The World Economy (2008)
doi: 10.1111/j.1467-9701.2008.01125.x

The Uneven Pace of Deindustrialisation in the OECD

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1. INTRODUCTION

A CENTRAL feature of economic growth in industrialised countries since the early 1970s is the secular decline in manufacturing's share of GDP and the secular rise in the share of service sectors. While the United Kingdom and United States were quick to 'de-industrialise', Germany and Japan have retained larger shares of manufacturing in GDP. Though this phenomenon is well known, the economic forces behind deindustrialisation and the reasons why its pace varied so markedly across OECD countries are not well understood. One of the reasons for the lack of agreement in this area is the challenge of explaining an inherently general equilibrium phenomenon. Manufacturing's share of GDP depends not only on manufacturing's productivity and prices, but also productivity and prices in all other industries, since these other industries provide competing uses for the factors of production employed in manufacturing. Additionally, there are a number of potential determinants of deindustrialisation to take into account, and the correct functional form for the influence of these variables is unclear.

To make progress on these issues, this paper uses the neoclassical theory of trade and production. The central contribution of the theory is to identify the determinants of deindustrialisation in general equilibrium and to derive an econometric specification consistent with producer optimisation, which can be

This paper is produced as part of the Labour Markets and Globalisation Programmes of the ESRC-funded Centre for Economic Performance at the London School of Economics. The views expressed are those of the authors alone and should not be attributed to any institution to which the authors are affiliated. We are grateful to the editor, anonymous referees, Charlie Bean, Francis Green, Susan Harkness, Jonathan Haskel, Tim Leunig, Jon Temple, Tony Venables, Anna Vignoles, and conference and seminar participants for helpful comments. We would also like to thank Damon Clark, Gunilla Dahlén, Simon Evenett, Maia Guella-Rotllan, Randy E. Ilg, Marco Manacorda, Steve McIntosh, Jan van Ours, Barbara Petrongolo, Glenda Quintini, Lupin Rahman, Toshiaki Tachibanaki, Ingrid Turtola and Colin Webb for their help with the data. We are grateful to Martin Stewart for research assistance. All opinions, results and any errors are the authors' responsibility alone.

used to decompose the decline in manufacturing and the rise in service sectors into the contributions of relative prices, technology and factor endowments. We estimate the empirical specification using a three-dimensional panel dataset on manufacturing and non-manufacturing industries across OECD countries over a period from the early 1970s to the early 1990s. We find that the more rapid decline in manufacturing's share of GDP in the United Kingdom and United States than in Germany and Japan is largely explained by patterns of total factor productivity (TFP) and changes in the relative price of manufacturing and non-manufacturing goods. Differential increases in educational attainment across OECD countries are important in explaining changes in service sector specialisation. The greater decline in agriculture's share of GDP in Italy and Japan than in other OECD countries is largely accounted for by movements in relative prices and patterns of TFP growth.

The neoclassical model imposes a number of testable parameter restrictions whose validity we examine in our empirical analysis. For example, constant returns to scale implies that the sum of the coefficients on factor endowments in the equation for an industry's share of GDP is equal to zero, so increasing all factor endowments in the same proportion leaves the shares of all industries in GDP unchanged. Similarly, the translog revenue function implies symmetric cross-industry effects of prices and technology, so that, for example, the *ceteris paribus* impact of manufacturing prices on agriculture is the same as the impact of agricultural prices on manufacturing. We find some support for both sets of parameter restrictions in our empirical analysis.

The neoclassical model assumes no costs of adjusting employment of factors of production. Therefore, movements in prices, technology and factor endowments that change equilibrium production structure are reflected in instantaneous changes in the shares of sectors in GDP. This assumption of instantaneous adjustment is clearly unrealistic and is rejected by the data. When we include a lagged dependent variable in the econometric specification to capture partial adjustment, the coefficient on the lagged dependent variable is highly statistically significant. Additionally, we find that the estimated coefficient on the lagged dependent variable varies systematically across countries, and the variation is correlated with measures of the strength of countries' employment protection policies. This finding is consistent with the idea that such policies can slow the reallocation of resources from declining to expanding sectors.

This paper is related to a number of strands in the literature. First, there is an empirical literature in international trade that has examined the relationship between production and factor endowments.[1] But despite this literature's focus

[1] Cross-country studies include Harrigan (1995, 1997), and Schott (2003), while Bernstein and Weinstein (2002), Davis et al. (1997) and Hanson and Slaughter (2002) analyse the relationship within countries.

on the empirical determinants of production, the phenomenon of deindustrialisation has received little attention, and indeed a number of studies focus on the manufacturing sector alone. Second, there is a relatively informal economic history literature that has examined deindustrialisation, often with particular emphasis on the United Kingdom and the United States.[2] Third, and related, both the development and macroeconomics literatures have examined the role of structural change in economic growth.[3] Nonetheless, econometric evidence on the uneven extent and timing of deindustrialisation across countries remains scarce. Finally, our paper is related to a number of strands of research within the labour economics literature, including work that has examined the role of labour market institutions in determining growth and unemployment,[4] and research that has found evidence of substantial differences in labour market outcomes between men and women.[5]

The remainder of the paper is structured as follows. Section 2 discusses the neoclassical model of trade and production and derives an equation from producer optimisation that relates the share of a sector in GDP to prices, technology and factor endowments. Section 3 introduces the data and presents evidence on the uneven pace of deindustrialisation across OECD countries. Section 4 discusses the econometric specification and estimation strategy. Section 5 presents our baseline empirical results, while Section 6 examines the speed of adjustment to structural change. Section 7 concludes.

2. THEORETICAL FRAMEWORK

The neoclassical model provides a general framework for analysing the determinants of production structure that allows for cross-country differences in preferences, technology and factor endowments (see, for example, Dixit and Norman, 1980). Under the assumption that markets are perfectly competitive and the production technology exhibits constant returns to scale, profit maximisation defines the equilibrium revenue function. Under the further assumption that technology differences across countries and industries are Hicks-neutral, the revenue function takes the following form: $r(\theta p, v)$, where p is the vector of goods prices, v is the vector of the economy's aggregate factor endowments, and θ is a diagonal

[2] See Broadberry (1997), Crafts (1996), Kitson and Michie (1996) and Rowthorn and Ramaswamy (1999).
[3] See, for example, Caselli and Coleman (2001), Echevarria (1997), Gollin et al. (2002), Ngai and Pissarides (2007), Syrquin (1988) and Temple (2001).
[4] For example, Hopenhayn and Rogerson (1993) find a negative effect of employment protection on aggregate productivity and growth using firm-level data, while Lazear (1990) and Nickell (1997) find effects on employment and unemployment using cross-country data.
[5] See Blinder (1973), Oaxaca (1973) and Swaffield (1999) among many others.

matrix of the Hicks-neutral industry technology parameters. We assume that the revenue function is twice continuously differentiable and, following Harrigan (1997) and Kohli (1991), that it takes the translog functional form, which provides an approximation to any constant returns to scale revenue function.[6] Under these assumptions, the neoclassical model implies the following supply-side relationship between the share of a sector in GDP, relative prices, technology and factor endowments, as derived formally in a separate web-based technical appendix:

$$\frac{\partial \ln r(\theta p, v)}{\partial p_j} = \frac{y_j(\theta p, v)}{r(\theta p, v)} \equiv s_j = \alpha_{0j} + \sum_{k=1}^{N} \alpha_{jk} \ln p_k + \sum_{k=1}^{N} \alpha_{jk} \ln \theta_k + \sum_{i=1}^{M} \gamma_{ji} \ln v_i, \quad (1)$$

where s_j denotes the share of sector j in GDP; $j, k \in \{1, \ldots, N\}$ index sectors; and $i, h \in \{1, \ldots, M\}$ index factors.

Equation (1) can be estimated for each industry using a panel of data on countries over time. Stacking the relationships for each industry together yields a system of equations that can be estimated using our three-dimensional panel dataset on countries across industries and over time. We note that equation (1) is a supply-side relationship that is derived from producer optimisation. Therefore this relationship is consistent with a wider range of forms for consumer preferences, which influence production structure through prices. As equation (1) represents a general equilibrium relationship, the share of an industry in GDP depends not only on the industry's price, but also on the price of all other industries. The intuition for this general equilibrium relationship comes from competition between industries for scarce factors of production.

As technology differences have been assumed to be Hicks-neutral, improvements in an industry's technology lead to proportionate reductions in unit cost. The effect of a 1 per cent reduction in unit cost in the zero-profit condition for an industry is the same as a 1 per cent increase in the price of the good. Therefore, improvements in an industry's technology have symmetric effects on production structure in equation (1) as increases in the industry's price. As a result of the symmetry between price and technology effects, improvements in technology that are followed by equi-proportionate reductions in price leave an industry's share of GDP unchanged. Similarly, improvements in technology that are followed by more than proportionate reductions in price, due, for example, to inelastic demand, lead to a contraction in an industry's share of GDP.

In deriving equation (1), we have not made any assumptions about whether countries are large or small or about whether goods are tradable or non-tradable.

[6] In the Heckscher–Ohlin model with identical preferences, identical technology and no trade costs, the assumption of more factors than goods ensures that production is determinate and the revenue function is twice continuously differentiable. In the neoclassical model, differences in technology and prices across countries help to make production determinate and the revenue function twice continuously differentiable even with more goods than factors.

If a country is small and *all* goods are freely tradable, the prices of goods are determined exogenously on world markets. If a country is large or some goods are non-tradable, the prices of goods are determined endogenously. In our empirical analysis below, we control for the endogeneity of the prices of goods by using exogenous shifters of prices as instruments.

The translog revenue function implies coefficients on relative prices, technology and factor endowments in equation (1) that are constant across industries and over time. This is true even without factor price equalisation. Indeed, with cross-country differences in technology, factor price equalisation will typically not be observed. The effect of cross-country differences in prices and technology on production structure is directly controlled for by the terms in prices and technology on the right-hand side of the equation.

The neoclassical model implies a number of testable restrictions on the parameters of this system of equations. First, constant returns to scale imply that the revenue function is homogeneous of degree one in factor endowments, which implies that the share of an industry in GDP is homogeneous of degree zero in factor endowments: $\sum_i \gamma_{ji} = 0$. Second, the model also yields two testable predictions for the symmetry of the estimated coefficients. The translog revenue function implies that the cross-price and cross-technology terms are symmetric between industries: $\alpha_{jk} = \alpha_{kj}$ for all j, k. For example, the effect of an increase in the price of agriculture on manufacturing should be the same as the effect of an increase in the price of manufacturing on agriculture. The assumption of Hicks-neutral technology differences implies another symmetry prediction: the coefficients on industry prices and technology should be the same. Before presenting our econometric estimates of these coefficients, we first turn to the description of our data.

3. DATA DESCRIPTION

a. Data Sources and Sample

The main source of data in the empirical application is the OECD's International Sectoral Data Base (ISDB), which provides information for one-digit manufacturing and non-manufacturing industries on current price value-added, constant price value-added, employment, hours worked and the real physical capital stock. Data on GDP and a country's aggregate endowment of physical capital are also obtained from the ISDB. Information on educational endowments comes from individual countries' labour force surveys, while data on arable land area are collected from the United Nations Food and Agricultural Organisation (FAO).[7]

[7] See the Appendix for further information concerning the datasets used.

TABLE 1A
Country Composition of Sample

Country	*Period*
1. Australia	1983–93
2. Belgium	1987–94
3. Canada	1976–92
4. Denmark	1984–92
5. Finland	1985–94
6. France	1983–92
7. West Germany	1985–93
8. Italy	1978–94
9. Japan	1976–94
10. Netherlands	1976–94
11. Norway	1976–91
12. Sweden	1976–94
13. United Kingdom	1976–93
14. United States	1976–93

TABLE 1B
Industry Composition of Sample (International Standard Industrial Classification (ISIC))

Industry	*Industry Code*	*Further Details*
1. Agriculture	10	Agriculture, Hunting, Forestry and Fishing (ISIC 10)
2. Manufacturing	30	Manufacturing (ISIC 30)
3. Other Production	40	Mining and Quarrying (ISIC 20)
		Electricity, Gas, and Water (ISIC 40)
		Construction (ISIC 50)
4. Other Services	601	Wholesale and Retail Trade, Restaurants and Hotels (ISIC 60)
		Transport, Storage, and Communication (ISIC 70)
		Community, Social, and Personal Services (ISIC 90)
5. Business Services	602	Financial Institutions and Insurance (ISIC 82)
		Real Estate and Business Services (ISIC 83)

Our sample is an unbalanced panel of 14 OECD countries and five one-digit industries during the period 1975–94. The distribution of observations across countries and over time is given in Table 1A. Our sample includes all market sectors, as listed in Table 1B, and excludes non-market services. Given that deindustrialisation is concerned with the decline in the share of aggregate manufacturing in GDP, we consider the manufacturing sector as a whole, as well as aggregates of the other major sectors of economic activity. These aggregates include agriculture and other production industries, where other production industries comprise mining, utilities and construction. The only exception to this aggregation is the service sector, which we divide into financial and business services on the one hand and other services on the other hand. The motivation for the disaggregation of the service sector is that financial and business services are likely to be more tradable than other services, and are therefore likely to experience different patterns of price movements across countries.[8]

b. GDP Shares

The model yields predictions for the share of current price value-added of each industry in current price GDP, and we therefore take current price shares of GDP as our left-hand-side variable. To illustrate the uneven pace of deindustrialisation across OECD countries, Figure 1 shows the share of industries in GDP in Japan, the United Kingdom and the United States over time. Deindustrialisation proceeds more rapidly in the United Kingdom and the United States than in Japan, where the decline in manufacturing does not begin in earnest until the early 1990s. The share of agriculture in GDP at the beginning of the sample period is much lower in the United Kingdom and the United States than in Japan, but specialisation patterns in agriculture converge as Japan experiences a more rapid decline in the share of this sector in GDP. The rise in the share of other services in GDP is greatest in Japan, while the United Kingdom experiences the most extensive growth in business services. Marked differences in the evolution of production structure over time are also observed in other OECD countries.

c. Prices

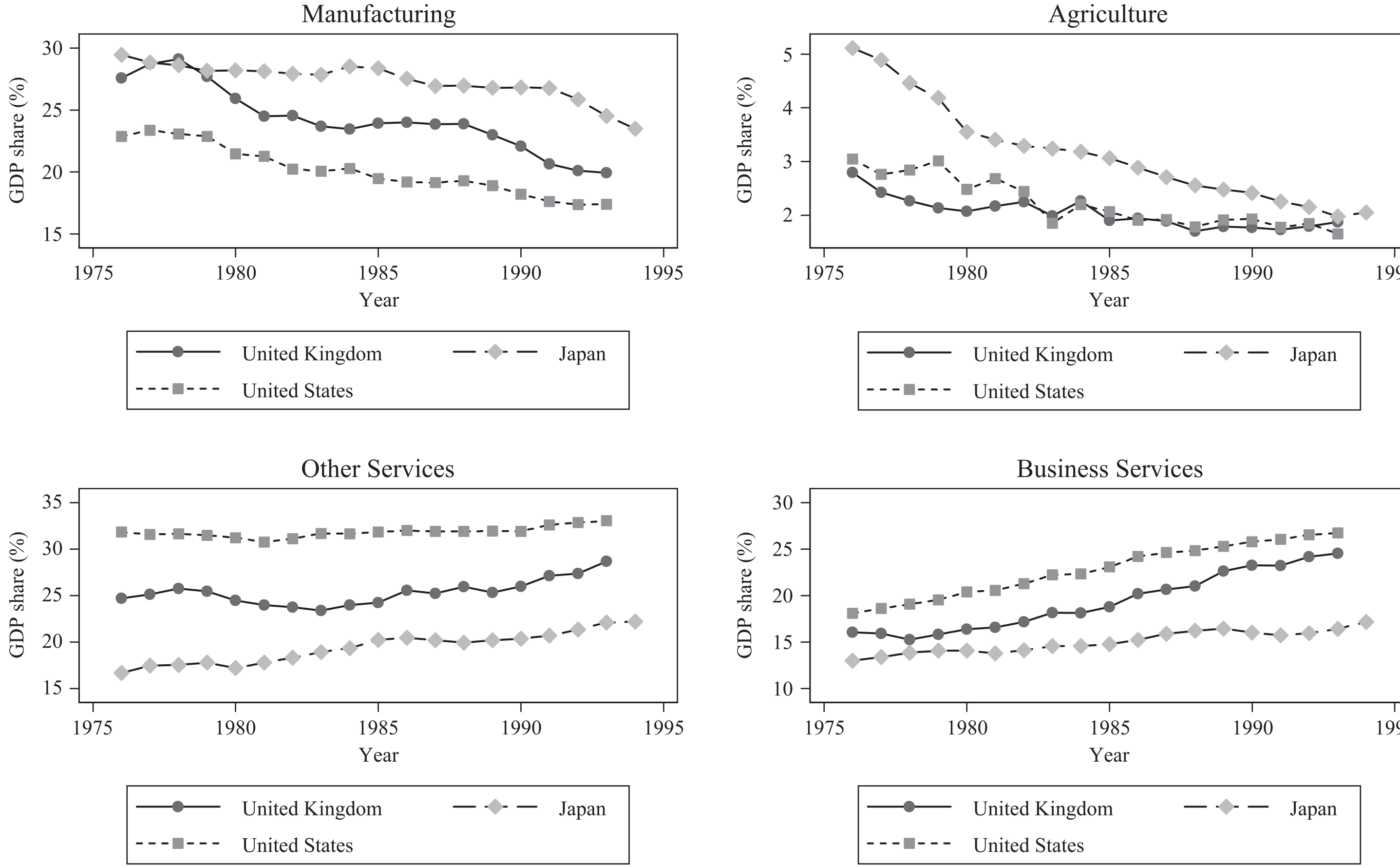
In the model, firms maximise profits, taking producer prices as given. Producer prices include the effects of tariffs and transport costs, since under perfect competition domestic producer prices equal foreign producer prices plus tariffs and transport costs. In our empirical analysis, we measure prices using producer price deflators, which correspond exactly to the variables emphasised by the model. The producer price deflator is an index of industry j prices in country c at time t relative to their value in the same country in 1990, and so takes the value 1 in 1990 in all countries. The producer price deflator provides information on changes in nominal prices in a particular country–industry over time. Although the deflator does not capture the level of prices across countries and industries in 1990, our econometric specification captures the level of prices in 1990 using a country–industry fixed effect.

d. Technology

We measure technology using a superlative index number measure of total factor productivity (TFP), which is derived under the neoclassical model's

[8] More detailed information on the disaggregated sectors included in each one-digit industry is contained in the working paper version of this paper: Nickell et al. (2004).

FIGURE 1
GDP Shares by Sector and Over Time



Note:
Scales vary between panels of the figure.

assumptions of constant returns to scale and perfect competition. Approximating constant returns to scale production technology with a translog functional form, this superlative index number evaluates productivity in each country and time period relative to a hypothetical geometric mean within the industry (see Caves et al., 1982; Harrigan, 1997) and is given by:

$$\ln(RTFP_{cjt}) = \ln\left(\frac{Y_{cjt}}{\bar{Y}_{jt}}\right) - \bar{\sigma}_{cjt} \cdot \ln\left(\frac{L_{cjt}}{\bar{L}_{jt}}\right) - (1 - \bar{\sigma}_{cjt}) \cdot \ln\left(\frac{K_{cjt}}{\bar{K}_{jt}}\right), \tag{2}$$

where an upper bar above a variable denotes a geometric mean; Y is real value-added; L is labour input (hours worked); and K is the real capital stock. The variable $\bar{\sigma}_{cjt} = 1/2 \cdot (\alpha_{cjt} + \bar{\alpha}_{jt})$ is the average of labour's share in value-added in country c (α_{cjt}) and the geometric mean labour share ($\bar{\alpha}_{jt}$). The lack of comparable cross-country data on employment and wages for each education group by industry, as well as the absence of industry-level data on the use and prices of different types of capital goods, limits our ability to control for factor quality, and so our TFP measures capture variation in both technology and factor quality.

The observed share of labour in value-added is typically quite volatile, which is suggestive of measurement error. Therefore, we use the structure of the neoclassical model to control for measurement error. Assuming perfect competition and approximating the constant returns to scale production technology with a translog functional form, the share of labour in value-added is the following log linear function of the capital–labour ratio:

$$\alpha_{cjt} = \xi_{cj} + \phi_j \cdot \ln(K_{cjt}/L_{cjt}). \tag{3}$$

If the measurement error in labour's share of value-added is independently and identically distributed, the parameters of this equation can be estimated using fixed effects panel data estimation and the fitted values provide consistent estimates of labour's true share of value-added. As a robustness test, and in order to check the appropriateness of the assumption that the measurement error is independently and identically distributed, we also re-estimate the model using TFP measures based on the raw labour shares.

e. Factor Endowments

Our measures of factor endowments include the real capital stock, which is calculated using the perpetual inventory method from real investment data deflated using an investment price deflator. The development of the agriculture sector in particular is influenced by the availability of land, and therefore we consider the supply of arable land as another factor endowment. Finally, both popular and academic discussions of cross-country industrial performance emphasise the supply of education and skills. Therefore, we break down our measure of labour endowment by education attainment.

Our educational attainment measures are constructed from the detailed information available in individual countries' labour force surveys. As a result, they are a considerable improvement over existing cross-country measures of educational attainment, such as those of Barro and Lee (1993, 2000), which are only available at five-year intervals and have been the subject of a number of concerns (see, for example, the discussion in Cohen and Soto, 2001; de la Fuente and Domenech, 2000; Krueger and Lindahl, 2001). We use standard definitions of low, medium and high educational attainment from the labour market literature, as discussed further in the data appendix. The detailed information from the individual country labour force surveys enables us to construct these measures of educational attainment in as consistent a way as possible across countries. We control for any remaining cross-country differences in the classification of educational attainment through the inclusion of country–industry fixed effects in our econometric specification.

As discussed above, a large labour market literature finds substantial differences in labour market outcomes between women and men. Among individuals with the same observed level of educational attainment, females and males are likely to differ along a variety of dimensions. For example, women and men choose different areas of specialisation at high school and university and may differ in terms of physical strength and other skills that are relevant for particular industries such as agriculture or other production industries.[9] In order to allow for unobserved differences in skills between women and men with the same observed level of educational attainment, we construct separate female and male education endowments. The economy's endowment of women (men) with a particular level of educational attainment is measured as the percentage of women (men) with the relevant level of educational attainment times the female (male) population.

4. ECONOMETRIC SPECIFICATION

Our econometric specification is derived directly from equation (1). Although non-market services are excluded from our estimation sample, and so data on price and TFP in this industry are not available, these variables should enter the GDP share equations for the other industries. Therefore, in the equations for the other industries, we treat price and TFP in non-market services as random variables. We model them with a country–industry fixed effect, industry–time dummies and

[9] For US evidence on sex differentials using matched employee–employer data, see Bayard et al. (2003).

a mean–zero stochastic error. Stacking equation (1) for each of the market sectors, we obtain the following system of equations:

$$
\begin{aligned}
s_{c1t} &= \alpha_{01} + \sum_{k=1}^{N-1} \alpha_{1k} \ln p_{ckt} + \sum_{k=1}^{N-1} \alpha_{1k} \ln \theta_{ckt} + \sum_{i=1}^{M} \gamma_{1i} \ln v_{cit} + \eta_{c1} + d_{1t} + u_{c1t} \\
&\vdots \\
s_{cjt} &= \alpha_{0j} + \sum_{k=1}^{N-1} \alpha_{jk} \ln p_{ckt} + \sum_{k=1}^{N-1} \alpha_{jk} \ln \theta_{ckt} + \sum_{i=1}^{M} \gamma_{ji} \ln v_{cit} + \eta_{cj} + d_{jt} + u_{cjt} \qquad (4) \\
&\vdots \\
s_{cN-1t} &= \alpha_{0N-1} + \sum_{k=1}^{N-1} \alpha_{N-1k} \ln p_{ckt} + \sum_{k=1}^{N-1} \alpha_{N-1k} \ln \theta_{ckt} + \sum_{i=1}^{M} \gamma_{N-1i} \ln v_{cit} + \eta_{cN-1} + d_{N-1t} + u_{cN-1t},
\end{aligned}
$$

where c denotes countries, j and k denote sectors and i indicates factors of production; the market sectors (agriculture, manufacturing, other production, other services and business services) are indexed by $j \in \{1, \ldots, N-1\}$; non-market services corresponds to $j = N$.

The country–industry fixed effect (η_{cj}) controls for time-invariant unobserved heterogeneity that is specific to individual countries and industries, and which we allow to be correlated with the explanatory variables. For example, the country–industry fixed effect will capture time-invariant influences of natural resources or geographical location on specialisation in individual industries. The fixed effect also controls for any time-invariant errors of measurement in prices, technology and factor endowment that may be specific to individual countries and industries. The industry–time dummies (d_{jt}) control for common macroeconomic shocks across countries within individual industries, and capture common technological change within industries, common trends in relative prices, and common changes in factor endowments. The industry–time dummies also control for any errors of measurement that are specific to individual industries and years but common across countries. The presence of the country–industry fixed effects and industry–time dummies implies that the coefficients of interest on prices, TFP and factor endowments are identified from differential changes in these variables over time within countries.[10]

[10] Measurement error may be of particular concern in non-manufacturing industries and so the presence of the country–industry fixed effects and industry–time dummies may be particularly important in these sectors. Any remaining classical measurement error will attenuate the estimated parameters of interest towards zero, biasing the results away from the economic relationships that we seek to identify. Although the potential for measurement error may be greater outside manufacturing, manufacturing is typically less than 30 per cent of GDP in OECD countries, and there is a need to understand the remaining 70 per cent of economic activity.

The equations that form the system in (4) capture static long-run equilibrium relationships between the share of a sector in GDP, prices, technology and factor endowments. By construction, the share of sector j in GDP (s_{cjt}) is bounded between 0 and 1 and cannot therefore have a unit root (i.e. cannot follow a random walk, $s_{cjt} = s_{cjt-1} + \varepsilon_{cjt}$, where ε is an independently and identically distributed stochastic error). However, in any finite sample, the share of a sector in GDP may behave like a unit root process (i.e. be statistically indistinguishable from a random walk). This is particularly true of our sample period (1975–94), which is characterised by a secular decline in the share of agriculture and manufacturing in GDP and a secular rise in the share of services. Similarly, in any finite sample, the measures of prices, technology and factor endowments may also behave like unit processes. Indeed, the panel data unit root tests of Maddala and Wu (1999) confirm that this is the case during our sample period (see Nickell et al., 2004, for further details). When left- and right-hand side-variables behave like unit root processes, the equations in (4) only have an interpretation as long-run equilibrium relationships if the residuals are stationary (i.e. the residuals do *not* behave like a unit root process). Therefore, one of the model specification tests that we consider to assess the empirical performance of the neoclassical model is a test for whether the residuals have a unit root.

Since non-market services is excluded from the system of equations in (4), the GDP shares of industries sum to less than 100 per cent, and the system of equations can be estimated by Ordinary Least Squares with two-way fixed effects (Within Groups).[11] With no price or TFP measure for non-market services, the prediction of constant returns to scale that the coefficients on prices and TFP sum to zero across industries cannot be tested, since the coefficients for non-market services are absorbed in the country–industry fixed effect and the industry–time dummies.[12] But constant returns to scale also implies that the sum of the coefficients on factor endowments is equal to zero, which can be tested alongside the other parameter restrictions of the neoclassical model.

One important concern in estimating the system of equations in (4) is that both prices and TFP are potentially endogenous. As discussed above, prices will be endogenous when countries are large or goods are non-tradable. A positive demand-side shock may lead to both a rise in the share of an industry in GDP and a rise in the industry's price, inducing an upward bias in the estimated coefficient on own-industry prices. In contrast, a positive supply-side shock may

[11] If all sectors are included, the system of equations in (4) is singular and Maximum Likelihood is the appropriate estimation technique. When data on all sectors are not available, Ordinary Least Squares or systems estimators such as 3SLS, which we consider below, are appropriate. See, for example, the discussion in Greene (1993).

[12] Under the assumption of constant returns to scale, the coefficients on prices and TFP for non-market services equal minus the sum of the coefficients on the price and technology variables for the other sectors.

induce a rise in the share of an industry in GDP and a decline in the industry's price, inducing a downward bias in the estimated coefficient on own-industry prices. Demand and supply-side shocks may also induce endogenous changes in TFP if technological change is influenced by the size of a sector, as suggested for example in the recent literature on directed technological change (see, for example, Acemoglu, 2002).

To control for the potential endogeneity of prices and TFP, we estimate the system of equations in (4) using Three-Stage Least Squares (3SLS). We consider three sets of price-shifters as instruments. The first is the share of government consumption expenditure devoted to each industry, which we extract from the OECD input–output tables, and which varies across countries, industries and over time. With large countries and non-tradable goods, an increase in the share of government consumption expenditure devoted to an industry will lead to an increase in the relative price of the industry. Therefore, we construct five instruments using the share of government consumption expenditure on agriculture, manufacturing, other production, other services and business services.

The second set of price-shifters is motivated by empirical findings from the international macroeconomics literature that short-run movements in the nominal exchange are hard to explain in terms of economic fundamentals. Indeed this literature finds that, in the short run, it is often difficult to outperform a random walk as a model of exchange rate fluctuations (see, for example, the survey by Frankel and Rose, 1995). These nominal exchange rate fluctuations induce variation in the cost of imported intermediate inputs and hence in industry prices. We extract information on the share of imported intermediate inputs in gross output from OECD input–output tables, where the imported intermediates share again varies across countries, industries and over time. We construct instruments for each of the five industries equal to the share of imported intermediate inputs in gross output interacted with the log of the nominal exchange rate.

Our third price-shifter exploits the idea that firms maximise profits taking domestic producer prices as given, but domestic producer prices are influenced by tariffs, because under perfect competition domestic producer prices equal foreign producer prices plus tariffs and transport costs. Consistent data on tariff barriers at the industry level are not available for most of the OECD countries in our sample prior to the introduction of the Harmonised System (HS) classification in the late 1980s and the associated development of the United Nations Trade Analysis and Information System (TRAINS).[13] Nonetheless, it is possible to

[13] An exception is the United States, where data on tariff barriers at the product level is available. While the United States data could be used to control for multilateral trade liberalisation that is common to all OECD countries, common changes in industry trade barriers are already controlled for in the industry-time dummies. Prior to the adoption of the HS classification, different OECD countries employed different tariff classifications.

construct an aggregate measure of average tariff duties paid using data on the share of tariff revenue in imports for each OECD country. We use this aggregate measure of tariff barriers, which varies across countries and over time, as an additional price-shifter.

Our choice of instruments for TFP is motivated by the concern that demand or supply-side shocks to the size of a sector could influence the pace of technological change. To construct technology-shifters, we exploit information on government expenditure on R&D, which is directed towards basic science and therefore less responsive to market incentives.[14] We build on the large empirical literature that has found positive externalities to research and development (R&D) expenditure (see, for example, Griliches, 1998). If improvements in a good's technology as a result of R&D are not fully reflected in higher prices, then downstream users of the good appropriate some of the social surplus created by the R&D expenditure. We combine this idea with the fact that R&D expenditure is overwhelmingly concentrated in a few manufacturing industries, including pharmaceuticals, electronic equipment, and office and computing machinery. For each industry in our sample, we construct a measure of the share of domestic intermediate inputs demanded from industries that the OECD classifies as R&D intensive. The data on domestic intermediate input use comes from the OECD input–output tables and varies across countries, industries and over time. We construct instruments for each of our five sectors equal to the share of domestic intermediate inputs demanded from R&D-intensive industries interacted with the log of real government expenditure on R&D.

In the 3SLS estimation, we follow a large empirical literature in international trade in treating factor endowments as exogenous (see, for example, Harrigan, 1997; Davis et al., 1997; Schott, 2003). We note that the current stock of working age individuals with a particular level of educational attainment is determined by the educational decisions of past cohorts in school, and is therefore pre-determined with respect to shocks to the share of a sector in GDP. For an individual of age 40, the decision whether to enter secondary school was determined 30 years ago and the decision whether to go to university was determined 20 years ago. As one of our robustness checks, we experiment with including lagged rather than current values of factor endowments, and find a very similar pattern of results. Finally, in our empirical results below, we report the results of a Hansen overidentification test, which examines the correlation between the exogenous variables of the model and the residuals of the GDP share equation.

[14] A related concern is that increasing returns to scale, imperfect competition and variable capacity utilisation could induce measured TFP to respond to the size of a sector over the business cycle (see, for example, Basu et al., 2006). As government expenditure on R&D is directed towards basic science, it is also less likely to respond to these business cycle fluctuations.

5. BASELINE EMPIRICAL RESULTS

Table 2 presents our baseline 3SLS result. The three sets of variables emphasised by the neoclassical model as determinants of production structure, prices, technology and factor endowments, are highly statistically significant. For each of the three sets of variables, the null hypothesis that the coefficients are equal to zero is rejected at the 1 per cent level. We find evidence consistent with the idea that women and men with the same observed level of educational attainment differ in terms of other unobserved dimensions of skills. The null hypothesis that the coefficients on female education endowments are equal to those on male education endowments is rejected at the 1 per cent level. Consistent with the predictions of the neoclassical model, we find coefficients on own-industry prices and TFP are typically positive and statistically significant.

In Table 3 we examine a number of specification tests for the 3SLS estimates as well as tests of the parameter restrictions imposed by the neoclassical model. In the first two rows of the table, we examine the power of the instruments in the first-stage regressions for prices and TFP. The first-stage F-statistic for prices is substantially above 10 for each of the five industries. The first-stage F-statistic for TFP exceeds 10 in three industries, is close to 10 in one more industry, and is 7.52 in the remaining industry, which is statistically significant at the 1 per cent level. The results confirm that the instruments do indeed have power in the first-stage regressions.

In the third row of Table 3, we report the results of a Hansen test of the model's overidentifying restrictions. We find no evidence that the exogenous variables of the model are correlated with the second-stage residuals and are unable to reject the null hypothesis of orthogonality at conventional significance levels. These results provide additional support for our 3SLS estimation strategy.

In the fourth row of the table, we examine the stationarity of the GDP shares residuals using the Maddala and Wu (1999) panel data unit root test. Since both left- and right-hand-side variables behave as unit root processes during the sample period, the GDP share residuals must be stationary in order for the system of equations in (4) to be interpreted as a long-run cointegrating relationship. In each of the five industries, we are able to reject the null hypothesis that the residuals are non-stationary at the 5 per cent significance level, thus supporting the interpretation of our econometric estimates as capturing a long-run cointegrating relationship.

We now turn to examine a number of the testable parameter restrictions imposed by the neoclassical model. In the fifth row of Table 3, we examine the prediction of constant returns to scale that the sum of the estimated coefficients on factor endowments is equal to zero. In each of the five industries, we are unable to reject the null hypothesis of constant returns to scale at conventional levels of statistical significance. The sixth row of the table examines the implication

TABLE 2
Three-Stage Least Squares Estimation

	(1) *Agriculture*	*(2)* *Manufacturing*	*(3)* *Other Production*	*(4)* *Other Services*	*(5)* *Business Services*
$\ln(P10/P10^{1990})$	0.024	0.049	–0.049	0.020	0.006
	(0.007)***	(0.038)	(0.031)	(0.038)	(0.025)
$\ln(P30/P30^{1990})$	–0.014	–0.004	–0.005	–0.010	–0.027
	(0.011)	(0.059)	(0.047)	(0.059)	(0.038)
$\ln(P40/P40^{1990})$	–0.016	–0.107	0.160	–0.007	–0.055
	(0.005)***	(0.028)***	(0.022)***	(0.028)	(0.018)***
$\ln(P601/P601^{1990})$	–0.017	0.155	–0.101	0.057	–0.082
	(0.014)	(0.069)**	(0.056)*	(0.070)	(0.045)*
$\ln(P602/P602^{1990})$	0.021	–0.150	0.041	–0.092	0.158
	(0.012)*	(0.062)**	(0.050)	(0.063)	(0.040)***
$\ln(TFP10/TFP10^{GM})$	0.020	–0.023	–0.029	0.060	–0.037
	(0.010)**	(0.050)	(0.040)	(0.051)	(0.033)
$\ln(TFP30/TFP30^{GM})$	–0.013	–0.133	0.110	–0.114	0.043
	(0.023)	(0.120)	(0.096)	(0.120)	(0.077)
$\ln(TFP40/TFP40^{GM})$	0.003	–0.017	–0.005	0.084	–0.061
	(0.011)	(0.056)	(0.045)	(0.056)	(0.036)*
$\ln(TFP601/TFP601^{GM})$	0.001	0.044	–0.089	0.088	–0.060
	(0.012)	(0.061)	(0.049)*	(0.061)	(0.039)
$\ln(TFP602/TFP602^{GM})$	0.025	–0.038	0.073	–0.174	0.163
	(0.018)	(0.091)	(0.073)	(0.092)*	(0.059)***
ln *Male Low*	0.038	–0.058	–0.048	0.135	–0.056
	(0.013)***	(0.065)	(0.052)	(0.066)**	(0.042)
ln *Male Med*	0.010	–0.099	–0.218	0.386	–0.180
	(0.026)	(0.131)	(0.105)**	(0.131)***	(0.084)**
ln *Male High*	0.000	0.003	–0.023	0.088	–0.033
	(0.008)	(0.042)	(0.034)	(0.042)**	(0.027)
ln *Female Low*	–0.039	0.031	0.093	–0.157	0.054
	(0.016)**	(0.083)	(0.066)	(0.083)*	(0.053)
ln *Female Med*	–0.012	0.129	0.075	–0.171	0.112
	(0.016)	(0.080)	(0.065)	(0.081)**	(0.052)**

TABLE 2 *Continued*

	(1) *Agriculture*	(2) *Manufacturing*	(3) *Other Production*	(4) *Other Services*	(5) *Business Services*
ln *Female High*	0.006	–0.045	0.003	–0.016	0.007
	(0.007)	(0.036)	(0.029)	(0.036)	(0.023)
ln *Capital*	0.007	–0.162	0.098	–0.004	–0.000
	(0.021)	(0.106)	(0.085)	(0.106)	(0.068)
ln *Arable Land*	–0.017	–0.034	–0.081	0.185	–0.156
	(0.030)	(0.153)	(0.123)	(0.153)	(0.099)
Observations	200	200	200	200	200
R^2	0.97	0.94	0.94	0.98	0.99
Country fixed effects	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
Estimation	3SLS	3SLS	3SLS	3SLS	3SLS

Notes:
GDP Share 10 is share of agriculture (ISIC 10) in GDP expressed as a percentage; GDP shares for the other industries are defined analogously; GDP shares sum to less than 100% due to the exclusion of Non-Market Services; ln $(P10/P10^{1990})$ is the log of the Producer Price Index in 1990 prices for agriculture (ISIC 10); producer prices for the other industries are defined analogously; ln $(TFP10/TFP10^{GM})$ is the log of total factor productivity relative to the geometric mean for agriculture (ISIC 10); total factor productivity for the other industries is defined analogously; ln *Male Low* is the log on the number of individuals with low education; the other education endowments are defined analogously; ln *Capital* is the log of the real capital stock expressed in 1990 prices; ln *Arable Land* is the log arable land area expressed in hectares. Endogenous variables: prices and total factor productivity. Exogenous variables: share of government consumption expenditure devoted to each industry; log nominal exchange rate interacted with share of imported intermediate inputs in gross output for each industry; log tariff; log government expenditure on R&D interacted with share of domestic intermediate inputs from R&D-intensive sectors for each industry. Standard errors in parentheses.
* Significant at 10%; ** significant at 5%; *** significant at 1%. See the data appendix for further details concerning the variable definitions and data sources.

TABLE 3
Specification Tests for Three-Stage Least Squares Estimates

	(1) Agriculture	*(2) Manufacturing*	*(3) Other Production*	*(4) Other Services*	*(5) Business Services*
Prices First-Stage *F*-statistic	17.81***	22.78***	18.52***	19.16***	21.28***
TFP First-Stage *F*-statistic	14.00***	15.07***	13.26***	9.51***	7.52***
Hansen Overidentification Test (*p*-value)	(0.683)	(0.123)	(0.176)	(0.815)	(0.626)
Maddala–Wu Residual Non-Stationary Test (*p*-value)	(0.001)***	(0.028)**	(0.001)***	(0.000)***	(0.001)***
Constant Returns to Scale (*p*-value)	(0.906)	(0.385)	(0.643)	(0.101)	(0.147)

Number of Rejections of Symmetry of Price and TFP Coefficients (5% level): 1 out of 25
Number of Rejections of Symmetry of Price Cross-Effects (5% level): 1 out of 10
Number of Rejections of Symmetry of TFP Cross-Effects: 1 out of 10

Notes:
All specification tests relate to the 3SLS estimates reported in Table 2. Prices First-Stage *F*-statistic is a test of the null hypothesis that the coefficients on the instruments are equal to zero in the first stage regression for prices. TFP First-Stage *F*-statistic is a test of the null hypothesis that the coefficients on the instruments are equal to zero in the first-stage regression for TFP. Hansen Overidentification Test regresses the GDP share residuals on all the exogenous variables of the system; under the null hypothesis of no correlation, the number of observations times the R^2 of the regression is distributed Chi-squared with degrees of freedom equal to the number of instruments minus the number of endogenous variables. Maddala–Wu is the panel data unit root test of Maddala and Wu (1999) that tests the null hypothesis that the GDP share residuals have a unit root. Constant Returns to Scale tests the null hypothesis that the sum of the coefficients on factor endowments is equal to zero. Symmetry of Price and Technology Coefficients summarises the results of tests for the equality of the price and TFP coefficients. Symmetry of Price Cross-Effects summarises the results of tests that the coefficient on the price of industry j in the equation for the GDP share of industry k is equal to the coefficient on the price of industry k in the equation for the GDP share of industry j. Symmetry of TFP Cross-Effects is defined analogously.
*** Denotes statistical significance at the 1% level; ** denotes statistical significance at the 5% level.

of Hicks-neutral technology differences that the estimated coefficients on prices and technology are the same. In each GDP share equation, there are five comparisons between the coefficients on prices and technology to be made. With five industries, this yields 25 comparisons of coefficients. In only one out of the 25 comparisons are we able to reject the prediction that the coefficients on prices and technology are the same at conventional levels of statistical significance.

In the seventh and eighth rows of Table 3, we examine the prediction of the translog revenue function that the cross-effects of prices and TFP are symmetric. For example, we examine whether the effect of an increase in the price of agriculture on manufacturing is the same as the effect of an increase in the price of manufacturing on agriculture. With five industries, there are 10 possible cross-effects to compare.[15] For both prices and TFP, we are only able to reject the null hypothesis of symmetry in one out of the 10 comparisons of the cross-effects.

Taken together, the results in Table 3 provide support for both our 3SLS estimation strategy and the testable parameter restrictions of the neoclassical model. The estimated coefficients in Table 2 are also consistent with the predictions of the neoclassical model for the relationship between production and factor endowments with many goods and many factor endowments (the generalisations of the Rybczynski Theorem to many goods and many factors, as discussed for example in Dixit and Norman, 1980). The first of these predictions is that 'every factor has at least one friend and at least one enemy'. Looking across industries for a given factor of production, we find that every factor has a positive and a negative coefficient in at least one industry. The second of these predictions was that an increase in a factor endowment increases on average the output of industries intensive in the factor and decreases on average the output of industries non-intensive in the factor. As a statement about an average or a correlation, this second prediction is harder to evaluate. Since the model does not yield predictions for the impact of an increase in a factor endowment on the output of individual goods, the coefficients on individual factors in individual industries may take counterintuitive signs that are driven by general equilibrium considerations. Nonetheless, some of the estimated coefficients are consistent with economic priors. For example, increases in the endowment of low education men have a positive and statistically significant effect on the share of agriculture in GDP, while increases in the endowment of medium education men raise the share of other services in GDP.

In Table 4, we use our econometric estimates to decompose the change in predicted shares of GDP into the contribution of individual explanatory variables.

[15] In testing the symmetry of the cross-effects, we compare the upper and lower off-diagonals of a 5×5 matrix, each of which contains 10 entries.

TABLE 4
Contribution of Explanatory Variables to Changes in Shares of GDP

	Agriculture	*Manufacture*	*Other Production*	*Other Services*	*Business Services*
United Kingdom (1976–93)					
Actual Change in GDP Share	−0.92	−7.65	−2.14	3.97	8.48
Predicted Change in GDP Share	−1.08	−10.15	−1.01	5.27	6.13
Education	0.72	−1.42	−8.74	13.28	−2.82
Capital	0.27	−6.73	4.08	−0.17	−0.01
Arable Land	0.21	0.44	1.04	−2.36	1.99
TFP	0.55	−2.69	−2.14	9.78	−7.85
Prices	−0.72	−14.1	9.59	−7.6	4.47
Year Effects	−2.11	14.35	−4.83	−7.67	10.35
France (1983−92)					
Actual Change in GDP Share	−1.52	−2.83	−1.0	1.75	4.56
Predicted Change in GDP Share	−1.54	−3.37	−1.59	3.55	2.79
Education	0.2	−0.17	−4.58	7.31	−2.21
Capital	0.14	−3.45	2.09	−0.08	0
Arable Land	−0.03	−0.07	−0.17	0.39	−0.33
TFP	0.36	0.26	−0.96	1.92	−0.97
Prices	−0.66	−5.14	2.82	−3.14	2.25
Year Effects	−1.55	5.21	−0.78	−2.84	4.06
Canada (1976–92)					
Actual Change in GDP Share	−1.99	−3.61	−2.42	0.81	5.57
Predicted Change in GDP Share	−2.37	−3.2	−0.92	0.39	6.05
Education	0.26	−2.2	−7.02	10.6	−3.28
Capital	0.41	−10.11	6.13	−0.25	−0.01
Arable Land	−0.05	−0.09	−0.23	0.51	−0.43
TFP	−0.11	1.99	0.05	−1.14	1.1
Prices	−0.67	−7.09	5.51	−3.74	0.87
Year Effects	−2.21	14.3	−5.36	−5.6	7.8
West Germany (1985–93)					
Actual Change in GDP Share	−0.71	−5.46	−0.78	6.34	0.38
Predicted Change in GDP Share	−1.44	−2.16	−1.74	6.77	−0.52

TABLE 4 *Continued*

	Agriculture	*Manufacture*	*Other Production*	*Other Services*	*Business Services*
Education	0.91	–1.88	–4.85	9.9	–3.28
Capital	0.13	–3.32	2.01	–0.08	0
Arable Land	0.04	0.08	0.19	–0.44	0.37
TFP	0.12	1.97	–2.06	2.12	–1.22
Prices	–1.4	–2.37	3.46	–0.71	–2.06
Year Effects	–1.24	3.36	–0.48	–4.02	5.67
Italy (1978–94)					
Actual Change in GDP Share	–3.62	–8.21	–0.83	10.62	0.2
Predicted Change in GDP Share	–3.42	–6.27	–1.41	8.47	1.39
Education	1.13	–0.74	–16.85	25.3	–8.18
Capital	0.31	–7.62	4.62	–0.19	–0.01
Arable Land	0.21	0.43	1.03	–2.34	1.97
TFP	–1.2	–0.58	1.74	–2.04	0.1
Prices	–1.84	–11.53	12.46	–4.86	–2.09
Year Effects	–2.03	13.76	–4.41	–7.4	9.6
Japan (1976–94)					
Actual Change in GDP Share	–3.06	–5.96	1.92	5.54	4.17
Predicted Change in GDP Share	–3.06	–3.67	1.12	4.9	4.06
Education	1.06	–1.03	–9.14	13.61	–3.59
Capital	0.69	–17.1	10.36	–0.42	–0.02
Arable Land	0.16	0.34	0.81	–1.83	1.54
TFP	–1.72	2.71	–1.4	3.04	–3.21
Prices	–0.99	–4.28	5.82	–1.28	–1.58
Year Effects	–2.27	15.7	–5.33	–8.21	10.91
United States (1976–93)					
Actual Change in GDP Share	–1.39	–5.48	–2.07	1.22	8.64
Predicted Change in GDP Share	–1.76	–5.35	–1.91	–0.17	10.14
Education	1.23	–1.83	–9.74	14.83	–4.79
Capital	0.3	–7.34	4.45	–0.18	–0.01
Arable Land	0.04	0.08	0.2	–0.45	0.38
TFP	–0.23	3.04	–1.77	0.1	–0.28

Prices	–0.97	–13.65	9.78	–6.78	4.48
Year Effects	–2.11	14.35	–4.83	–7.67	10.35
Australia (1983–93)					
Actual Change in GDP Share	–1.68	–3.2	–3.97	3.76	5.57
Predicted Change in GDP Share	–1.53	–2.47	–4.78	3.37	5.96
Education	0.29	–0.44	–5.64	8.65	–2.0
Capital	0.2	–4.89	2.97	–0.12	–0.01
Arable Land	–0.05	–0.11	–0.27	0.6	–0.51
TFP	–0.74	0.68	–0.53	2.48	–2.75
Prices	0.23	–2.96	–1.06	–3.32	4.6
Year Effects	–1.45	5.25	–0.25	–4.91	6.61
Sweden (1976–94)					
Actual Change in GDP Share	–2.71	–4.7	–2.44	0.2	8.98
Predicted Change in GDP Share	–2.53	–4.3	–3.95	1.85	8.66
Education	1.2	–0.73	–8.69	12.46	–3.1
Capital	0.29	–7.31	4.43	–0.18	–0.01
Arable Land	0.13	0.26	0.63	–1.43	1.2
TFP	–1.33	2.25	–3.54	7.51	–6.94
Prices	–0.55	–14.47	8.56	–8.3	6.59
Year Effects	–2.27	15.7	–5.33	–8.21	10.91
Denmark (1984–92)					
Actual Change in GDP Share	–2.38	–1.09	0.82	1.27	1.28
Predicted Change in GDP Share	–2.39	–0.99	–1.08	1.19	2.48
Education	–0.08	–0.02	–2.74	2.25	–0.26
Capital	0.1	–2.38	1.44	–0.06	0
Arable Land	0.05	0.1	0.23	–0.52	0.44
TFP	–0.34	3.25	–3.06	4.57	–3.13
Prices	–0.57	–5.86	3.85	–3.05	2.02
Year Effects	–1.54	3.92	–0.81	–2.01	3.41
Finland (1985–94)					
Actual Change in GDP Share	–2.59	–0.67	–2.79	–0.72	4.45
Predicted Change in GDP Share	–1.37	–6.93	–0.82	4.0	2.16
Education	0.51	–0.81	–3.47	5.79	–1.61
Capital	0.15	–3.66	2.22	–0.09	0
Arable Land	0.01	0.01	0.03	–0.07	0.06
TFP	–0.57	–2.11	–1.17	5.94	–5.9

TABLE 4 *Continued*

	Agriculture	*Manufacture*	*Other Production*	*Other Services*	*Business Services*
Prices	–0.07	–5.09	2.55	–3.01	3.38
Year Effects	–1.4	4.71	–0.98	–4.56	6.23
Norway (1976–91)					
Actual Change in GDP Share	–1.97	–8.14	7.32	–2.01	3.78
Predicted Change in GDP Share	–1.99	–7.03	3.23	0.95	3.19
Education	0.33	–4.76	0.74	2.43	–1.36
Capital	0.36	–8.99	5.45	–0.22	–0.01
Arable Land	–0.19	–0.39	–0.94	2.13	–1.8
TFP	–0.64	1.41	–0.42	6.92	–5.26
Prices	0.25	–8.21	3.61	–5.49	4.63
Year Effects	–2.11	13.91	–5.21	–4.82	6.98
Belgium (1987–94)					
Actual Change in GDP Share	–0.48	–1.9	0.36	3.46	–0.87
Predicted Change in GDP Share	–1.17	1.67	–1.55	2.64	–0.99
Education	0.42	–1.12	–2.35	3.55	–0.72
Capital	0.13	–3.29	1.99	–0.08	0
Arable Land	–0.25	–0.52	–1.23	2.8	–2.36
TFP	0.55	–0.1	0.37	–1.08	1.47
Prices	–1.23	2.5	0.45	1.61	–4.52
Year Effects	–0.79	4.2	–0.79	–4.15	5.13
Netherlands (1976–94)					
Actual Change in GDP Share	–1.26	–3.77	–4.09	2.75	9.77
Predicted Change in GDP Share	–0.76	–4.86	0.04	–1.76	11.48
Education	0.86	–0.16	–8.96	11.67	–2.01
Capital	0.26	–6.36	3.85	–0.16	–0.01
Arable Land	–0.23	–0.48	–1.14	2.6	–2.19
TFP	1.85	0.07	–2.16	–3.79	5.04
Prices	–1.23	–13.63	13.77	–3.87	–0.26
Year Effects	–2.27	15.7	–5.33	–8.21	10.91

Notes:
The table decomposes the change in the predicted share of a sector in GDP into the contributions of changes in the explanatory variables using the 3SLS estimates from Table 2.

As our regression specification is log linear in the explanatory variables, we can decompose the change in the predicted share of a sector in GDP between the beginning and end of the sample period into the contributions of changes in prices, TFP, factor endowments and the industry–year fixed effects. Note that the country–industry fixed effect is time-invariant and is therefore differenced out. Additionally, we break out the contribution of the change in factor endowments into the contributions of changes in education endowments, physical capital and arable land. The education contribution reflects the impact of changes in low, medium and high education endowments times the estimated coefficients on these endowments for each industry. Similarly, the contribution of prices for a particular industry reflects the impact of changes in each of the industries' prices times the coefficients on those prices. The contribution of the industry–year effects is common to all OECD countries, but as a result of the unbalanced nature of our sample, the beginning and end years are different for different countries, and therefore the contribution of the industry–year effects varies with the beginning and end years. While the industry–year effects capture the common component of deindustrialisation, the contributions of prices, TFP and factor endowments vary across countries, and account for the uneven pace of deindustrialisation.

Across countries and industries, the predicted change in GDP shares in Table 4 lies close to the actual change, providing evidence that the model is relatively successful in explaining the uneven pace of deindustrialisation. We are particularly interested in the relative contributions of prices, technology and factor endowments in Table 4 towards changes in the shares of sectors in GDP. In manufacturing, differences in TFP growth and the evolution of the relative price of manufacturing and non-manufacturing goods account for much of the variation in the growth of GDP shares. In the United Kingdom, which experienced a large decline in the share of manufacturing in GDP, there is a negative contribution of over 2 percentage points from TFP growth and a negative contribution from relative price changes. In Germany and Japan, which saw much smaller declines in manufacturing's share of GDP, there are positive contributions from TFP growth and smaller negative contributions from relative price changes. In agriculture, the two countries with the largest declines in this industry's share of GDP are Italy and Japan. In both countries, the decline in agriculture's share of GDP is largely accounted for by TFP growth and changes in relative prices.

Countries with large increases in the share of business services in GDP, such as Australia, Sweden, the United Kingdom and the United States, typically experience substantial positive contributions from changes in relative prices. In contrast, in other services differential changes in education endowments across OECD countries explain much of the variation in the evolution of this sector's share of GDP. In Australia, Canada, France, Italy, Japan, Netherlands, Sweden, West Germany, the United Kingdom and the United States, there are large positive contributions from increases in education endowments.

6. SPEED OF ADJUSTMENT TO STRUCTURAL CHANGE

Our regression specification in equation (4) corresponds to a long-run equilibrium relationship between the share of a sector in GDP and relative prices, technology and factor endowments. As we are able to reject the null hypothesis that the residuals from this relationship are non-stationary, it has an interpretation as a cointegrating relationship. Therefore equation (4) can be used to consistently estimate the long-run equilibrium coefficients on relative prices, technology and factor endowments. Nevertheless, in the short run, there may be costs of adjustment in reallocating resources in response to changes in long-run equilibrium patterns of specialisation, particularly in countries with labour market regulations that impede the hiring and firing of workers. Hence in this section we examine the short-run dynamics around the long-run equilibrium relationship.

Theoretical progress on modelling adjustment costs within the general equilibrium theoretical structure of the neoclassical model with many goods and factors of production has remained limited.[16] Hence we focus on the narrower task of testing the validity of the null hypothesis of instantaneous adjustment and examining whether there are any systematic patterns in the departures from instantaneous adjustment that we find. We augment the regression specification in equation (4) with the lagged value of the dependent variable. Under the null hypothesis of instantaneous adjustment, the coefficient on the lagged dependent variable should be equal to zero and statistically insignificant. Under the alternative hypothesis of partial adjustment, the coefficient on the lagged dependent variable is inversely related to the speed of adjustment towards long-run equilibrium.[17]

When the 3SLS regression specification in Table 2 is augmented with the lagged dependent variable, its coefficient is positive, substantially different from zero, and highly statistically significant. The regression results are summarised in the first row of Table 5, which reports the estimated coefficient and standard error for the lagged dependent variable for each industry.[18] These results confirm that the null hypothesis of instantaneous adjustment is strongly rejected by the

[16] While some progress has been made in this area, such as in the pioneering work of Neary (1978) and Davidson et al. (1988), we are still some way short of a full general equilibrium model of trade and labour market institutions with general functional forms and arbitrary numbers of goods and factors.

[17] The specification with the lagged dependent variable has an error correction model (ECM) representation. From Nickell (1981), the inclusion of the lagged dependent variable introduces a bias into the fixed effects estimator. As the coefficient on the lagged dependent variable has a negative bias, and we expect a positive coefficient on the lagged dependent variable under the alternative hypothesis of partial adjustment, this negative Nickell bias works against rejecting the null hypothesis of instantaneous adjustment. The size of the bias is asymptotically decreasing in the number of time-series observations, which in our case (around 20 years of data) is relatively large for a panel data application.

[18] In the interests of brevity, we do not report the full estimation results, which are available on request.

TABLE 5
Partial Adjustment

	(1) Agriculture	*(2) Manufacturing*	*(3) Other Production*	*(4) Other Services*	*(5) Business Services*
Panel A: 3SLS with lagged dependent variable					
Lagged dependent variable	0.376***	0.702***	0.620***	0.658***	0.720***
	(0.079)	(0.070)	(0.071)	(0.051)	(0.072)
Panel B: 3SLS with lagged dependent variable interacted with country dummies					
Chi-squared statistic for significance of country dummies interacted with lagged dependent variable (*p*-value)	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Chi-squared statistic for equality of coefficients on country dummies interacted with lagged dependent variable (*p*-value)	(0.000)***	(0.000)***	(0.000)***	(0.011)**	(0.000)***
Panel C: 3SLS with lagged dependent variable interacted with employment protection					
Lagged dependent variable	0.432***	0.632***	0.572***	0.653***	0.598***
	(0.060)	(0.066)	(0.057)	(0.058)	(0.061)
Lagged dependent variable × employment protection	0.013	0.015**	0.019*	0.007	0.014**
	(0.010)	(0.007)	(0.011)	(0.010)	(0.006)

Notes:
In panel A, the 3SLS specification in Table 2 is augmented with the lagged dependent variable. The first and second rows of panel A report the coefficient and standard error for the lagged dependent variable respectively. In panel B, the 3SLS specification in Table 2 is augmented with a full set of interactions between country dummies and the lagged dependent variable. The first row of panel B reports the Chi-squared statistic for a test that the coefficients on the interactions between the country dummies and the lagged dependent variable are jointly equal to zero. The second row of panel B reports the Chi-squared statistic for a test that the coefficients on the interactions between the country dummies and the lagged dependent variable are equal across countries. In panel C, the 3SLS specification in Table 2 is augmented with the lagged dependent variable and the lagged dependent variable interacted with employment protection. The first and second rows of panel C report the coefficient and standard error for the lagged dependent variable, respectively. The third and fourth rows of panel C report the coefficient and standard error for the interaction between the lagged dependent variable and employment protection, respectively.
*** Denotes statistical significance at the 1% level; ** denotes statistical significance at the 5% level.

data. We next explore how the estimated coefficient on the lagged dependent variable varies across OECD countries by including a full set of interactions between country dummies and the lagged dependent variable in each industry regression.[19] We allow the estimated coefficients on the country dummy interactions to vary across industries, although imposing a common coefficient for each country yields a similar pattern of results. The estimated coefficients on the country dummy interactions are highly statistically significant, as shown in the second row of Table 5. The null hypothesis that the coefficient on the lagged dependent variable is the same across countries is also rejected at conventional levels of statistical significance, as shown in the third row of the table.

Although the specification with interactions between country dummies and the lagged dependent variable imposes no prior structure on how the speed of adjustment varies across countries, we find a close relationship with an OECD measure of the strength of employment protection policies (see Nickell, 1997, and Nickell and Layard, 1999, for further discussion of the employment protection measure). Countries with stronger employment protection policies have higher estimated coefficients on the lagged dependent variable, implying slower adjustment towards long-run equilibrium production structure. Although there are only 14 observations, the correlation between the average estimated coefficient on the lagged dependent variable coefficient and the strength of employment protection is statistically significant at the 1 per cent level.

To explore further the relationship between departures from the null hypothesis of instantaneous adjustment and employment protection policies, we augment the 3SLS regression specification in Table 2 with the lagged dependent variable and the lagged dependent variable interacted with the employment protection ranking. Since the employment protection ranking is time-invariant, and each industry regression includes country fixed effects, the interaction term is identified from the variation in the speed of adjustment towards long-run equilibrium across countries depending on their strength of employment protection.[20] The regression results are summarised in Table 5, which reports the estimated coefficient and standard error for the lagged dependent variable and the lagged dependent variable interacted with employment protection for each industry.[21] Consistent with

[19] Each industry regression already includes country fixed effects, which control for direct effects of country heterogeneity that are independent of the interaction with the lagged dependent variable.

[20] The country fixed effects in each industry regression control for any direct effect of the time-invariant employment protection ranking on the shares of sectors in GDP. The use of a time-invariant ranking of countries in terms of their strength of employment protection helps to alleviate concerns about a feedback from shocks to the shares of sectors in GDP to employment protection. Since the origins of employment protection policies in many OECD countries pre-date the onset of deindustrialisation in the 1970s, it is unlikely that employment protection policies are simply a response to deindustrialisation.

[21] In the interests of brevity, the full estimation results are again not reported, but are available on request.

the above non-parametric results, we find evidence that the size of the departure from the null hypothesis of instantaneous adjustment varies across OECD countries with their strength of employment protection. The coefficient on the employment protection interaction is positive in all five industries and statistically significant in manufacturing, other production and other services.

7. CONCLUSIONS

A central feature of economic growth in industrialised countries since the early 1970s has been the secular decline in manufacturing's share of GDP and the secular rise in the share of service sectors. Though this phenomenon is itself well known, the economic forces behind deindustrialisation and the reasons why its pace varied so markedly across OECD countries are not well understood. This paper uses the neoclassical model of trade and production to derive an econometric specification consistent with producer optimisation that can be used to decompose the decline in manufacturing and the rise in service sectors into the contributions of prices, technology and factor endowments.

We find that the regression specification implied by the neoclassical model explains a substantial proportion of the uneven pace of deindustrialisation across OECD countries and find support for a number of testable parameter restrictions. The more rapid decline in manufacturing's share of GDP in countries such as the United Kingdom and the United States than in Germany and Japan is largely explained by patterns of productivity growth and differential changes in the relative price of manufacturing and non-manufacturing goods. The above-average decline in agriculture's share of GDP in countries such as Italy and Japan is also largely accounted for by productivity growth and relative price movements. Differential increases in education endowments are important in explaining why the share of other services in GDP rose by more in some OECD countries than in others.

We find evidence of partial adjustment towards a change in long-run patterns of specialisation, consistent with the idea that it takes time for resources to be reallocated from declining to expanding sectors. The size of the departures from the null hypothesis of instantaneous adjustment is correlated with variation across OECD countries in the strength of employment protection policies that impede the hiring and firing of workers. Additionally, we find evidence consistent with the idea that women and men with the same observed levels of educational attainment differ in terms of unobserved dimensions of skills. Taken together, these empirical results suggest that further theoretical modelling of the labour market in general equilibrium models of trade has the potential to enhance our understanding of the evolution of production structure over time.

APPENDIX: DATA SOURCES

a. Educational Attainment Data

The educational attainment data are from individual countries' labour force surveys and are collected separately for women and men. The education endowments are the share of men [women] with a particular level of educational attainment times male [female] population. Three levels of educational attainment are considered: (*low*) no education or primary education; (*medium*) secondary or vocational education; (*high*) college degree or equivalent. The use of detailed information from country labour force surveys enables definitions to be constructed in as consistent a way possible across countries. The appendix of the working paper version of this paper (Nickell et al., 2004) contains further information on the educational attainment measures for individual countries.

b. Production Data and Other Independent Variables

OECD International Sectoral Database (ISDB): data on current price value-added, real value-added (1990 US$), real physical capital stock (1990 US$), employment, and hours worked for the one-digit industries listed in Table 1B for the years 1976–94. Data on current price GDP and aggregate real physical stock (1990 US$) for 1976–94. Real physical capital stock is constructed using the perpetual inventory method from real investment data that has been deflated using an investment price deflator.

United Nations FAO: data on arable land area (thousands of hectares) for 1970−94.

OECD Structural Analysis Industrial Database (STAN): data on nominal exchange rates.

OECD Input–Output Tables: data by industry on government consumption expenditure, the share of imported intermediate inputs in gross output and the share of domestic intermediate inputs from R&D-intensive industries. The data are available approximately every five years for Australia, Canada, Denmark, France, West Germany, Italy, Japan, Netherlands, the United Kingdom and the United States. Linear interpolation used in between the five-year intervals. The values for the other countries are set equal to the mean of those countries for which data are available in each industry and year. R&D-intensive industries are high-R&D and medium-R&D industries as defined by the OECD.

OECD Main Science and Technology Indicators (MSTI): data on nominal government expenditure on R&D which are deflated using a GDP deflator.

IMF International Financial Statistics, IMF Government Finance Statistics, and Annual Reports of the European Commission: data on the ratio of tariff revenues to the value of imports. See Djankov et al. (1999) for further information concerning these data.

OECD Jobs Study: Evidence and Explanations: ranking of countries in terms of their strength of employment protection, 1989–94. The complete OECD ranking, including countries not in our sample, is: USA 1; New Zealand 2; Canada 3; Australia 4; Denmark 5; Switzerland 6; United Kingdom 7; Japan 8; The Netherlands 9; Finland 10; Norway 11; Ireland 12; Sweden 13; France 14; Germany 15; Austria 16; Belgium 17; Portugal 18; Spain 19; Italy 20.

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