stock over value added) in the NBER's productivity database is 1.72 (st. dev. 1.53) whereas the weighted average is 1.32 (see www.nber.org/nberces).

Figure 1
Capital stock estimates compared with the NBER's

3.1.3 TFP

The productivity parameters were calculated relative to the US using an index due to Caves et al. (1982) and described in some detail in Harrigan (1997).[6] That is, we assumed that for each industry, cross-country technology differences are Hicks-neutral.[7] For Cobb-Douglas technologies, the index's formula is

$$\theta_{jt}^{c} = \frac{y_{jt}^{c} / \left[\left(L_{jt}^{c} \right)^{\bar{\alpha}_j} \left(K_{jt}^{c} \right)^{1-\bar{\alpha}_j} \right]}{y_{jt}^{US} / \left[\left(L_{jt}^{US} \right)^{\bar{\alpha}_j} \left(K_{jt}^{US} \right)^{1-\bar{\alpha}_j} \right]} \qquad (1.11)$$

where $\bar{\alpha}_j$ is a geometric average of the share of labor in all countries in industry *j*, calculated using employment and wage data given in the TPDB using

$$\bar{\alpha} = \frac{\sqrt[100]{\prod_{c=1}^{100} W_c^{jt}}}{\sqrt[100]{\prod_{c=1}^{100} y_c^{jt}}} .$$

where W_c^{jt} is the wage bill and y_c^{jt} is value added in the TPDB. The resulting index values are noisy, which is to be expected as measurement errors leading to values of

[6] An alternative would be to estimate industry- and country-specific TFP values as residuals from estimated production functions. This alternative route has the drawback that TFP equations would have only 29 observations each, as they would have to be estimated on country- and industry-specific time series. We leave this alternative route to future research.
[7] Assumptions about the form of cross-country technology differentials vary across studies. Trefler (1993) allowed for general factor-augmenting technical parameters differing across countries, but showed that this made the Heckscher-Ohlin-Vanek (HOV) equation an identity, so that the factor content of trade could not be tested. Trefler (1995), by contrast, assumed a uniform Hicks-neutral technology parameter across all industries for each country. The formulation here is in between: we assume Hicks-neutrality but allow the technology parameter to vary across industries and countries. Note that we assumed a Cobb-Douglas technology in the calculation of the index. A more general version of the index exists for trans-log forms.

capital or labor near zero send the ratio in (1.11) to infinity. As a reality check, one would expect national averages of the productivity parameters to be somewhat correlated with GDP per capita across countries. Figure 2 shows a scatter plot of a weighted average of industry-specific productivity parameters, with industry shares in value added as weights, against GDP per capita, pooled over industries and time.

Figure 2
Productivity parameters and vs. relative GDP per capita

A simple pooled OLS regression of $\bar{\theta}_t^c / \bar{\theta}_t^{US}$ on GDP_t^c / GDP_t^{US} gives a coefficient of 0.58 significant at the 1% (robust t-stat 7.36). R^2 = 0.48, reflecting the index's noise. All in all, the crude plausibility test of an overall positive relationship between average technology and GDP per capita is passed.

3.2 Estimating Rybczynski elasticities

We estimated stochastic versions of (1.8) at the industry level (28 industries meaning 28 equations) with time and country fixed effects and measurement-error correction on a panel of 100 countries and 25 years, using 3SLS.[8] We included only own productivity and own tariffs so as to save on degrees of freedom. Cross-industry productivity effects (spillovers) would have been interesting to identify, but preliminary estimation exercises showed them to be all insignificant. Similarly for tariffs: cross-industry crowding-out effects would have been interesting to track, but they all proved insignificant. We estimated the industry equations simultaneously for groups of similar industries in order to control for cross-equation correlation in the error terms.[9]

Letting the superscript *c* stand for countries and dropping industry indices, we have thus

[8] The nominal sample size of 2'900 observations is however drastically reduced by missing values.
[9] Such correlation is implied by the symmetry restrictions and can also be the result of shocks on the omitted service sector. A Breusch-Pagan test rejects independence of the equations at the 1% level.

$$
\begin{aligned}
s_{ct} &= \eta_c + \delta_t + \alpha_1 PC_{ct} + \alpha_2 \ln \tau_{ct} + \alpha_3 \ln \theta_{ct} \\
&+ \alpha_4 \ln \frac{K_{ct}}{L_{ct}} + \alpha_5 \ln \frac{T_{ct}}{L_{ct}} + \sum_{h=6}^{8} \alpha_h \ln \frac{H_{type,ct}}{L_{ct}} + \varepsilon_{ct}
\end{aligned} \tag{1.12}
$$

where η_c is a country fixed effect, δ_t is a time effect, PC_{ct} is relative country public capital index, τ_{ct} is tariff, θ_{ct} is an industry productivity index, K_{ct}/L_{ct} is country *c*'s relative capital endowment, T_{ct}/L_{ct} is its relative land endowment and $H_{type,ct}/L_{ct}$ is human capital per worker.[10]

Two potential sources of measurement error on the right-hand-side must be taken care of. One is persistent errors due to differences in data collection across countries. The other, a classical measurement error, may be generated in the calculation of the productivity index. As shown by Harrigan (97), the measurement error's persistent component (the first) is controlled for by the country and time effects included in the equation. By contrast, the classical measurement error (the second) requires instrumentation if one is to get consistent estimates. Assuming that measurement errors are uncorrelated across countries, we instrument productivity in country *c* by the average value of productivity in all other countries (industry by industry). That is, θ_{jct} is instrumented by $1/(C-1)\sum_{k\neq c}^{C}\theta_{jkt}$, where $j=1,\ldots,N$ indexes industries (equations). Then, these instruments are used for correcting measurement error bias for each industry for country c at time *t*.

Finally, political-economy models suggest that tariffs are likely to be endogenous to production levels; for instance, the common-agency model (Grossman and Helpman 1994) makes tariffs an increasing function of the ratio of domestic production to imports. Alternatively, tariffs can be applied to protect infant industries, in which case they would be decreasing in the level of domestic production.[11] So we don't know which way the

[10] All regressions are performed in levels. A panel unit-root test rejects the null of a unit root at the 5% level. We also estimated a partial-adjustment version of (1.12) by GMM but with limited success, the sample size being too small for GMM to be efficient.

[11] The common-agency model's prediction that tariffs should rise with domestic production has been a subject of controversy (see Rodrik 1995), since it seems to imply that industries in which a

bias would go but what is clear is that tariffs are unlikely to be exogenous to production levels and hence to industry shares in GDP. In order to control for this likely endogeneity, we instrument tariffs the same way we instrument productivities, by using, in each industry-specific equation, the average tariff applied in that industry by all other countries.

4. Results

Three-stage least squares estimation results are shown in Tables 3a-3e, with one regression for each 3-digit category between 311 (food products) and 385 (professional & scientific equipment). In all cases, the dependent variable is the share of industry *j*'s value added in total value added in the manufacturing sector (as reported in the TPDB). For ease of reading, we have grouped ISIC 3-digit industries into broad categories corresponding roughly to those used by Harrigan (1997): food products, textiles & clothing, wood and paper, chemicals, glass products, metals, and machinery. In spite of the data's noisiness, results are largely as expected.

Own-TFP coefficients are all positive and significant at the 1%. As for Rybczynski effects, the Rybczynski theorem's logic is that industries that are, say, capital-intensive should have high shares in the GDP of capital-abundant countries. The coefficient on aggregate capital/labor ratios (national endowments) should thus be positive for capital-intensive industries and negative or insignificant for others. Our estimates are significant at the 5% level or higher for twenty three out of twenty-seven industries, and, by inspection, signs are plausible. Textiles, clothing, leather and rubber are negatively correlated with capital endowments. Chemicals ("industrial" and "other"), petroleum, steel and other mallurgical industries, machinery, transport and scientific equipment are all positively correlated with capital endowments. The only puzzling result is the positive

country has a comparative disadvantage (hence small production) are the least likely to be protected, a rather counter-intuitive prediction. However Goldberg and Maggi (1999) showed that that prediction is upheld by the data if politically organized sectors are treated distinctly from non-organized ones.

correlation of food products with capital endowments.[12] So unlike Harrigan (1997), using the World Bank's large database we find that most manufacturing industries are capital-intensive relative to the omitted category (services and non-tradables), which somehow accords better with intuition. Land endowments are negative or insignificant in most cases, possibly reflecting a higher share of agriculture in the GDP for countries with high land/labor endowments. Human capital endowments, broken down by level of education, show no particular pattern except for post-secondary education which is correlated (significant coefficients with high values) with the shares of capital-intensive and high-tech industries (fabricated metal products, machinery, electrical machinery, transport equipment). The only counter-intuitive case here −but it is *very* counter-intuitive− is scientific equipment, for which we have no particular explanation.

A more formal reality check on our Rybczynski effects consists of plotting our Rybczynski elasticities with respect to capital endowments against industry capital intensities (averaged across countries in the sample). The resulting scatter plot is shown in Figure 3.

Figure 3
Estimated Rybczynski elasticities against factor intensities

The cloud of points is upward-sloping, as expected, with electric machinery, machinery and transport being outliers. The share of these three sectors in GDP thus rises faster with capital endowments than warranted by their own capital-intensity, suggesting that they are also intensive in something else that is correlated with capital endowments −technology and education being obvious suspects.[13]

Tariffs are associated with higher shares for food, tobacco, wearing apparel, and fabricated metal products. They have negative and significant effects for machinery, transport equipment and scientific instruments, possibly reflecting infant-industry protection. Public infrastructure capital has a positive coefficient in the equations for

[12] Textiles can also be considered a dubious case, as upstream textile operations (weaving, dying and cutting) are rather capital-intensive.
[13] All three sector shares indeed have high coefficients on post-secondary education and own-TFP relative to other sectors.

machinery, electrical machinery and transport equipment, reflecting the complementarity of infrastructure with private capital.

5. Concluding remarks

Results so far should be treated cautiously, if only because the countries in our sample do not necessarily belong to the same diversification cone. A given industry can therefore have different factor intensities in different countries, implying that the relationship between endowments and intensities is fundamentally heterogeneous (on this, see Schott 2004). With a sufficiently small number of cones, an alternative to our approach would be to use switching-regime techniques. We leave this for future research.

This said, the results are broadly consistent with a Heckscher-Ohlin perspective on trade, confirming that production patterns are significantly influenced by factor endowments and "technology" (the latter taken in a broad sense that can include management quality, since it is measured as TFP). Tariffs, by contrast, appear to play but a minor role in the allocation of resources, suggesting that reliance on demand-side policies to channel resources to whatever industries are perceived by public authorities as "the ones to be in" is unlikely to have any long-term effects −without even talking about the inefficiencies involved in the process.

The obvious policy implication is that policies aimed at influencing a country's pattern on specialization should be essentially supply-side policies to encourage the accumulation of the right factors and horizontal policies to encourage the adoption of technological and managerial advances.

References

Barro, Robert J. and Lee Jong-Wha (2000), "International data on educational attainment: updates and implications", CID Working Paper No. 42

Caves, Douglas W., Christensen, Laurits R. and Diewert, W. Erwin (1982), "Multilateral comparisons of output, input, and productivity using superlative index numbers." Economic Journal 92, 73-86

Davis, Donald R. and D. Weinstein (2001), "An Account of Global Factor Trade"; American Economic Review 91, 1423-1454.

Dixit, Avinash K. and Norman, Victor (1980), Theory of International Trade, Cambridge University Press.

Goldberg, Pinelopi and Giovanni Maggi (1999), "Protection for Sale: an Empirical Investigation"; American Economic Review 89, 1135-1155.

Green, William H. (1993), *Econometric Analysis*; Prentice Hall.

Grossman, Gene, and E. Helpman (1994), "Protection for sale", American Economic Review 84, 833-850.

Gylfason, Thorvaldur (2004), "Natural Resources and Economic Growth: From Dependence to Diversification" CEPR Discussion Paper No. 4804.

Harrigan, James (1997), "Technology, Factor Supplies, and International Specialization"; American Economic Review 87, 475-494.

Hsiao, Cheng (2003), *Analysis of Panel Data*; Cambridge Econometric Series Monographs.

Hummels, David and Klenow, Peter J. "The Variety and Quality of a Nation's Exports", American Economic Review 95, 704-723.

Jorgenson, Dale W. (1990), "Productivity and Economic Growth," in Ernst R. Berndt and Jack E. Triplett, eds., *Fifty Years of Economic Measurement: The Jubilee of the Conference on Research in Income and Wealth*, University of Chicago Press, pp. 19-118.

Kohli, Ulrich R. (1978), "A gross national product function and the derived demand for imports and supply of exports" Canadian journal of economics XI, no. 2, 167-182

Leamer, Edward E. (1984) *Source of International Comparative Advantage: Theory and Evidence*, Cambridge, MA: MIT Press.

OECD (2001), *Measuring Capital: OECD Manual*; Organization of Economic Cooperation and Development, Paris.

Owens, Trudy, and A. Wood (1997), “Export-Oriented Industrialization through Primary Processing?” World Development 25, 1453-70.

Rodrik, Dani (1995), "Political economy of trade policy", in G. Grossman and K. Rogoff, eds., Handbook of International Economics, vol. III, North Holland.

Schott, Peter (2003), “One Size Fits All? Heckscher-Ohlin Specialization in Global Production”; American Economic Review 93, 686-708.

Schott, Peter (2004), “Across-product versus Within-product Specialization in International Trade”; Quarterly Journal of Economics 119, 647-678.

Trefler, Daniel (1993) “International factor price differences: Leontief was right!” Journal of Political Economy 101, 961-987.

−− (1995) “The case of the missing trade and other HOV mysteries,” American Economic Review 85, 1029-1046; reprinted in Edward Leamer, ed., *International Economics*, 2001.

Wood, Adrian, and B. Kersti (1997), “Exporting Manufactures: Human Resources, Natural Resources, and Trade Policy” Journal of Development Studies 34, 35-59.

Wood, Adrian, and K. Jordan (2000), “Why Does Zimbabwe Export Manufactures and Uganda Not? Econometrics Meets History”; Journal of Development Studies 37, 91-116.

Annexes

Annex 1: Data description

The data (data summary is presented in tables 2a and 2b) is taken from the "Trade, Production and Protection" database of July 27, 2006 (TPDB). This dataset was constructed for 28 manufacturing industries in 100 countries over time period 1976-2004 by the World Bank research group and is described in A. Nicita and M. Olarreaga (2006). The set of raw data chosen from the database for the present work is summarized in Table 4.

We dealt with missing observations by linear extrapolation and interpolation of the data. 451 negative investment observations, 64 negative values of value added variable, 74 values of tarif_iwAHS that are greater than 100%, 576 values of zero tariff, 255 observations of n_employees with value less than 20 units were treated as missing and completed the series using interpolation and extrapolation as mentioned.

Price deflator

We deflated current-dollar data from the TPPD using the US Producer Price Index (PPI) completed with data from the Bureau of Labor Statistics (BLS) and NBER-CES Manufacturing Industry Database. Using two different data sources may of course be a problem. Data on PPI is reported for the industries grouped by (SIC), and the TPDB is based on 3 digits ISIC (revision 2). Moreover, the BLS and NBER sources present data on different level of aggregation. So the first question is to find a concordance between the industries classified by SIC and ISIC (rev. 2); and the second question is to carry out an appropriate aggregation of PPI variable within the SIC.

The answer to the first question posed in the previous paragraph is presented by the following table where we show which concordance we used between SIC vs. ISIC (rev. 2).

ISIC 3digit 2 Rev.		SIC 2digit
Food products	311 - 20	FOOD AND KINDRED PRODUCTS
Beverages	313 - 20	FOOD AND KINDRED PRODUCTS
Tobacco	314 - 21	TOBACCO PRODUCTS
Textiles	321 - 22	TEXTILE MILL PRODUCTS
Wearing apparel, except footwear	322 - 23	APPAREL AND OTHER TEXTILE PRODUCTS
Leather products	323 - 31	LEATHER AND LEATHER PRODUCTS
Footwear, exc. rubber or plastic	324 - 31	LEATHER AND LEATHER PRODUCTS
Wood products, exc. furniture	331 - 24	LUMBER AND WOOD PRODUCTS
Furniture, except metal	332 - 25	FURNITURE AND FIXTURES

Paper and products	341 - 26	PAPER AND ALLIED PRODUCTS
Printing and publishing	342 - 27	PRINTING AND PUBLISHING
Industrial chemicals	351 - 28	CHEMICALS AND ALLIED PRODUCTS
Other chemicals	352 - 28	CHEMICALS AND ALLIED PRODUCTS
Petroleum refineries	353 - 29	PETROLEUM AND COAL PRODUCTS
Misc. petroleum and coal prod.	354 - 29	PETROLEUM AND COAL PRODUCTS
Rubber products	355 - 30	RUBBER AND MISC. PLASTICS PRODUCTS
Plastic products	356 - 30	RUBBER AND MISC. PLASTICS PRODUCTS
Pottery, china, earthenware	361 - 32	STONE, CLAY, AND GLASS PRODUCTS
Glass and products	362 - 32	STONE, CLAY, AND GLASS PRODUCTS
Other non-metallic mineral prod.	369 - 32	STONE, CLAY, AND GLASS PRODUCTS
Iron and steel	371 - 33	PRIMARY METAL INDUSTRIES
Non-ferrous metals	372 - 33	PRIMARY METAL INDUSTRIES
Fabricated metal products	381 - 34	FABRICATED METAL PRODUCTS
Machinery, except electrical	382 - 35	INDUSTRIAL MACHINERY AND EQUIPMENT
Machinery, electric	383 - 36	ELECTRONIC AND OTHER ELECTRIC EQ-T.
Transport equipment	384 - 37	TRANSPORTATION EQUIPMENT
Profess-l and scien-c equip.	385 - 38	INSTRUMENTS AND RELATED PRODUCTS
Other manufactured products	390 - 39	MISC. MANUFACTURING INDUSTRIES

In most cases the correspondence follows explicitly. However, sometimes an industry in ISIC corresponds to a subindustry in SIC. For example, beverages and food products are two industries standing on the same level in ISIC, whereas in SIC it is a component of the bigger food products industry. In such cases we consider beverages, taking the data on PPI for the food industry, as it would be the food industry in SIC.

The answer to the second question is best illustrated in Figure A1. There we show the comparison after the necessary aggregation of the US PPI taken from the NBER (denoted there as price deflator for shipments) and BLS (denoted as PPI -discontinued SIC). The available overlapping period is 1984-1997. Data are presented for the different industries grouped by SIC in the order as they follow in Table 1 with the base year 1984. We take the average price index among the disaggregated data within the required level of aggregation for a particular industry. This comparison shows that data from the two sources is pretty much comparable.

Finally, the PPI index in 1976-1997 is taken from NBER source, in 1998-2003 it is completed using the growth rates of PPI from the BLS source. In 2004 we use the extrapolated value. For the convenience the base year was changed from 1984 to 2000. We get the real values of output, value added and wage bill variables dividing by this PPI the respective nominal variables. In order to deflate the investment variable we used the PPI for the commodity group machinery and equipment taken completely from the BLS source for the period 1976-2004.

Missing variables

In an effort to avoid unduly reducing sample size, we used linear extrapolation and interpolation for all variables with the exception of tariffs. We linearly interpolated observations up to 4 missing values in a row and extrapolated up to 4 missing lead and lag values. For rapidly decreasing variables linear extrapolation can produce negative values. In such cases we treated negative values as missing.

For tariffs we used a slightly different procedure. In the sample period, 1976-2004, changes in the world tariff system took place in 1995, when the Uruguay Round was concluded. Before or after this year tariffs can be considered as stable. Thus, we did not interpolate *across* the year 1995, but for 1976-1994 and 1995-2004 time periods instead of linear extrapolation, we used the last values in the beginning or end of the series and repeated it up to the sub-period's last year.

TPPD observations for Luxemburg and Belgium are pooled together. Whenever we use data from sources other than the TPPD, it must be aggregated for these two countries. We do it by taking simple averages, although this underestimates Belgium's weight.

Variables for the estimation

Output share

In this paragraph we detail how we constructed the "s_j^c" variable, the percentage share of industry *j* in country c's GDP. In order to compute *s* we need the industry value added variable and aggregate real GDP for each country. The information on real GDP per capita (2000 constant prices: Laspeyres) was taken from the PWT Mark 6.2. Using this data and transforming the measurement units we get the real GDP in thousands of constant 2000 dollars.

Capital stock

Here we describe some details of the estimation of net capital stock. An important stage in the calculation is to determine the value of the initial capital stock. The initial capital is computed as $K_0 = \kappa \cdot Value\_Added$, where κ has to be chosen as a parameter. Using US data from the NBER, which provides estimates of the capital stock and value added in the manufacturing industry database we calculated κ for different industries. Using NBER data created the usual same problem of industrial classification concordance and aggregation, but we could carry out more detailed concordance than before. For example, we split the SIC food industry data which includes beverages. Thus, instead of taking the data on beverages as if it were food, we got different mutually exclusive data on these two industries. In order to get the 2-digits SIC we averaged the values of 4-digit SIC data over the sample period. Thus, we base the calculation of the initial capital stock on values of κ that differ for all 28 industries. Approximate values are presented in Table 1.

The adjustment factor depends crucially on two values, the service life in years L and the parameter of efficiency decline β, and it was difficult to pick out the most appropriate parameters. We took average parameters for the industries we have in the BLS sample. Thus, in our estimation we have $L = 23$ and $\beta = 0.625$.

Land

The data on land were taken from the World Development Indicators database (WDI). The variable that we use is presented by the area of arable land in 1000 Ha. We want to note that the data on land is available only up to 2003. To complete the series we used the data in 2003 as a proxy for 2004.

Labour

The Labour variable was taken from WDI database. This is a variable representing total number of people employed in the country c in year t. The variable is expressed in units. The available period is 1980-2004. In order to get the data for 1976-1980, we used, as usual, linear lag extrapolation.

Education

We use the data on educational attainment available from Barro and Lee (2000). We have chosen to use the data for age group over 25. Educational attainment is divided into 3 groups: people having primary, secondary and postsecondary education. The variable is expressed in percentage points of the total population (in our case over age 25) expressed in 1000s. The data are available in 5 years intervals for the period 1960-2004. In order to complete the series within the given data points, we use linear interpolation. Later on we use the data on population expressed in units to compute the number of people over 25 having one or another level of education. However, we have the problem of unavailability of the data from this sources fro19 countries we would like to have in our analysis. They are Armenia, Azerbaijan, Bulgaria, Cote d'Ivoir, Gabon, Kyrgyzstan, Sri Lanka, Macau, Morocco, Mongolia, Nigeria, Netherlands, Oman, Qatar, Russian Federation, Tanzania, Ukraine, and Yemen.

Tariff

The data on tariffs are available in the TPPD. There are 3 possible variables that can be used in the regressions. They are Weighted applied tariff, Simple MFN tariff and Weight MFN tariff. All tariffs are reported percentage points. The manipulation that we carried out in order to use this variables in the estimations we explained above, in the section missing variables.

Public Capital

The following lines present four techniques that can be used to construct a public-capital index (PCI). A PCI combines two or more variables, each capturing the state of a given component of public infrastructure, into a one-dimensional synthetic measure. In our case, only public equipment relevant for trade was considered. Given data availability, our attention was focused on the state of roads, the density of rail network, the access to air transport, the state of power grid, the density of phone lines and the access to IT. These dimensions are captured by the following series, which were constructed using data drawn mainly from the World Bank's WDI database (see Table 6)

Not all series were available for all countries and for the entire time sample (1970-2005). When only two or more (but not all) observations of a given series and for a given country were available, the series was completed through linear interpolation and linear or geometric extrapolation. Since extrapolation often resulted into overshooting trends, the choice between linear and geometric extrapolation was made, for a given country, according to whichever involved the narrower gap between the highest and the lowest value of the series. Estimated shares above 100% or negative values were replaced with 100 and 0, respectively.

The construction of a few series required information on the population size: when this value was missing for all but a few years, it was estimated applying the population growth rate reported by the CIA to the available observations.

This procedure completes series, for a given country, as long as at least one observation was originally available; it does not result in all series to be available for all countries.

Four methods to compute a PCI

For each country, the value of the PCI was computed applying weights to all the series (duly transformed) available for that country. Appropriate series transformations and weights can be chosen following various criteria, which results in the design of a number of methods to construct a PCI. In the remaining lines, we will present four of them; two hinge on simple averages and two on principal component analysis (PCA).

Principal components analysis combines series into an index which best represents their common pattern. When performing a PCA, series are previously normalized, although normalization is often part of the PCA algorithm included in econometric package, when available.

1st method

In the first method, the PCI of each country is calculated by performing a PCA using those countries whose data include all the series which are available for the country in question.

2nd method

The second method performs a PCA for those countries with no incomplete series. Mean and standard deviation computed for these countries are used to "normalize" the series of all countries. The resulting series are then combined into a PCI using the (scaled-up) PCA weights.

3rd method

The third method normalizes all the series and combines them into a PCI, for each country, using uniform weights.

4th method

The fourth method divides all series by their mean and combines them into a PCI for each country, using uniform weights (as is done in Limao and Venables, 2001), and by subtracted one from the resulting index. This is equivalent to using the mean, rather than the standard deviation, in the denominator used for the normalization of method nr 3.

Optional adjustments to the PCI

In theory, the four indexes described above range between -∞ to +∞. In case a bounded index is necessary, the following transformation can be suggested:

$$PCI\hat{} = PCI/(1+|PCI|)$$

The transformed index PCI^ ranges between $]-1,1[$ and, when used in econometric estimations, it dampens the impact of outliers on the estimates.

Tables and figures

Tables

Table 1
ISIC 3-digit industries and coefficient used to calculate initial capital

	Type of asset and industry	coef
1	· 311 Food products	1.4
2	· 313 Beverages	1.4
3	· 314 Tobacco	1
4	· 321 Textiles	1.3
5	· 322 Wearing apparel, except footwear	0.4
6	· 323 Leather products	1.1
7	· 324 Footwear, except rubber or plastic	0.6
8	· 331 Wood products, except furniture	1.4
9	· 332 Furniture, except metal	0.6
10	· 341 Paper and products	1.7
11	· 342 Printing and publishing	1.2
12	· 351 Industrial chemicals	2
13	· 352 Other chemicals	1.3
14	· 353 Petroleum refineries	1
15	· 354 Miscellaneous petroleum and coal products	1
16	· 355 Rubber products	0.5
17	· 356 Plastic products	0.5
18	· 361 Pottery, china, earthenware	1.6
19	· 362 Glass and products	1.1
20	· 369 Other non-metallic mineral products	2
21	· 371 Iron and steel	2.3
22	· 372 Non-ferrous metals	2
23	· 381 Fabricated metal products	1
24	· 382 Machinery, except electrical	1
25	· 383 Machinery, electric	0.9
26	· 384 Transport equipment	0.8
27	· 385 Professional and scientific equipment	0.6
28	· 390 Other manufactured products	0.8
	· mean	~ 1.2

Table 2a
Summary statistics

	# of obs-s	mean	St. dev.	Min	Max
GDP share	54972	.4224045	.7244915	4.38e-06	18.7972
Tariff	56166	14.49044	20.42839	0	349.1
Public capital	75180	-.0432877	.3733612	-.476144	.955331
TFP	32209	.56282	.3448961	.0005478	2.49599
Capital ind	45052	113.9718	2334.378	.0015464	93627.8
Capital	73892	53.61715	50.69451	.413685	231.569
Land	73472	.0006888	.000762	4.63e-07	.0067401
Primary educ.	60900	.196377	.1506267	.0042019	1.15718
Secondary educ.	60900	.1597826	.1330986	.0015446	.695144
Postsec. educ.	60900	.0811598	.0715105	.0007608	.577095

Table 2b
Summary statistics: standard deviation decomposition

	Within standard deviation	Between standard deviation
GDP share	.6631058	.3054802
Tariff	15.51972	12.71417
Public capital	.6631058	.3054802
TFP	.2791058	-.4403098
Capital ind	2270.046	605.6412
Capital	13.31412	48.28449
Land	.0001612	.0007374
Primary educ.	.0485005	.1419196
Secondary educ.	.0443556	.1255971
Postsecondary educ.	.0306633	.0645484

Table 3a
Sector share 3SLS with effects regression, food and textile industries[14]

	Food			Textiles & apparel			
	Food	Beverages	Tobacco	Textiles	Apparel	Leather	Footwear
Public capital	-0.132	-0.082	-0.129	0.018	-0.014	-0.017	-0.006
	[0.059]**	[0.027]***	[0.028]***	[0.024]	[0.016]	[0.004]***	[0.007]
Ln tariff	0.145	0.03	0.166	-0.034	0.052	0.001	-0.002
	[0.085]*	[0.033]	[0.025]***	[0.013]***	[0.008]***	[0.003]	[0.009]
Ln TFP	0.966	0.434	0.214	0.48	0.233	0.052	0.084
	[0.067]***	[0.033]***	[0.026]***	[0.033]***	[0.016]***	[0.003]***	[0.008]***
Ln capital	0.409	0.205	0.016	-0.086	-0.05	-0.016	-0.011
	[0.083]***	[0.038]***	[0.043]	[0.039]**	[0.025]**	[0.005]***	[0.012]
Ln land/labor	0.011	0.004	0	0.001	0	0	0
	[0.009]	[0.004]	[0.004]	[0.003]	[0.002]	[0.000]	[0.001]
Ln prim. ed.	-0.076	-0.025	-0.129	0.218	0.19	0.009	0.027
	[0.129]	[0.059]	[0.073]*	[0.039]***	[0.026]***	[0.006]	[0.012]**
Ln sec. ed.	-0.337	-0.252	-0.311	0.061	0.212	0.011	0.011
	[0.156]**	[0.069]***	[0.072]***	[0.051]	[0.033]***	[0.007]	[0.016]
Ln post-sec.	0.275	0.247	-0.21	0.224	0.225	0.027	0.122
	[0.131]**	[0.058]***	[0.063]***	[0.051]***	[0.034]***	[0.007]***	[0.016]***
Observations	406	406	406	382	382	382	382

Table 3b
Sector share 3SLS fixed effects regression, wood & paper industries

	Wood	Furniture	Paper	Printing
Public capital	-0.048	0.058	-0.002	0.072
	[0.012]***	[0.018]***	[0.022]	[0.024]***
Ln tariff	-0.014	0.148	0.005	0.073
	[0.030]	[0.042]***	[0.026]	[0.027]***
Ln TFP	0.234	0.153	0.203	0.46
	[0.021]***	[0.020]***	[0.028]***	[0.028]***
Ln capital	-0.004	0.078	0.172	0.222
	[0.018]	[0.019]***	[0.031]***	[0.036]***
Ln land/labor	0.002	0.002	0	-0.002
	[0.002]	[0.002]	[0.003]	[0.003]
Ln prim. ed.	0.075	0.012	-0.136	-0.132
	[0.025]***	[0.027]	[0.041]***	[0.047]***
Ln sec. ed.	-0.116	-0.189	0.09	-0.126
	[0.029]***	[0.048]***	[0.043]**	[0.047]***
Ln post-sec.	0.254	0.184	0.054	-0.009
	[0.037]***	[0.040]***	[0.042]	[0.046]
Observations	552	552	530	530

[14] Standard errors in brackets, * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3c
Sector share 3SLS fixed effects regression, chemical industries

	Ind. Chem.	Oth. Chem.	Petroleum	Petr., coal	Rubber	Plastic
Public capital	-0.064	0.005	-0.026	-0.006	-0.018	0.036
	[0.016]***	[0.021]	[0.055]	[0.006]	[0.005]***	[0.010]***
Ln tariff	0.013	0.023	-0.047	0.002	0.002	-0.002
	[0.040]	[0.032]	[0.049]	[0.009]	[0.012]	[0.023]
Ln TFP	0.436	0.482	0.325	0.043	0.102	0.277
	[0.025]***	[0.027]***	[0.031]***	[0.004]***	[0.007]***	[0.019]***
Ln capital	0.331	0.298	0.399	-0.006	-0.027	0.136
	[0.030]***	[0.030]***	[0.076]***	[0.009]	[0.008]***	[0.015]***
Ln land/labor	-0.006	0.003	0.006	-0.001	0	0
	[0.003]**	[0.003]	[0.006]	[0.001]	[0.001]	[0.002]
Ln prim. ed.	-0.006	0	0.015	-0.028	0.015	-0.015
	[0.036]	[0.036]	[0.075]	[0.010]***	[0.010]	[0.020]
Ln sec. ed.	0.051	-0.062	0.021	0.008	0.016	-0.152
	[0.039]	[0.043]	[0.077]	[0.009]	[0.015]	[0.027]***
Ln post-sec.	0.194	-0.076	-0.154	0.018	0.033	0.034
	[0.043]***	[0.044]*	[0.150]	[0.015]	[0.013]***	[0.024]
Observations	550	550	212	212	565	565

Table 3d
Sector share 3SLS fixed effects regression, glass and metals industries

	Glass			Metals	
	Pottery	Glass	Non-metallic	Iron, Steel	Nonferr. met.
Public capital	-0.004	0	-0.017	-0.046	0.028
	[0.003]	[0.005]	[0.017]	[0.023]**	[0.014]*
Ln tariff	0.005	0	-0.019	0.034	0.043
	[0.003]	[0.005]	[0.016]	[0.025]	[0.034]
Ln TFP	0.036	0.1	0.345	0.387	0.119
	[0.004]***	[0.006]***	[0.020]***	[0.025]***	[0.015]***
Ln capital	0.01	0.053	0.141	0.162	0.096
	[0.005]**	[0.006]***	[0.023]***	[0.034]***	[0.025]***
Ln land/labor	0	0	0.003	-0.003	-0.005
	[0.000]	[0.001]	[0.002]	[0.003]	[0.002]**
Ln prim. ed.	0.015	0.007	0.043	0.172	0.022
	[0.006]**	[0.009]	[0.030]	[0.042]***	[0.027]
Ln sec. ed.	-0.002	-0.016	0.002	0.184	0.007
	[0.008]	[0.012]	[0.040]	[0.053]***	[0.033]
Ln post-sec.	0.033	0.062	0.203	0.302	-0.002
	[0.007]***	[0.011]***	[0.037]***	[0.064]***	[0.040]
Observations	382	382	382	481	481

Table 3e
Sector share 3SLS fixed effects regression, machinery industries

	Fabric. met. p.	Machinery	Elect. mach.	Transport	Scient. eq.
Public capital	0.033	0.211	0.227	0.175	0.037
	[0.032]	[0.055]***	[0.087]***	[0.045]***	[0.025]
Ln tariff	0.144	-0.112	-0.036	-0.144	0.055
	[0.047]***	[0.066]*	[0.115]	[0.051]***	[0.033]*
Ln TFP	0.681	0.774	1.556	0.666	0.237
	[0.049]***	[0.060]***	[0.106]***	[0.038]***	[0.020]***
Ln capital	0.316	0.648	0.87	0.602	0.146
	[0.047]***	[0.066]***	[0.110]***	[0.054]***	[0.029]***
Ln land/labor	0.002	-0.014	-0.011	0.003	-0.004
	[0.004]	[0.007]*	[0.013]	[0.008]	[0.004]
Ln prim. ed.	0.007	-0.411	-0.547	0.088	-0.134
	[0.064]	[0.110]***	[0.167]***	[0.088]	[0.047]***
Ln sec. ed.	-0.115	-0.476	-0.428	-0.094	-0.227
	[0.083]	[0.143]***	[0.225]*	[0.119]	[0.062]***
Ln post-sec.	0.393	0.482	0.491	0.321	-0.093
	[0.070]***	[0.123]***	[0.188]***	[0.098]***	[0.053]*
Observations	327	327	327	327	327

Table 4
The subset of raw data from TPPD

Variable	Unit	№ of obs.	Min	Max
year	Year	81200	1976	2004
industry code	Code	81200	311	390
value added	1000's $	44557	-2801545	2.53e+08
investment	1000's $	32963	-2517834	4.82e+07
n_employees	units	50114	1	9890000
wage bill	1000's $	46793	0.063	8.13e+07
tarif_iwAHS	%	20495	0	349.1
tarif_iwMFN	%	55812	0	350
tarif_savgMFN	%	56276	0	1634.29

Table 5
The subset of revised data from TPPD

Variable	Unit	№ of obs.	Min	Max
year	year	81200	1976	2004
industry code	code	81200	311	390
value added	1000's $	55945	1.28932	2.57e+08
investment	1000's $	43201	0.0016184	6.39e+07
n_employees	units	63106	1	1.19e+07
wage bill	1000's $	59428	0.0353235	8.28e+07
tarif_iwAHS	%	50407	0	349.1

Table 6
Variables used in construction of public capital

Code	Description
air	Air transport, registered carrier departures worldwide (per 1000 people)
comp	Personal computers installed in education (per 1000 people)
elec.	Electricity (100% minus %of managers surveyed ranking this as a major business constraint)
ph	Telephone mainlines (per 1000 people)
rail	Rail lines(total route-km, per 1000 people)
roads	Roads, paved(%of total roads)

Figures

Figure 1
Capital stock estimates against NBER estimates

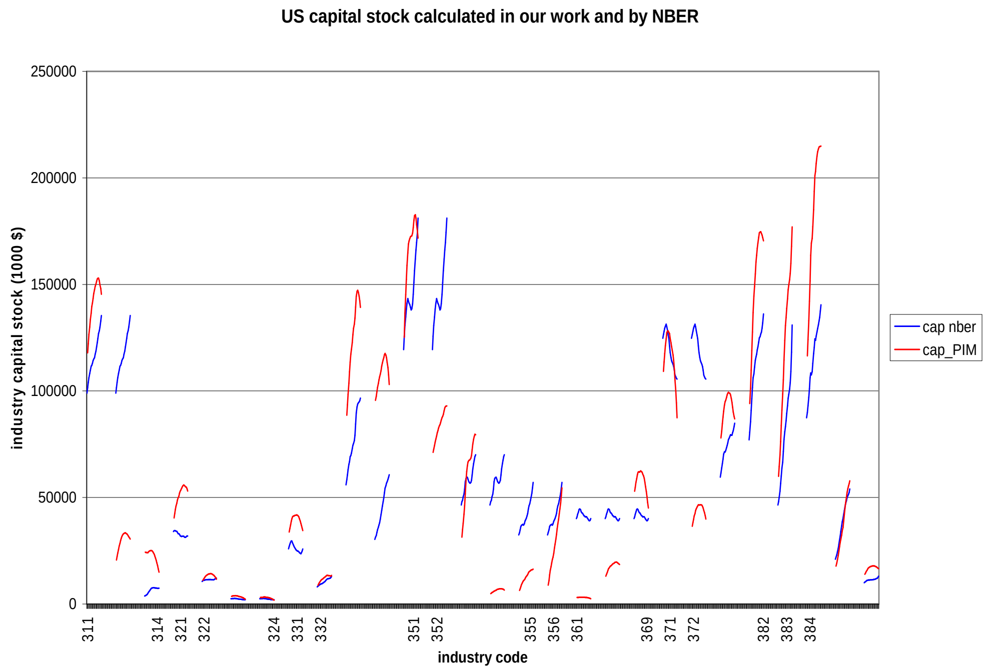

Figure 2
Productivity parameters and vs. relative GDP per capita

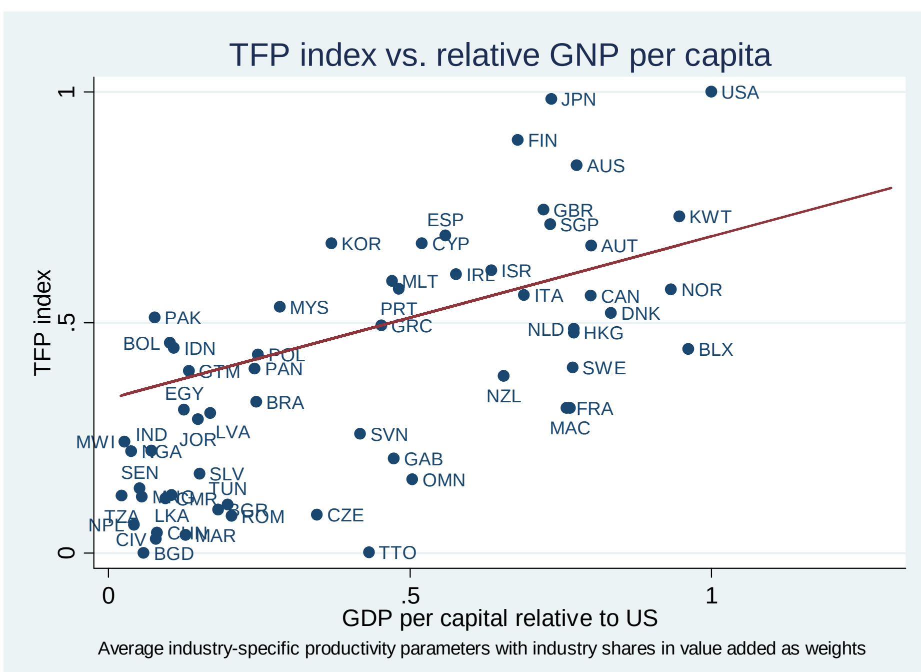

Figure 3
Estimated Rybczynski elasticities against factor intensities

(a) Capital-labor ratio

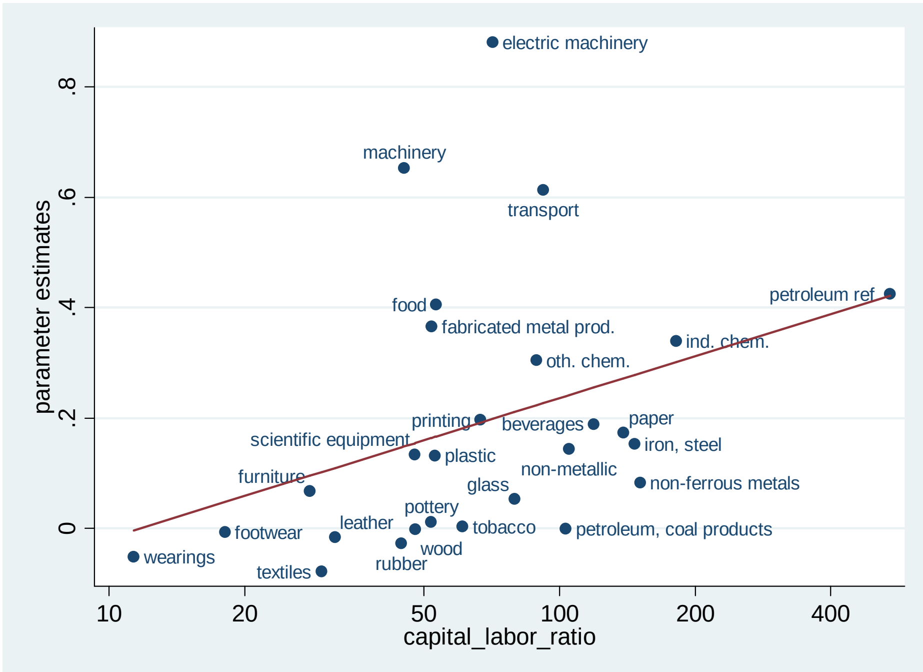

Figure A1
Comparison pf the PPI by industry taken from NBER and BLS with overlapping period (1984-1997)