Board of Governors of the Federal Reserve System

International Finance Discussion Papers

Number 731

July 2002

Factor Endowments and Industrial Structure

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Abstract: What determines industrial structure? Do sector-specific characteristics such as unionization, regulation, and trade policy dominate production patterns? One is inclined to believe so based on countless industry-level studies and the many political battles that are continually fought over trade and industrial policy. In contrast, standard neoclassical trade theory suggests that industrial structure is primarily driven by relative factor supplies. This paper demonstrates that aggregate factor endowments explain much of the structure of production—independent of industry idiosyncrasies—and quantifies the extent to which shifts in industrial structure in a cross section of countries are driven by the broad forces of factor accumulation. This result has important implications for policy. In particular, investment in physical capital and education may have as great an impact on the pattern of production as sector-specific trade and industrial policies. Thus, general equilibrium effects should not be ignored in efforts either to understand industrial structure or to form policies that attempt to alter it. These conclusions are reached through an empirical application of the factor proportions model of production.

Keywords: Factor Proportions, Endowments, Production, International Trade, Heckscher-Ohlin.

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1. Introduction

Shifts in the structure of industrial production stimulate vast amounts of economic research and fuel countless political debates. During the 1970s and 1980s, many believed that the United States was experiencing adverse structural change as foreign production seemed to displace domestic industry. Similar concerns resurged in the debates on the NAFTA in the 1990s and, most recently, with the steel industry's success in obtaining protective tariffs and the legislative deliberations over fast track trade promotion authority. Changes in the structure of production, whether actual or feared, will assuredly be a recurrent source of academic and political dispute.

What causes the pattern of production to change? What determines industrial structure? The answers to these questions are central to our understanding of the basic structure and workings of the economy. Efforts to explain changes in an industry's production commonly focus on the characteristics of that industry. Anti-trust regulation, unionization, labor and environmental standards, tax treatment, credit subsidies, and trade policy have all been advanced as possible explanations for the performance of industries. The prevalence of this sector-specific focus is evident in the industrial policy debates of the 1980s and the trade policy debates of the 1990s.[1]

Industry output is surely influenced by sector-specific attributes and policies. However, analyzing industries in isolation ignores the linkages that exist among industries, markets, and countries. Standard economic theory suggests that such linkages are important. In order to

[1] Evidence of the political importance of these issues and examples of this approach are found in numerous Congressional hearings and policy symposia [see Business Roundtable (1984), Congressional Budget Office (1987, 1983), the Federal Reserve Bank of Kansas City (1983), the President's Commission on Industrial Competitiveness (1985), U.S. Congress, Joint Economic Committee (1983a, 1983b, 1984a, 1984b), U.S. House of Representatives (1993, 1992, 1983, 1982), U.S. International Trade Commission (1993), and U.S. Senate (1993a, 1993b, 1983)].

account for these relationships, one must adopt a general equilibrium approach. Too frequently, the effects of general equilibrium are ignored or dismissed, especially in empirical work.

This paper demonstrates that through the forces of general equilibrium, factor endowments explain much of the observed structure of production, independent of industry-specific characteristics. This conclusion is reached through an empirical application of standard neoclassical general equilibrium theory—the factor proportions model of international trade. Two messages emerge from this result. First, in order to understand industrial structure, one must account for these general equilibrium forces. Second, factor endowments are an important determinant of the structure of production and as such, should be considered in the formulation of trade and industrial policy.

In contrast to previous studies, this paper separates the effects of factor accumulation from the effects of changes in the techniques of production. Industry output is determined both by the quantities of available resources and by how those resources are combined in the production process. By analyzing changes over time within the factor proportions framework, this paper quantifies the extent to which the broad forces of national factor accumulation have contributed to changes in industrial structure in a cross section of industrialized economies.

As a preview of the results, the factor proportions model explains, on average, about 40 percent of relative production patterns across countries. Although the prediction errors from this model are relatively large, a substantial proportion of the observed structure of production can be explained using general equilibrium theory and a relatively small set of information in the form of aggregate quantities of capital, various categories of labor, and land. Nearly all manufacturing industries depend heavily on capital and moderately educated labor. High-educated labor, on the other hand, tends to depress production in manufacturing industries.

From 1970 to 1990, national factor accumulation appears to be about twice as important as changes in the global techniques of production in accounting for *changes* in industrial structure. The relative importance of factor accumulation varies by industry, though for only one industry (textiles) do changes in the techniques of production dominate. The analysis suggests that investment in physical capital and education will have predictable effects on the structure of production, but that these effects can be augmented or offset by changing techniques, in addition to the idiosyncratic characteristics and policies that are not captured by the model.

The bottom line is that to explain industrial structure, one must account for general equilibrium forces. Studies of individual industries, while important, cannot capture the important and complex relationships among industries and countries. Moreover, factor accumulation significantly contributes to changing patterns of production. Policies that attempt to alter industrial structures must acknowledge, and even exploit the general equilibrium effects of factor endowments.

2. Background

2.1 *The Industry-Specific Approach*

What explains the relative behavior of industries? Why do some industries expand while others contract? In examining questions such as these, studies routinely confine their attention to a particular industry. Indeed, it seems natural to look within the industry to explain its behavior. Focusing on industries in isolation allows the analysis to be conducted with great detail. Clearly, knowledge of unique characteristics, events, and policies is essential to our understanding of industry performance.

But industries do not exist in isolation. Rather, they are interconnected by a variety of forces. General equilibrium theory represents an attempt to characterize these linkages. Most industry-specific studies simply ignore general equilibrium effects. Even when acknowledged, general equilibrium is often dismissed on the grounds that it represents second-order phenomena. Porter (1990) exemplifies this perspective. He states, "While we can identify national characteristics that apply to many industries, my experience has been that these are overshadowed...by particular and often industry-specific circumstances, choices, and outcomes" [p. *xiii*]. Porter continues, "We must focus not on the economy as a whole but on *specific industries and industry segments*" [p. 9, italics in original].[2]

Working within this industry-specific frame of reference, Porter (1990) ascribes the decline in the U.S. steel and auto industries to a "lack of dynamism" caused by institutional rigidities, management problems, and an unfavorable regulatory environment. Similarly, the MIT Commission on Industrial Productivity [Dertouzos, Lester, and Solow (1989)] emphasizes management failures (especially with respect to technology adoption), inflexible organizational structures, and burdensome labor contracts in explaining the behavior of the steel and auto industries. Adams and Brock (1995) draw similar conclusions.

While studies such as these are informative, the validity of their conclusions depends, at least in part, on the unimportance of broader, general equilibrium effects. The goal here is to quantify the extent to which industrial structure can be explained using *only* aggregate factor endowments. Naturally, sector-specific characteristics or policies that alter general equilibrium relationships will be captured within this framework. In this sense, the approach taken here is complementary to industry-level analysis. The results indicate that general equilibrium forces

[2] Abowd and Freeman (1991) provide another explicit statement of this view: "While there is no inherent conflict between these two types of research approaches [partial and general equilibrium], our decision to concentrate on

play a substantial role in the behavior of industries. Hence, industry-level studies that focus only on industry-specific variables may miss a significant part of the explanation.

2.2 *Factor Proportions Theory*

The production side of the factor proportions model of international trade is utilized as the general equilibrium framework to explain industrial structure. This model provides a theoretically sound, structural framework for analyzing patterns of industry output in general equilibrium. The factor proportions theory of international trade is fundamentally a model of production. As Davis, Weinstein, Bradford, and Shimpo (1997) have noted, three of the four core theorems of factor proportions theory (Factor Price Equalization, Stolper-Samuelson, and Rybczynski) emerge from the production side alone. Simply adding an assumption on consumption generates the implications for international trade (the Heckscher-Ohlin theorem). The core insight of the factor proportions model is that countries tend to produce—hence export—relatively more of those goods that intensively use their abundant factors of production. Thus, the theory establishes relative factor endowments as the determinant of industrial structure and the source of comparative advantage.[3]

With constant returns to scale production functions and perfect competition in goods and factor markets, a country's national product is given by its revenue function

$$\Pi(\mathbf{p},\mathbf{v}) = \max_{\mathbf{y}}\{\mathbf{p}\cdot\mathbf{y} \mid \mathbf{y}\in Y(\mathbf{v})\},$$

individuals and markets was a conscious one…Our approach pins down the first-order effects…" (p. 20).

[3] Porter (1990) and Dertouzos et al. (1989) do acknowledge a role for factor endowments. Rather than viewing them as determinants of industrial structure, however, they see factors as a general necessary condition—more of a pre-condition—for the establishment of industry. This perspective is very common, but it is misleading to the extent that factor endowments themselves drive production patterns through the forces of general equilibrium.

where **p** is an $(N \times 1)$ vector of goods prices, **v** is an $(M \times 1)$ vector of inelastic factor supplies, **y** is an $(N \times 1)$ vector of net outputs and $Y(\mathbf{v})$ is a compact production set.[4] Assuming $\Pi(\mathbf{p},\mathbf{v})$ is twice continuously differentiable, the gradient with respect to **p** gives the net supply vector,

$$\mathbf{y} = \Pi_{\mathbf{p}}(\mathbf{p}, \mathbf{v}) .$$

Differentiating again with respect to factor supplies gives the matrix of Rybczynski derivatives,

$$\mathbf{R} = \Pi_{\mathbf{pv}}(\mathbf{p}, \mathbf{v}) .$$

Since the supply function is homogeneous of degree one in **v**,

$$\mathbf{y} = \Pi_{\mathbf{pv}}(\mathbf{p}, \mathbf{v}) \cdot \mathbf{v} = \mathbf{R} \cdot \mathbf{v} ,$$

and net outputs are a linear function of factor supplies. So far only net output has been considered, but the analysis here is concerned with gross output. Net and gross output are related by

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1} \mathbf{y} ,$$

where **x** is an $(N \times 1)$ vector of gross outputs and **A** is the $(N \times N)$ input-output matrix. Substituting in the expression for **y**,

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1} \mathbf{R} \cdot \mathbf{v} ,$$

and gross output is a linear function of factor endowments. Defining $\mathbf{\Omega} \equiv (\mathbf{I} - \mathbf{A})^{-1} \mathbf{R}$ gives the fundamental equation

$$\mathbf{x} = \mathbf{\Omega} \cdot \mathbf{v} . \qquad (1)$$

What takes equation 1 from a standard neoclassical model of output to a model of the international location of production are the assumptions and conditions that allow the Ω matrix to be identical across countries. For this to be the case, countries must produce the same set of

[4] This exposition draws from Harrigan (1995) and Dixit and Norman (1980)

goods with the same techniques. Producing the same set of goods—diversified production—requires that relative factor endowments not be "too" dissimilar across countries.[5] Use of the same techniques of production depends on common technologies and prices. Goods prices will be equalized across countries with free trade and zero transport costs. A crucial condition for factor price equalization is that the number of goods exceed the number of factors, $N \geq M$. However, in order for the supply function to be single-valued, there must be at least as many factors as goods, $M \geq N$. Thus, what is left is the "square" model in which there are equal numbers of goods and factors, $N = M$. In this case, equation 1 holds for each country and forms the basis for the empirical work to follow.

2.3 *Caveats*

Before proceeding there are two issues to address. The first is the assumption of equal numbers of goods and factors. Casual observation suggests that there may be more goods than factors. In this case, there does not exist a unique mapping between factor endowments and production. Nevertheless, equation 1 can be heuristically defended. Leamer (1984) has postulated that small transaction costs pin down the location of production in such a way as to minimize total transaction costs.[6] Bernstein and Weinstein (2002) provide indirect evidence to support this idea. If true, then the relationship in equation 1 continues to exist, albeit in some altered form relative to the underlying model. Alternatively, Davis (1995) demonstrates that small Ricardian technical differences may resolve the indeterminacy without disturbing the basic factor proportions relationship. Yet another possibility is that forward and backward linkages may create "industry complexes" that tie together production levels across industries [Helpman

[5] That is, countries' endowments must lie in the same "cone of diversification" [see Dixit and Norman (1980)]. See Schott (2001) for criticisms of the one-cone assumption for a broad set of countries.

and Krugman (1985)]. The bottom line is that in order to interpret equation 1, there must be some common underlying structural relationship between factor endowments and outputs, and this is what is assumed here.[7] The existence of this structural relationship is all that really matters for the present analysis, whereas if the goal were to test factor proportions model against alternatives, then more careful investigation of the assumptions would be warranted. [See Harrigan (2001) for an overview of the relevant empirical research.]

The second caveat is that the deeper issue of accumulation is ignored by taking factor endowments to be exogenous. The forces that are responsible for differing patterns of accumulation across countries are not addressed here. Ignoring the endogeneity of factors is potentially troublesome when the model is used to examine changes over time, and in particular, when the role of factor accumulation in changing industrial structure is isolated. In this context, the assumption of exogenous factors is problematic to the extent that aggregate endowments are determined by developments within industries. Evidence suggests, however, that accumulation depends primarily on broad forces that are largely external to a given sector. For example, educational attainment seems to be driven largely by demographic characteristics and domestic educational policy [Freeman (1986), Katz, Loveman, and Blanchflower (1995), Russell (1982)].[8] Similarly, domestic investment depends on aggregate forces such as life-cycle behavior, macroeconomic conditions, and tax policy [Bosworth (1993), Jorgenson (1996), Schmidt-Hebbel, Servén, and Solimano (1996)]. Thus, to a first order, the assumption of exogenous

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[6] These costs need to be sufficiently small so as not to affect the common factor usage ratios or consumer demand.

[7] Another set of contentious issues revolves around treating ISIC industries as industries in the factor proportions sense. See Schott (2001) for further discussion.

[8] Freeman (1986) argues that a change in the composition of industries actually does have a measurable impact on the demand for education. This conclusion is based on highly aggregated industry definitions (manufacturing, professional services, etc.). It also requires that (fixed) input coefficients differ greatly across these industrial categories. Within manufacturing, differences in input intensities are much smaller, implying that at the present level of aggregation, compositional effects are also likely to be small.

factor endowments should not be a serious transgression. Future work could take this issue more seriously, however, by explicitly accounting for the endogeneity of factor endowments.

2.4 *Related Work*

Harrigan (1995) performs the first empirical examination of the production side of the factor proportions theory. He predicts industry output as a function of factor endowments under three different specifications. The first two use country fixed effects with constant coefficients and thus cannot be used to examine changes over time. The third specification is a time-varying parameter model in which the coefficients are assumed to follow a random walk.[9] Harrigan concludes that while the model does have explanatory power, it cannot fully explain the international location of production. This paper extends Harrigan's basic methodology of relating industry-level production to factor endowments. Specifically, movements over time are exploited in order to identify the sources of change in the structure of production. Work in a similar vein, but using a somewhat different approach, includes Harrigan (1997) and Harrigan and Zakrajšek (2000).

Bernstein and Weinstein (2002) investigate the production side of the factor proportions theory using a cross-section of international and regional data. They demonstrate that equation 1 holds relatively well internationally, but poorly across regions within a country. Since transaction costs should be lower within a country than between countries, they interpret this as evidence that production patterns may be rendered determinate by transaction costs. Davis and Weinstein (1996, 1999) provide additional evidence that equation 1 fits reasonably well on an international cross-section.

[9] Bernstein and Weinstein (1998) give a critique of these approaches.

Data

The data used in this paper come from a variety of sources. Twenty OECD countries are represented in the sample. These are listed in Table 1. The selection of countries was mandated by data availability, but the sample can be justified on theoretical grounds as well. The assumptions used to derive equation 1, such as common technology and prices and diversified production, are more likely to hold in this sample than in a broader selection of countries. The time period considered is 1970 to 1990.

Endowment data includes five factors: capital stock, arable land, high-educated labor, medium-educated labor, and low-educated labor. The capital stock data are from the Penn World Tables (PWT), version 5.6. Arable land data are from the World Resource Institute. The labor categories are constructed from the PWT's data on numbers of workers and the Barro-Lee educational attainment data, which is expressed as percentages of the population. High-educated labor represents workers who have at least some higher education. Medium-educated workers have completed primary education and have at least some secondary education. Low-educated workers have at most completed primary education. Endowment data for a sample of eleven countries have been made available by James Harrigan in Feenstra, Lipsey, and Bowen (1997). To expand coverage to the current sample of twenty countries, all endowment data have been reconstructed from the original sources.[10]

Increasing the number of explanatory variables by using more specific factor endowment definitions would improve the fit of the model. For example, diaggregated categories of land and labor could be included. The problem with doing so, as discussed in Davis et al. (1997), is that the more the definition of a factor is refined, the better proxy it becomes for production in certain sectors. For example, one would not want to include agricultural workers as a factor for explaining agricultural output because doing so comes close to reducing the factor proportions model to a tautology. Hence, the endowment data are restricted to the five factors given above. Evidence from Leamer (1988) suggests this is a reasonable number of factors.

Table 2 reports the average annual growth rates of the five factors over the period 1970 to 1990. For the OECD sample as a whole, the capital stock grew at an average rate of 4.8 percent per year. High-educated labor and medium-educated labor grew by 5.8 and 2.3 percent, respectively. Low-educated labor, however, decreased by 1.4 percent per year. Arable land changed little. The countries differ greatly in their accumulation rates. Capital stocks grew the fastest in Japan and the slowest in Norway. Low-educated labor fell most rapidly in the United States, but grew in Australia and New Zealand. Growth of high-educated labor in the United States was similar to the OECD sample, but was notably more rapid in Germany and Japan.

Measures of the relative abundance of the five factors are presented in Table 3 for 1970 and 1990. The table reports each country's *relative* endowment shares, i.e., the share of total (within-sample) endowments relative to its GDP share, $\frac{v_{mc} / \sum_c v_{mc}}{GDP_c / \sum_c GDP_c} \times 100$.[11] Japan's accumulation is striking. In 1970 its proportion of total capital stock and high-educated labor were roughly equal to its GDP share. By 1990 its capital and high-educated labor shares were 39 and 12 percent larger than its GDP share, respectively. Japan's relative abundance of medium- and low-educated labor fell dramatically as well. The United States saw declines in its relative

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[10] For exact data definitions, see Feenstra et al. (1997). It should be noted that there are no discrepancies between the data given by Harrigan and the data constructed here.

[11] The traditional measure of factor abundance in trade theory is $f_{mc} = v_{mc} - s_c v_{mW}$, where v_{mc} is country c's endowment of factor m, $v_{mW} = \sum_c v_{mc}$ is the world endowment, and $s_c = GDP_c/GDP_W$ is country c's GDP share. A country is said to be abundant in factor m if f_{mc} is positive. In this notation, the measure used in Table 3 is $(v_{mc} / v_{mW})/s_c$. Note that $f_{mc} > 0 \Leftrightarrow (v_{mc}/ v_{mW})/s_c > 1$.

abundance of capital and low-educated labor, but little relative change in high-educated labor. Relative land endowments have remained stable. Tables 2 and 3 reveal that the sample of countries contains substantial variation in relative factor endowments, both over time and in the cross section.

Three-digit ISIC annual gross output data are from the OECD's Structural Statistics for Industry and Services (SSIS) Database and the OECD's Compatible Trade and Production (COMTAP) Database.[12] Output is given in current U.S. dollars and is converted to 1985 U.S. dollars using the U.S. Producers' Price Index for corresponding industry categories. The analysis is conducted on the 15 largest manufacturing industries in the OECD, where "large" is defined on the basis of average share of GDP. Table 1 lists the ISIC codes, abbreviations, and descriptions for the 15 industries.

Percentage changes in industry output as a share of total manufactures are given in Table 4. Expressing these changes relative to manufacturing output allows us to focus on the compositional differences among industries. When deflating by GDP, nearly all of the changes are negative due to the secular decline in the manufacturing sector as a proportion of national income. The most striking increases for most countries are in Transportation Equipment, with strong gains also apparent in Electrical Machinery & Appliances and Non-electrical Machinery. The largest decreases occurred for most countries in Iron & Steel. Nearly all countries have experienced declines in the relative output of Textiles.

Table 5 summarizes production patterns by reporting the ratio of each country's share of (within-sample) production to its share of GDP in 1990 (this table is analogous to Table 3). These values are equivalently defined as the country's production-to-GDP ratio divided by that

[12] James Harrigan has made the COMTAP data available in Feenstra et al. (1997).

for the OECD sample as a whole. Thus, Table 5 contains information about differences in production patterns relative to the rest of the sample. Japan, once again, is notable for its disproportionately high share of output in almost all industries in the sample. The United States, on the other hand, tends to have smaller than average shares, reflecting the prominence of the services sector in the U.S. economy.

These twenty developed countries are striking in their differences. An interesting question is whether these countries have become more or less similar over time. That is, do the data support the notion of convergence in industry structure or relative endowments? Table 6 reports coefficients of variation for production shares and endowment ratios. The countries have indeed become more similar in the quantity of capital per worker and in the ratio of college educated workers to non-college educated workers. Per worker GDP has also become more similar. These findings are consistent with much of the convergence literature [see Baumol, Nelson, and Wolff (1994) and Dollar and Wolff (1993)]. However, convergence in production structures does not generally appear. Tables 4, 5, and 6 reveal that changes in production structures have varied greatly across countries.

4. Econometrics

Equation 1 is defined for each industry in each year. It can be rewritten with an additive error term,

$$x_{nc}^{t} = \mathbf{v}_{c}^{t}\mathbf{\Omega}_{n}^{t} + \varepsilon_{nc}^{t}. \qquad (2)$$

Here, x_{nc}^{t} is country *c*'s gross output in industry *n* in year *t*. Country *c*'s $(1 \times M)$ vector of factor endowments in year *t* is given by $\mathbf{v}_{c}^{t}$. The $(M \times 1)$ vector $\mathbf{\Omega}_{n}^{t}$ represents the factor proportions mapping from endowments to outputs for industry *n*. Collecting observations across countries,

$$\mathbf{x}_n^t = \mathbf{V}^t \boldsymbol{\Omega}_n^t + \boldsymbol{\varepsilon}_n^t \tag{3}$$

for industry *n* in year *t*. Now, $\mathbf{x}_n^t$ and $\boldsymbol{\varepsilon}_n^t$ are $(C \times 1)$ vectors and $\mathbf{V}^t$ is the $(C \times M)$ endowment matrix.

Rather than estimating each equation individually, a multivariate regression model is formed for each industry *n* in which each equation represents equation 3 for a particular year. The model for industry *n* is,

$$\begin{bmatrix} \mathbf{x}_n^1 \\ \vdots \\ \mathbf{x}_n^T \end{bmatrix} = \begin{bmatrix} \mathbf{V}^1 \boldsymbol{\Omega}_n^1 \\ \vdots \\ \mathbf{V}^T \boldsymbol{\Omega}_n^T \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_n^1 \\ \vdots \\ \boldsymbol{\varepsilon}_n^T \end{bmatrix}. \tag{4}$$

The main advantage of this approach is the ability to test hypotheses across equations, i.e., across time. Moreover, since it is likely that the disturbances across equations are correlated, the multivariate approach may lead to efficiency gains. This framework is a seemingly unrelated regression (SUR) model. Typically, the SUR framework defines a separate equation for the cross-sectional units, each of which contains observations over time. Here, each equation contains cross-sectional observations with the time dimension defining the equations.

The system in equation 4 should not yet be estimated because of scale problems. A convenient normalization is to deflate all variables by GDP. Since interest lies not in levels of production, but in relative structures, this is a sensible normalization. Moreover, it eliminates the scale problem and adequately corrects for heteroskedasticity.[13] Two methods of estimation were computed: one-step generalized least squares (GLS) and iterated GLS. These two methods have the same asymptotic properties. If the residuals are normally distributed, however, the iterated procedure will produce the maximum likelihood estimator. The results for the two methods were

[13] The appendix critiques a heteroskedasticity correction that has been used in several previous studies.

very similar. Since there is no reason for preferring one method to the other, only the results for the one-step GLS estimation are reported.

There is an additional issue of endogeneity. Factor endowments are not exogenous, but respond to factor returns. In turn, factor returns depend on goods prices and so output. Nevertheless, endogeneity should not be a problem here because industry-specific output flows are being regressed on economy-wide factor stocks. In order for endogeneity to be a concern, production in a single industry would contemporaneously have to affect factor endowments for the economy as a whole. To a first approximation, these effects, while present, are safe to ignore.

Finally, land was dropped as an explanatory variable. Including it did little to improve the fit of the equations as the estimated coefficient was almost never statistically significant. Given that there are relatively few degrees of freedom per equation, dropping land may improve the estimation of the remaining parameters of interest.

5. Results

5.1 Performance of the Model

How well does the factor proportions model explain production structures? Table 7 reports mean absolute percentage prediction errors by industry and year. The overall average absolute prediction error is 52 percent, which falls between the 40 percent average prediction error of Harrigan (1995) and the 67 percent average prediction error of Bernstein and Weinstein (2002). Harrigan, however, examined a smaller set of industries over a shorter sample period and used different labor endowment data. The contrasting results of Bernstein and Weinstein result from a shorter estimation period, a less selective sample of industries and countries (they include Turkey and Yugoslavia), and the choice of weights used in the estimation. Moreover, neither Harrigan nor Bernstein and Weinstein appear to deflate the nominal production data, which is not a problem in the cross-sectional regressions of Bernstein and Weinstein, but does matter for the fixed effects estimation of Harrigan. As a crude benchmark for comparison, these prediction errors are contrasted with those based on the prediction of relative production using the cross-sectional mean. These errors are also presented in Table 7. This naïve estimator has an overall mean absolute prediction error of 88 percent—36 percentage points larger than the average error based on the factor proportions model.[14]

Prediction errors vary substantially by industry. The factor proportions model consistently works relatively well for Food Products, Textiles, Other Chemicals, Mineral Products, and Fabricated Metal Products. The model performs the worst for Non-electrical Machinery, for which the fit is no better than the naïve estimator. Wood Products, Paper Products, and Basic Metals, which depend on natural resources that are not included in the estimation, also have relatively large prediction errors.

In contrast to Harrigan (1995), there do not appear to be large, systematic prediction errors. Harrigan's estimation consistently under-predicted production levels in Japan and the United States. He interpreted this as evidence that productivity differences may be important across industrialized countries [see Harrigan (1999, 1997)]. Here, the prediction errors are not generally consistent in sign. For Japan, positive and negative prediction errors appear to be equally likely. For the United States, prediction errors do tend to be positive, but are roughly half the size of Harrigan's.

[14] Similar results are reached by examining root mean squared errors.

Table 8 reports the R-squared measures for goodness of fit by industry and year. The average R-squared over all years and industries is 0.38. These are substantially lower than the average of 0.86 reported by Bernstein and Weinstein (2002). The difference owes entirely to the fact that Bernstein and Weinstein weight their equations by one over the square root of GDP rather than one over GDP, and therefore allow size effects to influence the fit of the equation. Repeating the estimation in this paper with their weights replicates their results (the unweighted regressions have an average R-squared of 0.98). There does not seem to be a notable change in the fit of the model over time.

Based on the explanatory power of the factor proportions model, the general equilibrium effects of factor endowments appear to be important in understanding industrial structure. This conclusion, however, does not diminish the importance of industry-specific characteristics. Clearly, sector-specific attributes and policies matter. In fact, such characteristics may be extremely important at a more disaggregated level, i.e., in determining the product-level composition of a particular industry's output. The message here is that efforts either to explain the pattern of production or to devise policies that attempt to alter it must recognize the general equilibrium forces of factor endowments on industrial structure.

5.2 Importance of Factors

The signs and significance of the coefficients from the estimation of equation 4 can be interpreted in terms of comparative advantage. Leamer (1984) and Harrigan (1995) view a significantly positive coefficient as an indication that the associated factor is a source of comparative advantage for that industry; conversely for a negative coefficient. The actual coefficient estimates and standard errors are presented in Table A1 in the appendix. These parameter estimates, however, are difficult to interpret in terms of the underlying economic variables of the model. The economic significance of the parameter estimates is better reflected in standardized or beta coefficients. These are given in Table 9. Beta coefficients, discussed in Leamer (1984), indicate the expected number of standard deviation changes in the dependent variable induced by a one standard deviation increase in the independent variable, conditional on the other regressors.[15]

Capital is almost always a significant source of comparative advantage. Capital plays a particularly strong role in Petroleum Refining, Chemicals, Fabricated Metal Products, Basic Metals, and Printing & Publishing. Medium-educated labor is also frequently a significant source of comparative advantage and is particularly important in Industrial Chemicals, Petroleum Refining, Mineral Products, and Electrical Machinery & Appliances. High-educated labor tends to be a source of comparative disadvantage, reflecting the tendency for highly skilled labor to reduce production in the manufacturing sectors (and presumably increase it in service sectors). Other Chemicals and Transport Equipment, in contrast, tend to benefit from high-educated labor. Low-educated labor is generally less important and its coefficients, while sometimes significant, vary in sign. Low-educated labor, however, is extremely important for Textiles. These results suggest that investment in physical capital and medium-educated labor will tend to increase the relative production of most manufacturing industries. Investing in higher education, on the other hand, will tend to decrease relative production of many manufactures. Note that these are not normative statements; changes in the size and composition of the manufacturing sector do not necessarily imply consequences for welfare.

[15] Formally, if the least squares model is $y = a + bx + e$, the beta coefficient for x is $b \cdot \mathrm{sd}(x)/\mathrm{sd}(y)$ where sd() is the standard deviation. Equivalently, the beta coefficient is the least squares coefficient estimate for a model in which all variables have been standardized to have unit variance.

5.3 Sources of Change in Industrial Structure

The structure of production depends on the relative quantities of available resources and on how those resources are combined in the production process. Changes either in factor endowments or in the techniques of production will therefore alter industrial structure. To what extent are changes in the structure of production driven by changes in factor endowments? The answer to this question is important not only in understanding changes in production patterns, but also in determining how policies that promote accumulation will ultimately impact industrial structure.

As a first step, it is important to determine if there have been statistically significant shifts in the estimated parameters of equation 4 over time. If not, then the techniques of production can be thought of as roughly constant, and changes in factor endowments will themselves account for the changes in industrial structures that can be captured by the factor proportions model of production. Table 10 reports Wald test statistics for the null hypotheses of constant coefficients over the 1970s, the 1980s, and from 1970 to 1990. In nearly every case the null of constant coefficients can be rejected at standard levels of significance. Thus, changes in the techniques of production, as measured by the parameter estimates, are also a potentially important source of change in industrial structure.

In order to identify the forces acting on production structures, the estimation results from equation 4 can be used to decompose the change in output from time *t-s* to time *t* as[16]

$$\begin{aligned}\mathbf{x}_n^t - \mathbf{x}_n^{t-s} &= (\mathbf{V}^t - \mathbf{V}^{t-s})\overline{\hat{\boldsymbol{\Omega}}}_n + \overline{\mathbf{V}}(\hat{\boldsymbol{\Omega}}_n^t - \hat{\boldsymbol{\Omega}}_n^{t-s}) + (\hat{\boldsymbol{\varepsilon}}_n^t - \hat{\boldsymbol{\varepsilon}}_n^{t-s}) \\ &= \Delta_s \mathbf{V}^t \overline{\hat{\boldsymbol{\Omega}}}_n + \overline{\mathbf{V}}\Delta_s \hat{\boldsymbol{\Omega}}_n^t + \Delta_s \hat{\boldsymbol{\varepsilon}}_n^t\end{aligned} \tag{5}$$

[16] I thank Gordon Hanson for suggesting this particular form of the decomposition.

where $\overline{\mathbf{V}}$ is the average value of factor endowments in periods *t* and *t-s*, and $\overline{\hat{\mathbf{\Omega}}}_n$ is the average estimated coefficient matrix in periods *t* and *t-s* for industry *n*. The first term, $\Delta_s \mathbf{V}^t \overline{\hat{\mathbf{\Omega}}}_n$, captures the contribution of changes in factor endowments, holding fixed $\hat{\mathbf{\Omega}}$, the estimated techniques of production. The Rybczynski theorem characterizes how output responds to changes in endowments at fixed prices and technology, i.e., at fixed techniques of production. Hence, the term $\Delta_s \mathbf{V}^t \overline{\hat{\mathbf{\Omega}}}_n$ can also be interpreted as a Rybczynski effect.

The second term in equation 5, $\overline{\mathbf{V}} \Delta_s \hat{\mathbf{\Omega}}_n^t$, is the effect that changes in production techniques have on shifts in production, holding fixed endowments. Here, "technique" refers not only to the technology, but also to factor usage which depends on relative factor prices, and so indirectly on good prices. The techniques can change for a wide variety of reasons. These include changes in the more primitive forces of technology and preferences. Other sources of change include trade liberalization with the rest of the world, the emergence of new industrialized trading partners, overall factor accumulation within the sample, and even industry-specific shocks. These components of change in techniques cannot be distinguished in the present framework. In this sense, the $\hat{\mathbf{\Omega}}$ matrix is somewhat of a black box. The goal here is not to explain the changes in the techniques, but merely to distinguish them from the factor endowment effect. The final term, $\Delta_s \hat{\boldsymbol{\varepsilon}}_n^t$, is the difference in the residuals.

The results of this decomposition for two ten-year intervals and for the 1970 to 1990 period are presented in Table 11. The values reported in Table 11 are the percentage contributions of the terms in equation 5, expressed as cross-country averages. Since the terms in equation 5 can be of either sign, a simple average obscures their true contributions. Therefore, the averages are reported in terms of absolute values. Moreover, these components have been normalized to sum to 100 percent.[17]

The overall contribution of factor accumulation, across all industries and years, is about 50 percent. Changes in the techniques of production contribute about 25 percent. The residual term comprises the remaining 25 percent. These overall averages mask important differences across industries. Changes in factor endowments appear to have been most important for Printing & Publishing, Basic Metals, Fabricated Metal Products, and Transport Equipment. Factors have been the least important for Textiles, where changes in techniques appear to have played a larger role. The remaining industries are more or less in line with the overall averages reported above. Looking across time periods, changes in factors tend to have been somewhat more important in the 1970 to 1980 period as compared to the 1980 to 1990 period, but the differences are not great.

It is important to note that the decomposition presented in Table 11 does not convey information on the goodness of fit of equation 5. Rather, it separates the gross forces that impact production structures. These gross forces typically differ in sign and therefore offset each other to some degree. It is the net impact of these forces that gives the predicted change in output. Prediction errors for equation 5 (not shown) average about 100 percent. Compared to predicting production levels, predicting changes in production is much more difficult. This may result from the fact that the data in differences are noisier than the data in levels and to the fact that the parameters do not appear to be constant over time, meaning that equation 5 is misspecified as a regression equation (not as an algebraic identity).

[17] To understand this normalization, let $A=B+C$. Averages of $|B/A|$ and $|C/A|$ will not sum to 100 percent. To remedy this, average $|B/\tilde{A}|$ and $|C/\tilde{A}|$ where $\tilde{A}=|B|+|C|$.

To conclude, national factor accumulation has tended to be the most important gross force acting on production patterns as reflected in the factor proportions model of production. Shifts in the global techniques of production have also strongly contributed to changes in relative outputs.

6. Conclusion

What determines industrial structure? This is obviously a difficult question, and no single study can hope to capture the full complexity of the answer. Industry-specific studies provide essential information but, as this paper has shown, may miss a significant part of the explanation. The broad forces of accumulation explain much of the observed changes in production at the industry level. Ignoring these general equilibrium effects leads to an incomplete understanding of industry behavior.

Understanding industrial structure is not only important intellectually, but also because of its serious pragmatic implications. The heated political battles that are continually fought over industrial and trade policy are largely motivated and justified by the belief that sector-specific policies are the main determinant of industry behavior. The fact that factor accumulation appears to have a direct, significant, and predictable impact on the pattern of production means that policy should account for, and even exploit these general equilibrium forces. Failure to do so may lead to inefficient or even counterproductive policy.

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Appendix

Note on the Choice of Weights

In estimating the factor proportions model, some authors have utilized an "endogenous" heteroskedasticity correction. This approach is endogenous in that it estimates the factor of (inverse) proportionality for the exogenously specified weighting variable. It is first used in a factor-proportions context by Leamer (1984). The starting point is to model the residual variance for industry *n* as function of GDP to some power, $\sigma_n^2 = \alpha \mathrm{GDP}_n^{\theta}$. The three-step procedure begins with estimating the model using the raw (unweighted) data. The logarithm of the squared residuals is then regressed on the log of real GDP to obtain an estimate of the parameter θ. The predicted values from this second regression are estimates of $\ln \sigma_n^2$. The inverses of the exponential of these fitted values are then used as weights in the original specification. For a detailed treatment of the statistical properties of this procedure, see Harvey (1976).

In order for this method to work, it must be the case that observations with a relatively large GDP (i.e., large error variance) tend to have correspondingly larger residuals in the first-stage regression. In the present application, however, this condition is not met. The reason for this is the presence of an influential outlier, the United States. One expects that the observation for the United States should have a relatively large error variance and, therefore, a relatively large residual in the first-stage regression. If this were true, it would translate into a large fitted value for $\ln \sigma_n^2$, and hence an appropriately smaller weight. The fact that the United States is such a large outlier, however, forces the unweighted regression line to pass very close to the U.S. observation, resulting in a relatively *small* residual and a relatively *large* weight. Applying this method to the data used in this paper results in a U.S. weight that is occasionally the largest and is almost always considerably larger than the mean weight. Clearly, this is undesirable since less weight should be given to the observations with greater variability. This explains Leamer's (1984) observation that his estimated heteroskedasticity parameters are "lower than expected" and sometimes "actually negative."

Table 1: Data Coverage, 1970 to 1990

countries		
Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, United Kindom, United States		
3-digit ISIC industries		
311	FOOD	Food and Food Products
321	TEXT	Textiles
331	WOOD	Wood and Wood Products, except Furniture
341	PAPER	Paper and Paper Products
342	PRINT	Printing, Publishing and Allied Industries
351	ICHEM	Industrial Chemicals
352	OCHEM	Other Chemical Products
353	PETRO	Petroleum Refineries
369	MINER	Other Non-Metallic Mineral Products
371	STEEL	Iron and Steel Industries
372	METAL	Non-Ferrous Metal Basic Industries
381	FABMT	Fabricated Metal Products, except Machinery
382	MACH	Non-Electrical Machinery
383	APPLI	Electrical Machinery, Appliances
384	TRANS	Transport Equipment

Table 2: Factor Accumulation, 1970 to 1990

	capital stock	high-educated	medium-educated	low-educated	arable land
Canada	5.3	3.9	3.8	-2.2	0.3
Australia	4.2	2.4	2.1	1.9	0.8
Austria	5.7	6.9	2.2	-0.8	-0.6
Belgium	3.5	5.5	2.0	-0.7	-0.6
Denmark	3.7	2.1	1.9	-0.4	-0.2
Finland	4.5	5.5	2.7	-1.0	-0.5
France	4.5	8.5	5.5	-0.9	0.0
Germany	5.1	6.9	1.4	-0.1	-0.1
Greece	4.7	4.7	5.8	-0.9	0.0
Ireland	4.8	5.8	3.3	-1.2	-1.9
Italy	3.9	6.9	3.6	-1.0	-1.1
Japan	7.9	7.9	2.4	-2.1	-0.9
Netherlands	3.8	5.6	1.4	0.4	0.2
New Zealand	3.8	11.5	-2.4	1.3	-1.7
Norway	2.6	5.3	3.8	-0.1	0.3
Portugal	5.3	7.6	3.8	0.6	0.1
Spain	6.0	5.9	7.6	-0.5	-0.1
Sweden	4.1	5.0	2.0	-1.1	-0.4
United Kingdom	3.5	3.4	2.0	-0.9	-0.4
United States	3.8	5.6	1.7	-4.2	-0.1
OECD sample	4.8	5.8	2.3	-1.4	0.0

Note: Values are the annualized growth rate (percent) from 1970 to 1990.

Table 3: Relative Factor Abundance

	capital stock		high-educated		medium-educated		low-educated		arable land	
	1970	1990	1970	1990	1970	1990	1970	1990	1970	1990
Australia	125	107	177	89	130	122	43	81	539	614
Austria	92	111	30	38	135	134	124	142	52	47
Belgium	117	99	49	49	87	89	107	133	20	19
Canada	114	107	127	75	123	138	58	41	351	311
Denmark	119	114	161	94	116	127	91	131	97	111
Finland	159	144	75	67	96	99	149	153	124	107
France	101	101	29	51	36	72	143	164	71	75
Germany	123	146	30	42	61	57	132	194	23	25
Greece	121	114	75	59	66	124	284	300	183	176
Ireland	96	77	73	58	141	139	186	157	162	90
Italy	103	88	28	35	61	79	149	163	64	51
Japan	101	139	99	112	194	150	193	129	13	8
Netherlands	98	89	59	62	122	111	67	104	13	14
New Zealand	111	112	53	184	154	73	59	123	38	33
Norway	244	142	79	63	72	84	134	152	45	42
Portugal	77	61	40	40	55	52	392	423	179	133
Spain	74	89	47	45	24	62	197	222	180	167
Sweden	111	119	74	78	102	118	88	113	61	69
United Kingdom	78	68	89	62	106	110	123	150	26	27
United States	94	81	145	147	99	92	41	24	124	128

Note: Values are the ratio of the countries' share of total (within-sample) endowments to the countries' share of total GDP. A value of 100 indicates that the country's share of the factors equals its GDP share.

Table 4: Changes in Industry Output Shares, 1970 to 1990

	FOOD	TEXT	WOOD	PAPER	PRINT	ICHEM	OCHEM	PETRO	MINER	STEEL	METAL	FABMT	MACH	APPLI	TRANS
Australia	0.0	-0.5	-0.6	-0.8	1.5	-0.5	-0.2	3.2	0.3	-2.3	2.1	-0.1	-1.8	-1.0	-0.5
Austria	1.9	-1.3	2.1	-0.9	1.1	-0.8	-0.5	-0.4	-1.1	-6.4	0.1	-0.6	3.1	3.6	1.8
Belgium	-8.1	6.4	0.0	2.6	4.1	14.0	0.4	6.0	-3.3	-7.1	3.9	-4.7	-7.9	-5.0	-8.9
Canada	-0.7	-0.5	0.2	-2.1	1.1	0.9	0.2	-1.0	-0.2	-1.8	-0.8	-1.6	0.9	-1.1	6.5
Denmark	5.9	-0.8	-0.6	-0.7	-0.5	0.4	1.1	-3.3	-1.8	-0.4	-0.8	0.6	1.2	-0.8	-0.3
Finland	-2.5	-1.8	-1.1	-6.0	2.8	0.6	0.3	-0.5	0.9	0.4	-1.0	1.4	3.1	2.2	0.9
France	1.1	-1.1	-0.3	-0.3	1.8	0.1	0.5	-8.4	0.7	-4.0	-0.2	2.2	0.4	2.6	5.1
Germany	1.4	-0.6	0.4	-0.6	0.2	-6.2	1.2	-1.4	-0.5	-6.5	0.0	1.4	2.6	2.5	6.9
Greece	2.4	0.7	-0.5	-1.0	-0.3	-1.8	1.0	5.1	0.4	-0.4	0.2	-1.8	-0.5	-2.1	0.0
Ireland	1.7	-3.6	-0.1	-1.4	-0.7	4.8	-0.8	-5.4	1.2	-0.4	-0.2	-0.2	12.9	5.7	-4.3
Italy	1.2	1.8	-0.2	-0.5	0.5	-3.0	-3.5	-2.3	-3.1	-3.4	0.4	-0.8	4.4	2.8	0.6
Japan	1.0	-1.9	-2.0	-1.3	1.1	-2.8	0.2	-1.1	-0.4	-5.1	-0.9	-0.1	2.9	3.8	4.8
Netherlands	3.2	-1.7	-0.6	-0.4	0.6	2.7	0.4	-3.1	-1.2	-6.5	0.2	-0.2	2.1	1.1	2.6
New Zealand	0.7	-1.0	-1.1	-0.2	1.3	0.3	1.3	-3.2	-0.4	0.0	1.0	1.2	-1.3	0.6	1.3
Norway	0.6	-1.1	-1.1	-4.1	1.9	0.8	-0.6	2.2	-0.5	-2.0	-0.2	-1.1	9.5	-0.2	-3.9
Portugal	-1.5	-3.2	1.2	-2.3	-2.0	-2.8	-1.3	-2.0	0.6	-3.1	0.6	4.2	3.2	4.2	-1.4
Spain	5.0	-2.3	1.0	-0.7	2.1	-3.2	0.9	-2.5	1.5	-10.4	-1.9	-1.2	3.3	1.4	6.1
Sweden	-1.5	-0.8	-0.3	-2.0	1.3	0.5	0.3	0.9	-0.7	-3.6	-0.5	-0.2	1.9	1.2	3.6
United Kingdom	1.9	-1.4	-0.3	-0.5	2.1	-1.3	1.0	1.9	0.6	-3.9	-0.9	-1.4	1.3	0.9	1.8
United States	-0.2	0.0	0.0	-0.3	1.4	0.0	0.0	-1.1	-0.3	-2.8	-0.4	-1.7	0.4	-0.4	2.8
OECD sample	0.2	-0.5	-0.3	-0.8	1.0	-1.3	0.0	-1.8	-0.2	-3.5	-0.4	-0.6	1.7	1.8	3.4

Note: Values indicate the percentage point change in the share of each industry of total manufacturing output from 1970 to 1990.

Table 5: Relative Production Patterns, 1990

	FOOD	TEXT	WOOD	PAPER	PRINT	ICHEM	OCHEM	PETRO	MINER	STEEL	METAL	FABMT	MACH	APPLI	TRANS
Australia	94	63	103	46	83	45	57	62	116	92	226	86	31	27	47
Austria	114	144	214	146	81	114	99	88	216	151	154	131	106	138	45
Belgium	n.a.	216	59	103	86	249	72	121	n.a.	164	215	n.a.	n.a.	n.a.	n.a.
Canada	94	62	179	158	76	68	73	100	71	58	107	69	42	41	117
Denmark	239	72	96	65	96	73	105	56	124	26	15	110	91	47	34
Finland	182	51	424	570	191	122	64	112	178	141	164	119	118	70	52
France	132	106	87	87	107	93	127	122	120	105	113	114	89	90	109
Germany	109	119	98	88	64	154	173	169	126	135	133	179	180	176	168
Greece	89	182	47	36	23	30	67	128	125	56	103	39	7	23	13
Ireland	356	108	87	50	76	302	6	33	200	25	8	73	161	125	18
Italy	75	179	48	62	53	73	51	71	85	125	67	67	93	70	60
Japan	111	142	133	111	144	114	129	80	169	218	129	169	193	245	170
Netherlands	179	57	47	84	118	233	93	158	74	38	85	91	55	109	47
New Zealand	189	89	182	133	86	50	55	28	85	31	79	87	29	28	36
Norway	177	31	210	161	142	97	47	118	87	70	336	72	125	44	49
Portugal	108	271	203	88	52	50	73	92	134	37	29	75	24	46	31
Spain	130	88	102	64	73	75	114	67	161	99	76	78	43	51	89
Sweden	143	48	442	351	157	104	96	93	134	159	144	171	159	97	145
United Kingdom	102	81	71	84	117	116	104	115	123	83	82	89	98	81	86
United States	81	73	78	96	98	85	85	95	58	51	76	70	71	58	80

Note: Values are the ratio of the countries' share of total (within-sample) production to the countries' share of total GDP.
A value of 100 means that a country's production share equals that for the sample as a whole.

Table 6: Dispersion of Factors and Production Patterns

Factors	1970	1980	1990	change
capital/worker	0.42	0.31	0.28	-0.14
college/non-college	0.89	0.88	0.84	-0.05
real GDP/worker	0.28	0.22	0.18	-0.10

Production	1970	1980	1990	change
FOOD	0.43	0.49	0.48	0.05
TEXT	0.33	0.45	0.57	0.24
WOOD	0.77	0.79	0.76	-0.01
PAPER	0.94	1.05	0.97	0.04
PRINT	0.40	0.45	0.42	0.02
ICHEM	0.58	0.56	0.63	0.05
OCHEM	0.39	0.40	0.44	0.05
PETRO	0.53	0.47	0.40	-0.13
MINER	0.30	0.33	0.35	0.06
STEEL	0.60	0.60	0.61	0.01
METAL	0.74	0.63	0.68	-0.06
FABMT	0.43	0.30	0.39	-0.04
MACH	0.68	0.53	0.61	-0.06
APPLI	0.60	0.55	0.69	0.08
TRANS	0.58	0.51	0.66	0.08
mean	0.55	0.54	0.58	0.02

Note: Values are coefficients of variation for production shares and factor ratios. "Change" is the difference from 1970 to 1990.

Table 7: Mean Absolute Prediction Errors (Percent)

	1970		1975		1980		1985		1990		mean	
	model	naïve	model	naïve	model	naïve	model	naïve	model	naïve	model	naïve
FOOD	24	64	23	56	34	61	29	59	28	57	28	59
TEXT	20	64	22	67	28	64	37	65	39	71	29	66
WOOD	69	77	84	68	69	70	69	72	73	72	73	72
PAPER	69	82	75	85	78	83	79	85	69	82	74	84
PRINT	31	69	32	73	41	76	50	78	41	75	39	74
ICHEM	42	70	47	70	48	73	51	71	59	84	49	74
OCHEM	30	88	18	93	24	87	24	90	32	143	26	100
PETRO	47	64	99	142	69	163	57	143	27	96	60	122
MINER	19	71	14	65	21	65	20	61	24	66	20	66
STEEL	74	94	63	99	54	105	46	90	49	85	57	94
METAL	106	284	60	125	62	125	64	152	90	180	76	173
FABMT	34	94	19	75	24	66	19	69	30	70	25	75
MACH	220	172	54	86	72	91	111	115	116	110	115	115
APPLI	57	83	33	74	46	68	59	67	68	75	53	73
TRANS	62	75	48	77	45	70	65	80	66	80	57	76
mean	60	97	46	84	48	85	52	87	54	90	52	88

Note: Values = 100 * mean(|actual - predicted|/actual). "Model" refers to the prediction of output based on the factor proportions model. "Naïve" refers to the prediction using the cross-sectional mean.

Table 8: Goodness of Fit (R-squared)

	1970	1975	1980	1985	1990	mean
FOOD	0.70	0.65	0.43	0.52	0.53	0.57
TEXT	0.55	0.51	0.54	0.49	0.50	0.52
WOOD	0.41	0.27	0.21	0.25	0.14	0.26
PAPER	0.25	0.17	0.12	0.12	0.19	0.17
PRINT	0.53	0.43	0.27	0.31	0.24	0.36
ICHEM	0.09	0.18	0.03	0.04	0.09	0.09
OCHEM	0.42	0.51	0.60	0.68	0.57	0.55
PETRO	0.01	0.07	0.27	0.33	0.33	0.20
MINER	0.31	0.43	0.33	0.55	0.32	0.39
STEEL	0.41	0.52	0.65	0.58	0.47	0.53
METAL	0.71	0.43	0.43	0.38	0.40	0.47
FABMT	0.58	0.28	0.21	0.63	0.37	0.42
MACH	0.44	0.55	0.44	0.27	0.27	0.39
APPLI	0.48	0.51	0.39	0.33	0.19	0.38
TRANS	0.37	0.43	0.44	0.59	0.56	0.48
mean	0.42	0.40	0.36	0.40	0.35	0.38

Table 9: Standardized Coefficient Estimates

		FOOD	TEXT	WOOD	PAPER	PRINT	ICHEM	OCHEM	PETRO	MINER	STEEL	METAL	FABMT	MACH	APPLI	TRANS
1970	capital	0.50	0.05	0.28	0.32	0.47	0.35	0.51	0.28	0.56	0.38	0.57	0.38	0.30	0.20	0.37
	high-ed	0.12	0.07	0.05	-0.03	0.38	-0.05	0.13	0.06	-0.02	-0.16	0.10	0.37	0.11	0.22	0.35
	medium-ed	0.13	0.59	0.20	0.04	0.22	0.32	0.40	0.24	0.73	0.37	-0.05	0.41	0.31	0.39	0.13
	low-ed	-0.20	0.95	-0.01	-0.06	-0.08	0.29	0.48	0.41	0.31	0.30	-0.05	0.08	0.15	0.24	0.08
1975	capital	0.32	0.12	0.25	0.28	0.64	0.45	0.56	0.30	0.48	0.49	0.48	0.49	0.55	0.48	0.49
	high-ed	0.10	0.05	0.03	-0.04	0.04	-0.12	0.27	-0.16	-0.06	-0.04	0.12	0.26	-0.03	-0.05	0.25
	medium-ed	0.02	0.27	0.07	-0.04	0.13	0.10	0.14	0.34	0.48	0.08	-0.14	0.37	0.05	0.29	-0.02
	low-ed	-0.01	0.77	-0.02	-0.11	-0.31	0.11	0.55	0.40	0.22	0.22	-0.03	0.17	-0.09	0.13	-0.01
1980	capital	0.32	0.09	0.27	0.23	0.60	0.32	0.48	0.36	0.37	0.39	0.51	0.60	0.50	0.29	0.46
	high-ed	-0.11	0.01	-0.04	-0.09	-0.09	-0.15	-0.02	-0.25	-0.23	-0.17	-0.01	0.11	-0.17	0.00	0.11
	medium-ed	0.03	0.20	0.01	-0.01	0.08	0.18	0.18	0.23	0.36	0.28	-0.11	0.23	0.13	0.26	0.07
	low-ed	-0.07	0.79	0.01	-0.05	-0.32	0.04	0.49	0.48	0.42	0.13	-0.02	0.13	-0.06	0.24	0.11
1985	capital	0.28	0.02	0.24	0.21	0.48	0.23	0.33	0.30	0.34	0.35	0.50	0.44	0.39	0.07	0.25
	high-ed	0.04	0.19	0.02	0.03	0.22	-0.14	0.25	-0.16	-0.24	-0.08	0.01	0.33	-0.02	0.14	0.25
	medium-ed	0.03	0.16	0.09	-0.06	-0.03	0.22	0.19	0.25	0.52	0.22	-0.12	0.21	0.02	0.28	0.11
	low-ed	-0.11	0.75	-0.12	-0.05	-0.36	0.09	0.49	0.59	0.16	0.16	-0.14	-0.08	-0.16	0.21	0.00
1990	capital	0.29	-0.03	0.18	0.27	0.65	0.18	0.41	0.46	0.32	0.36	0.58	0.51	0.42	0.12	0.39
	high-ed	-0.13	0.07	-0.08	-0.06	0.03	-0.13	0.20	-0.18	-0.11	-0.04	-0.23	0.00	-0.22	0.01	0.08
	medium-ed	0.04	0.15	0.10	-0.06	-0.06	0.21	0.04	0.15	0.20	0.12	-0.11	0.11	0.06	0.21	0.03
	low-ed	0.02	0.74	0.12	-0.03	-0.20	-0.06	0.42	0.49	0.41	0.18	-0.09	0.14	-0.04	0.23	0.10

Note: These standardized coefficients give the expected number of standard deviation changes in production induced by a one-standard deviation increase in the associated factor, conditional on the remaining factors. Double (single) underlining indicates statistical significance at the 95 (90) percent level.

Table 10: Hypothesis Tests for Constant Coefficients

	1970 to 80	1980 to 90	1970 to 90		1970 to 80	1980 to 90	1970 to 90
FOOD	6.10	4.58	9.14	MINER	5.89	1.34	6.33
TEXT	31.18	7.94	22.95	STEEL	2.76	26.55	9.98
WOOD	8.27	6.86	5.13	METAL	7.91	15.09	13.28
PAPER	2.82	8.67	12.15	FABMT	18.55	1.61	8.96
PRINT	26.68	8.75	24.24	MACH	23.46	1.07	9.91
ICHEM	1.06	8.15	2.42	APPLI	14.72	2.07	6.94
OCHEM	12.86	15.99	15.51	TRANS	43.52	3.50	29.09
PETRO	10.54	2.79	6.97	mean	14.42	7.66	12.20

Note: Values are the Wald test statistics for the null hypothesis of constant coeffients on the factors over the intervals indicated. The 95 (90) percent $\chi 2(4)$ critical value is 9.49 (7.78).

Table 11: Decomposition of Output Change

		1970-80	1980-90	1970-90			1970-80	1980-90	1970-90
FOOD	factor	42	49	48	MINER	factor	40	45	45
	technique	29	29	29		technique	31	21	29
	residual	30	22	23		residual	29	34	26
TEXT	factor	22	24	19	STEEL	factor	47	42	47
	technique	51	29	48		technique	26	42	31
	residual	26	47	33		residual	28	16	22
WOOD	factor	51	46	50	METAL	factor	59	54	60
	technique	20	21	18		technique	20	22	20
	residual	29	32	32		residual	21	24	20
PAPER	factor	54	48	57	FABMT	factor	63	56	64
	technique	15	35	20		technique	18	13	15
	residual	31	17	22		residual	19	31	22
PRINT	factor	61	55	62	MACH	factor	58	45	47
	technique	19	23	16		technique	22	20	25
	residual	20	22	22		residual	20	35	28
ICHEM	factor	50	46	47	APPLI	factor	49	33	41
	technique	16	26	24		technique	23	31	29
	residual	34	29	28		residual	28	36	31
OCHEM	factor	58	53	57	TRANS	factor	59	56	59
	technique	19	25	19		technique	22	19	19
	residual	23	23	24		residual	20	25	22
PETRO	factor	39	44	53	mean	factor	50	46	50
	technique	31	21	22		technique	24	25	24
	residual	30	35	25		residual	26	29	25

Note: Values indicate the cross-country average percentage contributions of the three effects in terms of relative magnitudes, normalized to sum to 100 percent (aside from rounding).

Table A1: Coefficient Estimates

		FOOD	TEXT	WOOD	PAPER	PRINT	ICHEM	OCHEM
1970	constant	1095.502	-74.866	-33.713	196.949	-22.867	-529.755	-407.472
		(228.614)	(67.053)	(120.967)	(267.156)	(64.694)	(219.952)	(79.356)
	capital	0.051	0.001	0.010	0.028	0.011	0.019	0.011
		(.007)	(.002)	(.003)	(.005)	(.002)	(.007)	(.003)
	high-ed	1.651	0.217	0.279	-0.401	1.197	-0.381	0.419
		(1.232)	(.431)	(.43)	(.642)	(.358)	(1.241)	(.485)
	medium-ed	0.612	0.666	0.362	0.178	0.236	0.843	0.427
		(.381)	(.133)	(.156)	(.247)	(.11)	(.394)	(.158)
	low-ed	-0.258	0.285	-0.006	-0.067	-0.023	0.199	0.136
		(.123)	(.038)	(.061)	(.112)	(.035)	(.123)	(.045)
1975	constant	2240.212	-79.031	103.369	612.711	4.353	-498.822	-360.607
		(361.964)	(124.713)	(200.602)	(448.64)	(103.84)	(294.521)	(73.299)
	capital	0.042	0.005	0.013	0.036	0.019	0.032	0.012
		(.009)	(.004)	(.004)	(.006)	(.003)	(.008)	(.002)
	high-ed	1.310	0.203	0.146	-0.536	0.140	-0.877	0.585
		(1.005)	(.394)	(.547)	(.647)	(.276)	(.929)	(.248)
	medium-ed	0.100	0.490	0.160	-0.256	0.180	0.338	0.142
		(.48)	(.179)	(.272)	(.313)	(.124)	(.427)	(.115)
	low-ed	-0.026	0.448	-0.013	-0.202	-0.141	0.121	0.175
		(.214)	(.079)	(.114)	(.198)	(.061)	(.181)	(.046)
1980	constant	3442.335	4.499	146.695	635.547	27.293	-260.645	-613.188
		(802.408)	(173.64)	(262.576)	(582.091)	(166.621)	(443.342)	(111.465)
	capital	0.066	0.004	0.016	0.033	0.023	0.028	0.016
		(.016)	(.004)	(.005)	(.007)	(.003)	(.01)	(.002)
	high-ed	-1.727	0.051	-0.203	-0.967	-0.279	-1.031	-0.054
		(1.253)	(.366)	(.39)	(.547)	(.31)	(.945)	(.232)
	medium-ed	0.330	0.482	0.029	-0.083	0.154	0.777	0.289
		(.839)	(.224)	(.272)	(.364)	(.189)	(.569)	(.149)
	low-ed	-0.236	0.636	0.011	-0.121	-0.202	0.062	0.260
		(.44)	(.104)	(.137)	(.239)	(.092)	(.259)	(.065)
1985	constant	2798.865	-103.993	112.804	423.675	-73.536	103.862	-580.623
		(563.035)	(144.904)	(166.088)	(404.845)	(155.703)	(400.346)	(84.42)
	capital	0.039	0.001	0.008	0.018	0.016	0.016	0.008
		(.01)	(.003)	(.003)	(.004)	(.003)	(.008)	(.002)
	high-ed	0.596	0.687	0.052	0.272	0.736	-1.035	0.626
		(.965)	(.388)	(.34)	(.433)	(.393)	(.937)	(.235)
	medium-ed	0.259	0.316	0.174	-0.295	-0.048	0.903	0.266
		(.557)	(.201)	(.181)	(.248)	(.206)	(.495)	(.124)
	low-ed	-0.267	0.433	-0.065	-0.067	-0.199	0.109	0.201
		(.286)	(.081)	(.082)	(.154)	(.082)	(.216)	(.047)
1990	constant	5312.873	-231.828	267.042	866.874	150.488	928.675	-903.745
		(930.183)	(279.422)	(337.621)	(578.787)	(293.705)	(657.543)	(192.044)
	capital	0.053	-0.002	0.009	0.027	0.028	0.016	0.015
		(.016)	(.006)	(.005)	(.006)	(.005)	(.012)	(.004)
	high-ed	-2.131	0.322	-0.376	-0.517	0.115	-1.034	0.672
		(1.464)	(.578)	(.496)	(.639)	(.468)	(1.126)	(.347)
	medium-ed	0.477	0.561	0.361	-0.460	-0.186	1.345	0.110
		(.886)	(.362)	(.313)	(.38)	(.299)	(.695)	(.215)
	low-ed	0.086	1.035	0.168	-0.080	-0.246	-0.154	0.440
		(.571)	(.191)	(.201)	(.276)	(.182)	(.425)	(.127)

Note: Standard errors are in parentheses.

Table A1: Coefficient Estimates, Continued

		PETRO	MINER	STEEL	METAL	FABMT	MACH	APPLI	TRANS
1970	constant	-386.423	-146.787	-1173.720	-164.133	-431.838	-980.010	-752.889	-630.748
		(276.822)	(57.88)	(268.997)	(67.178)	(109.017)	(251.549)	(172.331)	(259.168)
	capital	0.017	0.008	0.032	0.017	0.015	0.024	0.013	0.029
		(.01)	(.002)	(.01)	(.002)	(.003)	(.008)	(.005)	(.006)
	high-ed	0.486	-0.051	-1.906	0.387	1.998	1.230	1.891	3.800
		(1.818)	(.406)	(1.798)	(.282)	(.509)	(1.283)	(.916)	(.827)
	medium-ed	0.662	0.526	1.474	-0.075	0.770	1.173	1.168	0.478
		(.553)	(.127)	(.553)	(.102)	(.189)	(.416)	(.316)	(.332)
	low-ed	0.303	0.058	0.321	-0.020	0.040	0.152	0.192	0.075
		(.158)	(.034)	(.155)	(.035)	(.059)	(.139)	(.094)	(.123)
1975	constant	-714.906	109.806	-1065.693	-114.720	-346.964	-806.892	-821.021	-912.301
		(390.771)	(75.438)	(237.696)	(104.359)	(162.876)	(331.022)	(216.935)	(422.329)
	capital	0.025	0.010	0.037	0.015	0.019	0.058	0.033	0.056
		(.011)	(.002)	(.007)	(.002)	(.004)	(.009)	(.006)	(.009)
	high-ed	-1.385	-0.119	-0.298	0.367	1.028	-0.358	-0.358	3.040
		(1.29)	(.335)	(.988)	(.202)	(.597)	(1.056)	(.753)	(1.266)
	medium-ed	1.330	0.461	0.299	-0.208	0.654	0.260	0.929	-0.086
		(.576)	(.15)	(.446)	(.106)	(.301)	(.503)	(.36)	(.603)
	low-ed	0.503	0.069	0.259	-0.013	0.097	-0.143	0.132	-0.019
		(.25)	(.05)	(.155)	(.054)	(.102)	(.205)	(.138)	(.233)
1980	constant	-846.413	75.560	-1244.735	-193.551	-370.882	-930.231	-1212.158	-1697.640
		(358.708)	(115.004)	(225.048)	(127.41)	(195.36)	(457.814)	(369.962)	(500.273)
	capital	0.029	0.010	0.030	0.017	0.025	0.059	0.028	0.058
		(.008)	(.003)	(.006)	(.002)	(.004)	(.01)	(.008)	(.008)
	high-ed	-1.571	-0.483	-1.030	-0.031	0.364	-1.517	-0.019	1.087
		(.663)	(.369)	(.584)	(.164)	(.452)	(.971)	(.853)	(.646)
	medium-ed	0.906	0.468	1.033	-0.176	0.464	0.756	1.232	0.403
		(.423)	(.208)	(.343)	(.115)	(.29)	(.606)	(.51)	(.473)
	low-ed	0.621	0.187	0.162	-0.012	0.084	-0.109	0.385	0.226
		(.214)	(.073)	(.137)	(.061)	(.112)	(.266)	(.212)	(.244)
1985	constant	-761.594	78.174	-731.440	-104.035	-322.833	112.582	-1045.622	-1918.025
		(280.381)	(60.214)	(176.96)	(120.919)	(117.052)	(492.212)	(435.582)	(454.35)
	capital	0.017	0.005	0.016	0.014	0.014	0.038	0.007	0.029
		(.006)	(.001)	(.004)	(.002)	(.002)	(.01)	(.008)	(.007)
	high-ed	-0.948	-0.385	-0.410	0.030	1.090	-0.174	1.391	3.075
		(.672)	(.235)	(.518)	(.207)	(.327)	(1.307)	(1.071)	(1.196)
	medium-ed	0.799	0.448	0.579	-0.190	0.375	0.089	1.460	0.744
		(.368)	(.114)	(.252)	(.104)	(.156)	(.655)	(.515)	(.605)
	low-ed	0.560	0.041	0.122	-0.064	-0.045	-0.262	0.323	0.000
		(.158)	(.036)	(.099)	(.054)	(.062)	(.268)	(.224)	(.22)
1990	constant	-798.428	200.605	-903.122	-11.362	-472.743	297.287	-1102.217	-3065.025
		(345.245)	(160.085)	(321.131)	(195.712)	(337.176)	(997.32)	(945.201)	(817.024)
	capital	0.024	0.008	0.020	0.020	0.027	0.063	0.016	0.063
		(.007)	(.004)	(.006)	(.003)	(.006)	(.019)	(.016)	(.012)
	high-ed	-0.842	-0.256	-0.194	-0.716	0.001	-2.967	0.159	1.081
		(.677)	(.377)	(.638)	(.274)	(.674)	(1.827)	(1.74)	(1.217)
	medium-ed	0.594	0.381	0.480	-0.265	0.419	0.624	2.155	0.382
		(.436)	(.239)	(.375)	(.147)	(.381)	(1.122)	(.945)	(.713)
	low-ed	0.727	0.301	0.288	-0.082	0.211	-0.163	0.880	0.430
		(.236)	(.114)	(.215)	(.105)	(.218)	(.651)	(.586)	(.464)

Note: Standard errors are in parentheses.