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Skill Classification and the Effects of Trade on Wage Inequality*

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Abstract

The extent to which rising wage inequality in developed nations can be attributed to increased North-South trade has been a contentious issue over the last 20 years or so. We contribute to the debate by outlining a new skill classification method and evaluating the link between trade and wages using an economy-wide model. Our skill classification considers both academic and vocational qualifications and uses cluster methods to group together occupations with similar skill characteristics.

JEL classification: F16, J24, J31

Keywords: Skill classification; human capital; trade and wages

I. Introduction

The coincidence of rising wage inequality in the North and increased North-South trade over the final quarter of last century generated renewed interest in the Stolper-Samuelson (S-S) theorem. As noted by Wood (1994), Krugman (1995) and others, if the global economy can be thought of as Heckscher-Ohlin (H-O), with skilled and unskilled labour as the factors of production, the North can be expected to export the skilled-labour-intensive (SLI) good and the South the unskilled-labour-intensive (ULI) good.[1] When trade barriers or frictions are reduced, trade increases and the relative price of the SLI good rises in the North. Following S-S, this results in the relative return to skilled labour increasing. This posited link between trade and relative wages has motivated a large empirical literature targeted at evaluating the role of trade, generally relative to technology shocks.[2]

Although a small number of studies find that trade has had a significant effect on wages (Wood, 1994, 1998, and Leamer, 1998), the consensus from the literature investigating the drives of increased wage inequality is that trade has played a modest role. In fact, one study (Francois and Nelson 2003) suggests trade may be associated with *falling* wage inequality. We contribute to this literature by constructing a new method for identifying groups of workers with similar skill characteristics. Our skill classification draws on occupational data and considers academic and vocational qualifications as well as the acquisition of skills via informal channels. We then use cluster analysis to group together occupations with similar skill characteristics and provide an indication of the appropriate number of labour groups when weighing up

[1] Most of the literature linking trade to increased wage inequality starts from this point, which is a quite natural thing to do. However, as demonstrated by Francois and Nelson (2000), declining relative wages of the unskilled can be an outcome of models of trade between industrialised economies.

[2] See, for example, Slaughter (1999).

the loss of information associated with combining two or more occupations against the appeal of working with a small number of labour groups.

We also assess the impact of trade on inequality in the context of our new skill classification using an economy-wide analysis. Our labour data facilitates a richer analysis of the link between trade and wages than provided by other analyses which only identify two broad labour types.[3] Our simulations focus on the UK, which is an interesting case to investigate since, as well as being a relatively open economy, outside of the US it is the OECD country that has recorded the largest increase in wage inequality over the latter part of the twentieth century.

This paper has four further sections. Section II describes and applies our skill-classification method, and analyses UK wage inequality in the context of our new labour classification. Section III describes our economy-wide model. The form and outcomes of a number of simulations are detailed in Section IV together with results from a number of sensitivity analyses. Section V concludes.

II. A New Method for Determining Labour Types

Two methods are commonly used to divide aggregate labour into different components: one uses job classifications to create proxies for skilled and unskilled labour, and the other employs educational characteristics to measure skills. Job classification approaches rely on the *International Standard Classification of Occupations*. Most frequently, occupations are divided into non-production and production groups to approximate skilled and unskilled labour respectively,[4] although

[3] See, for example, Abrego and Whalley (2000), Cortes and Jean (1999), De Santis (2002, 2003), and Tyers and Yang (1997, 2000).

[4] Lawrence and Slaughter (1993), Berman, Bound, and Griliches (1994), Sachs and Shatz (1994), Feenstra and Hanson (1996), Leamer (1998), Tyers and Yang (1997, 2000), Francois and Nelson (1998) use a production/non-production classification.

white collar/blue-collar and non-manual/manual classifications are occasionally adopted as in, for example, Haskel and Slaughter (2001). Methods using educational characteristics are generally based on academic qualifications. Bound and Johnson (1992) identify four groups based on educational attainment (high school dropouts, high school graduates, some college, and college graduates). Baldwin and Cain (2000), by contrast classify employees with 1-12 years of education as unskilled labour and workers with 13 or more years of education as skilled.[5]

While Berman, Bound, and Griliches (1994) show that identifying skilled and unskilled labour on the basis of job classifications and educational attainment are quite similar, it is generally acknowledged that the latter is superior. First, classifications based on educational data can easily be extended to incorporate several types of labour. Second, as Hall (1993, p.213) observes, job classification procedures misclassify too many workers: *"many non-production workers are clerical workers, janitors, security guards, and the like, not the elite of the labour force. Many production workers have significant problem-solving role*s…". Additionally, Leamer (1998, p. 185) notes that *"there is a very substantial amount of wage inequality across sectors within the production and non-production categorie*s". Methods that draw on educational characteristics also have their limitations. Specifically, such methods only consider academic qualifications and boundaries defining different skill levels are determined exogenously.

Leamer (1998, p. 183) argues that a proficient method for determining different types of labour should identify "*subcategories of workers with skill levels that are fairly uniform within groups and substantially different across groups*". In order to do just

[5] Mincer (1993), Krueger (1994), and Cline (1997) are other authors who establish skill classifications based on educational characteristics.

this, we employ cluster analysis. Our strategy starts from a situation where, given a set of n objects, each of which is described by a set of p characteristics, we separate the objects into consistent groups or clusters.

We start with seventy-seven minor-group occupations identified by the *Standard Occupational Classification* (SOC) 1990. This is produced by the UK's Office for National Statistics and draws on the International Labour Organization's *International Standard Classification of Occupations*. Occupations are described by two characteristics: each occupation's average educational attainment, and each occupation's average wage. We use *National Vocational Qualification* (NVQ) scores to characterise attainment, which allows us to include both academic and non-academic qualifications. It is interesting to note that the education measure in the US *Current Population Survey* primarily focuses on academic qualifications. As such, our study of the link between trade and wage inequality may be more revealing than US-focused studies. NVQs are administered by the UK Department for Education and Skills and are based on an individual's competence at a particular task. The governing body also lists NVQ equivalents. The six possible NVQ scores, with summaries of qualifications in parenthesis, are: Level 5 (higher degree), Level 4 (undergraduate degree or other post-high-school qualification), Level 3 (high school graduate or trade apprenticeship), Level 2 (GCSE or equivalent vocational training), Level 1 (high school qualifications below GCSE or equivalent vocational training), and Level 0 (no qualification).[6] In cases where employees hold more than one qualification, individuals are classified by their highest NVQ score.[7] The sample size is restricted to

[6] See the 1995 Labour Force Survey Users' Guide (Organisation for national Statistics 1995) for a complete breakdown of educational qualifications and their NVQ equivalents.

[7] We source data on NVQ scores from the Labour Force Survey (Office for National Statistics, 1997a) and collect data on hourly wages from the New Earnings Survey (Office for National Statistics, 1997b).

full-time employees on adult rates whose pay was not affected by absence, and wage calculations include overtime pay. Finally, as units of measurement differ across characteristics, the data are standardised in the interval zero to one.

We apply a range of agglomerative hierarchical clustering techniques to the data. Our preferred set of results are obtained using Ward's method[8] and the optimal number of labour groups is determined by examining the loss of information resulting from different amounts of groupings in a dendrogram.[9] The results are presented in Table A1, which lists occupational groups, hourly wages and NVQ scores by occupation, and flags whether each is manual or non-manual. Four distinct types of labour are identifiable: highly-skilled, skilled, semi-skilled, and unskilled.

Examining the manual/non-manual classification of each occupation across labour types highlights the potential shortcomings of using job classification methods. The two more-skilled groups consist almost exclusively of non-manual occupations. Mixtures of manual and non-manual occupations, however, are present in the two less skilled labour categories. This indicates that occupations such as sales assistants and checkout operators are misclassified when manual and non-manual groups are identified.

What do changes in relative wages look when we use this finer classification? Table 1 reports proportional changes between 1990 and 2001.[10] Column titles are numerators and row titles denominators. Thus, for example, the ratio of highly-skilled

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[8] Ward's method is a technique that creates clusters in a manner that minimises the loss of information created by each grouping of observations. Information loss is measured using an error sum of squares (ESS) criterion. At each step, Ward's method considers all possible pairs of clusters and combines the two clusters that generate the lowest ESS.

[9] We prefer results generated using Ward's method because this method performs relatively well in a wide range of circumstances (Everitt, 1993) and dendrograms for other methods do not identify a particular number of groupings as being optimal in our analysis.

to skilled wages increased by 10.4% over the sample period. The data reveal that inequality between any pair of labour types increased during the 11 year period. The most extreme measure of wage inequality, the ratio of highly-skilled to unskilled,increased by more than 27%. Conversely, the skilled wage rose by just under 4% relative to the wages of semi-skilled. Both semi-skilled and unskilled labour, however, experienced non-negligible growth in unit returns relative to that of unskilled labour.

It is interesting to compare changes in wage inequality as measured using our classification with those under a manual-non-manual taxonomy. The increase in the non-manual to manual wage ratio was 24% between 1980 and 2001 and 6% over 1990-2001. These figures indicate that, in recent years at least, a manual-non-manual split masks the severity of the increase in wage inequality. We also find a high degree of correlation between the non-manual-manual relative wage and indicators of wage in our classification. This indicates that increases in relative wages under our classification system between 1980 and 2001 are more acute than those presented in Table 1.

Changes in employment shares by labour type are reported in Table 2.[11] The data reveal that employment shares for the two more-skilled labour types increased while those for the two less-skilled groups have fallen. This observation is consistent with the stylized fact that supply of skilled labour has risen relative to unskilled labour in recent decades. A noteworthy feature is the large decrease in the employment share of

[10] Due to changes in the SOC system, we are unable to track wages for our four labour types prior to 1990.

[11] As for our calculations concerning changes in relative wages, the earliest date for which we can calculates changes in employment shares is constrained by changes in the SOC system, and changes in employment shares under a non-manual-manual categorisation of labour are highly correlated with changes in employment shares in our analysis. In this connection, increases in non-manual employment shares between 1990 and 2001 and 1980 and 2001 were 3% and 19% respectively.

semi-skilled labour, which indicates that employment share changes are in the right direction to increase wage inequality between semi-skilled and unskilled labour. This is not the case for other measures of wage inequality. Combined with observations on movements in relative wages, employment share changes have profound implications for demand side influences. Specifically, in the presence of relative supply shocks which would, *ceteris paribus*, decrease the relative return to more-skilled labour, demand side shocks are likely to have favoured such workers and have been large, particularly for highly-skilled labour.

III. Labour Demand in an Economy-Wide Context

To assess the impact of trade on wages we use a model that captures both bilateral trade flows amongst regions and inter-sectoral linkages within regions; that is, we use a global computable general equilibrium model. An overview of the model, which is set out in detail by Rutherford and Paltsev (2000), is provided below.

Expenditure on final goods and services in each region is controlled by a representative consumer who allocates expenditure in a utility-maximising fashion across investment, government consumption, and private consumption. Total investment and government expenditure are fixed in each region. Private consumption is governed by a Cobb-Douglas utility function, where each commodity is represented by a composite of domestically produced and imported varieties. Government expenditure is modelled in an identical fashion, which allows the composition of public expenditure to respond to changes in relative prices even though the aggregate level of public expenditure is exogenous.

Turning to production, composites of intermediate inputs and primary factors are combined in a Leontief nest in the top level of the production specification for each sector. The intermediate input composite is derived from a further Leontief aggregation of intermediate inputs by product type. Instead of using a Cobb-Douglas primary factors aggregator as stipulated in our base model, we allow substitution possibilities between different labour groups to differ from those between labour and other factors to better suit our needs. Specifically, we specify a two-level nest of primary factors. Substitution possibilities between different types of labour, which enter in the bottom level of the value added nest, are governed by a constant elasticity of substation function. The labour composite and other primary factors are combined using a further constant elasticity of substitution aggregator in the upper level of this nest. This specification is outlined in Figure 1. We denote substitution possibilities in the upper and lower levels of the value added nest σ_{VA} and σ_{VL} respectively. [12] Guided by Johnson (1997), we chose a value of 1.5 for σ_{VL} and, to maintain consistency with out base model we set σ_{VA} equal to one.

With regard to trade, imports are differentiated from domestic commodities and by region of origin according to the Armington assumption (Armington, 1969). That is, for each good, imports from different regions are gathered in a constant elasticity of substitution (CES) nest to create an import composite.[13] The import composite is combined in a further CES nest with the domestically produced variety to generate a composite that is purchased by firms, the government, or the private household. Transport costs are also included in the import specification. Transport services from

[12] Krusell *et al.* (2000) and Tyers and Yang (2000) examine the causes of increased wage inequality using production structures that exhibit capital-skill complementarity. However, as two or more capital assets are required to accurately model such a production specification and our database only identifies one, we do not include such a requirement in our model. Also, since our focus is the impact of increased trade on wage inequality, and not skilled-biased technical change, modelling complementarities between more skilled labour and the equipment component of the capital stock is not crucial to our analysis. We do, however, consider the roll of capital-skill complementarity in a related paper (Winchester and Greenaway, 2004).

[13] Our elasticity parameters in the import specification are sourced form the GTAP database.

different regions are brought together by a Cobb-Douglas aggregator to produce a transport composite. This and exports are used in fixed proportions.

We conduct simulations using several different aggregations, outlined in Table A2. Aggregations differ with respect to the identification of sectors and UK labour types. To provide a benchmark for simulations that involve our new labour data, factor aggregation (1) distinguishes groups of differently skilled labour using GTAP's labour classifications. Our labelling of GTAP labour types, professional and production workers, reflects the use of occupational classifications to set apart different types of labour.[14] Factor aggregations (2) and (3) employ our new labour data. Aggregation (2) combines highly-skilled with skilled labour and semi-skilled with unskilled labour. These composite factors are labelled more-skilled and less-skilled respectively.[15] Our remaining factor aggregation maintains four separate labour types. Professional and production labour are identified in all regions outside the UK in all aggregations.

There are two different sectoral aggregations. The small number of sectors in aggregation (A), five, aids the identification of H-O production and trade patterns. There is also a finer aggregation (B), which identifies 19 sectors. This is important as Falvey, Tyers and McDougall (1997) show that simulated changes in factor returns can be sensitive to differences in factor cost shares across industries. Five regions are identified in all six possible aggregations (A1, A.2, A.3, B.1, B.2, and B.3).

[14] Liu *et al.* (1998) describe the method employed to disaggregate labour types in the GTAP Database in greater detail.

[15] The increase in the more-skilled to less-skilled relative wage, calculated as an employment weighted average, is 16.0% during the period 1990-2001.

Turning to implied labour demand elasticities, following Keller (1980, Ch. 5, Appendix), the own-price elasticity of demand for labour type L, η_L, takes the following form:

$$\eta_L = -\theta_L [\sigma_{VL}(\theta_L^{-1} - \theta_{LAB}^{-1}) + \sigma_{VA}(\theta_{LAB}^{-1} - \theta_{VA}^{-1})] \tag{1}$$

where θ_L is the share of labour type L, θ_{LAB} the combined share of all labour types, and θ_{VA} the share of value added in total cost.

When there are only two labour types, most elasticity parameters are between -0.7 and -1.2. The majority of own-price elasticities are flanked by -1.0 and -1.5 when four labour types are identified. Therefore, as expected, the responsiveness of labour demand to wage changes is greater when four labour types are present.

As noted earlier, sectoral aggregation (A) allows us to identify H-O patterns in the database. Labour cost shares, which we use to characterise relative factor intensity, for aggregation (A.3) including and excluding the factor content of intermediate inputs are displayed in Table 3. The data indicate that, with the exception of the cost share of highly skilled labour in unskilled manufacturing, labour cost shares including intermediates are not significantly different from the corresponding shares in value added. The table also reveals that skilled services is the most skill-intensive sector and unskilled manufacturing the least, services as a group use more-skilled labour more intensively than aggregate manufacturing, and, with the exception of skilled services, labour cost shares are not starkly different across sectors – for example, the two manufacturing sectors and unskilled services have similar highly-skilled labour shares.

Turning to relative factor abundance, the ratio of professional to production labour payments in the North (United Kingdom, Western Europe, Other Developed) is about 0.7, whereas the corresponding ratio in the South (Rapidly Developing and Rest of World) is less than 0.4.[16] In line with H-O predictions, production in the North is concentrated in skilled services, and that in the South is skewed towards agriculture and unskilled manufacturing. There is also other evidence that trade is (partially) driven by factor endowments: 32.2% of UK trade with the South is in the form of inter-industry trade compared to 10.7% of trade with the North.

IV. Decomposition of Changes in Relative Wages

To simulate the impact of trade on relative wages since the time when the UK skill premium started to rise, we apply a globalisation shock that removes changes in UK sectoral imports relative to GDP between 1980 and 2001. We do this by specifying a set of endogenous export taxes in regions other than the UK so as to fix UK imports (by source and in total) at values observed in 1980. This is an indirect approach to modelling the effect of reduced trade distortions. However, data on trade taxes and transport costs are scarce, whereas trade volumes are more readily accessible. Disaggregated data on trade in services are also rare. In response to this constraint, and the small proportion of services trade in total UK trade, only trade in manufactured commodities is controlled in the simulation.[17] Backcast shocks to import volumes for sectoral aggregation (A) are reported in Table A3.

Table 4 reports results for changes in UK relative wages for all six aggregations. As can be seen, the largest movement in relative wages occurs in aggregations A.3 and

[16] We use a professional/production worker classification to determine factor abundance as our new labour data are only available for the UK.

[17] An alternative approach is to set UK import tariffs so as to achieve the desired amount of imports. We do not follow this approach as doing so would have an undesirable effect on UK tax

B.3, where the ratio of highly-skilled to unskilled wages increases by 1.3% and 1.5% respectively. All other simulated changes in relative wages are less than one percent. These changes are only a small fraction of actual changes occurring between 1990 and 2001 (see Table 1), which are almost certainly smaller than movements in relative wages between 1980 and 2001. The results, therefore, are clearly consistent with the view that trade has not been the main driver of increased wage inequality in the UK. Comparing results for factor aggregations (1) and (2) illustrates that the simulated increase in wage inequality is only marginally larger when our new labour data are employed. Simulations involving four labour types reproduce the pattern of increased wage inequality present in the data, although simulated changes are much smaller than actual movements. The results also suggest that the degree of sectoral aggregation has little impact on the results.

To reconcile movements in relative wages with Stolper-Samuelson predictions, we report computed changes in product prices for sectoral aggregation (A) in Table 5.[18] In all aggregations manufacturing prices fall relative to prices for services, which are more skill-intensive, and the largest sectoral price increase occurs in skilled services, which uses aggregate labour more intensively than all other sectors. In accordance with the S-S correlation, this results in an increase in the skill premium as measured by the ratios of professional to production and more-skilled to less-skilled wages in aggregations A.1 and A.2 respectively. Turning to changes in relative wages, in aggregation A.3 skilled services, which is the sector that experiences the largest price increase, is highly intensive in its use of highly-skilled and skilled labour relative to

revenue. In any case, whether export taxes in other nations or UK import tariffs are made endogenous does not alter our conclusions.

[18] As our model has more than two sectors and factors, we connect changes in product and factor prices using the S-S correlation: "*there is a tendency for changes in relative commodity prices to be accompanied by increases in the rewards of factors employed most intensively by those goods whose*

all other sectors, including skilled manufacturing. By contrast, sectors which make relatively intensive use of semi-skilled and unskilled labour experience falling prices relative to the price of skilled services. Movements in relative wages and product prices therefore also follow Stolper-Samuelson correlations in this aggregation.

Sensitivity Analysis

How sensitive are these results to changes in the values of assigned parameters? Key parameters in our analysis include elasticity parameters in the Armington nest of imports and domestic products, and the elasticity of substitution between labour types in the value added nest. To investigate sensitivity, we multiply all Armington elasticities by a common proportion. Results from this experiment under aggregations B.1 and B.2 are illustrated in Figure 2.[19] Changes in domestic product prices more closely follow changes in import prices when substitution possibilities are greater, so a positive relationship between changes in relative wages and elasticity parameters in the Armington nest is present.

Simulated changes in relative wages in aggregations B.1 and B.2 for different values of the elasticity governing substitution possibilities between labour types are presented in Figure 3.[20] Like our other sensitivity analysis, the expected pattern is observed. Specifically, when factors are less substitutable, the decrease in the price of less-skilled labour produces a smaller shift in relative labour demand favouring this factor, which results in a larger decrease in the relative price of unskilled labour.

Simulated changes in wage inequality range from 0.76% to 0.92% and 0.78% to 1.01% in aggregations B.1 and B.2 respectively when Armington elasticities are

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prices have relatively risen the most and employed least intensively by those goods whose prices have fallen the most."(Ethier, 1984, p.164)

[19] Relative wages in other aggregations follow a similar pattern.

[20] Again, the output is representative of results from other aggregations.

changed. The corresponding figures in our second sensitivity analysis are 0.55% to 1.23% and 0.57% to 1.25%. We also conduct simulations where we quadruple all Armington elasticities and assign a value of 0.9 as the elasticity of substitution between labour types. Estimated changes in wage inequality are 1.44% and 1.55% in aggregations B.1 and B.2 respectively. Hence, our sensitivity exercises reinforce our conclusion that trade is not the main driver of increased wage inequality.[21]

V. Conclusions

This paper has outlined a new method for determining groups of differently skilled labour using cluster analysis. The link between increased trade and growing wage inequality was assessed in the context of our new labour data using an economy-wide analysis. The model was built on several different sectoral and factor aggregations. All variants of the model were subjected to a shock that backcast the model to 1980 values of regional GDPs and UK imports. The results indicate that our new labour data is better equipped than data constructed using traditional labour classification methods to capture changes in relative wages due to trade pressures. In simulations involving a small number of sectors, we were able to reconcile changes in relative wages with Stolper-Samuelson predictions. Our results do not, however, overturn the majority view in the literature that trade has had a relatively modest role to play in explaining increasing wage inequality in the UK over the last two decades of the twentieth century.

[21] We also conduct two further exercises. First, although our focus is the impact of unskilled labour-intensive imports on relative wages, we examine the impact of decreased tariffs on UK exports. Second, as our globalisation shock does not control imports of services, we conduct simulations with various restrictions on imports of services imposed. Our conclusions are unaltered in bother experiments.

References

Abrego, L., and Whalley, J. (2000). The Choice of Structural Model in Trade-Wages Decompositions. *Review of International Economics*, 8 (3): 462-77.

Armington, P.S. (1969). A Theory of Demand for Products Distinguished by Place of Production. IMF Staff Papers, 16: 159-76.

Baldwin, R.E. and Cain, G.G. (2000). Shifts in US Relative Wages: The Role of Trade, Technology and Factor Endowments. *Review of Economics and Statistics*, 82 (4): 580-95.

Berman, E., Bound, J. and Griliches, Z. (1994). Changes in Demand for Skilled Labour within US Manufacturing: Evidence from Annual Survey of Manufactures. *Quarterly Journal of Economics*, 109 (2): 367-97.

Bound, J. and Johnson, G. (1992). Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations. *American Economic Review*, 82: 371-92.

Cline, W.R. (1997). *Trade and Income Distribution*, Washington, DC, Institute for International Economics.

Cortes, O. and Jean, S. (1999). Does Competition from Emerging Countries Threaten Unskilled Labour in Europe? An Applied General Equilibrium Approach. In P. Brenton and L. Pelkmann (eds.), *Global Trade and European Workers*, London: Macmillan, 1999: 96-122.

De Santis, R.A. (2002). Wage Inequality Between and Within Broups: Trade-Induced or Skill-Bias Technical Change? Alternative AGE Models for the UK. *Economic Modelling*, 19: 725-746.

De Santis R.A. (2003). Wage Inequality in the United Kingdom: Trade or/and Technology. *The World Economy*, 26: 893-910.

Dimaranan, B.V. and McDougall, R.A. (2005). *Global Trade, Assistance, and Production: the GTAP 6 Data Base*, Centre for Global Trade Analysis, Purdue University.

Ethier, W.J. (1984). Higher Dimensional Issues in Trade Theory. In E. W. Jones and P. B. Kenen (eds.) *Handbook of international economics, Vol. I.* Amsterdam: North-Holland, 1984: 131-184.

Everitt, E.S. (1993). *Cluster Analysis*. 3rd ed. London: Edward Arnold.

Falvey, R., Tyers, R., and McDougall, R. (1997). Trade Shocks and the Magnitude of Transmitted Wage Adjustment. Working Papers in Economics and Econometrics 318, The Faculties, Australian National University.

Feenstra, R.C., and Hanson, G.H. (1996). Foreign Investment, Outsourcing and Relative Wages. In R.C Feenstra, G.M. Grossman, and D.A. Irwin (eds.) *The Political Economy of Trade Policy.* Essays in honor of Jagdish Bhagwati. Cambridge: MIT Press, 1996: 89-128.

Francois, J.F. and Nelson, D. (1998). Trade, Technology and Wages: General Equilibrium Mechanics. *Economic Journal*, 108, pp.1483-99.

Francois, J.F. and Nelson, D. (2000). Victims of Progress: Specialisation and the Wages of Unskilled Labour. CEPR Discussion Paper 2527.

Francois, J.F. and Nelson, D. (2003). Globalization and Relative Wages: Some Theory and Evidence. mimeo, Tulane University.

Hall, R.E. (1993). Comment. *Brookings Papers on Economic Activity*, 2: 211-14.

Haskel, J.E., and Slaughter, M.J. (2001). Trade, Technology and U.K. Wage Inequality. *Economic Journal*, 111 (468): 163-87.

Johnson, G.E. (1997). Changes in Earnings Inequality: The Role of Demand Shifts. *Journal of Economic Perspectives*, 11 (2): 41-54.

Keller, W.J. (1980), *Tax Incidence: A General Equilibrium Approach*. Amsterdam: North Holland.

Krueger, A.B. (1994). How Computers have Changed the Wage Structure: Evidence from Microdata, 1984-1989. *Quarterly Journal of Economics*, 108 (1): 33-60.

Krugman, P. (1995). Growing World Trade: Causes and Consequences. *Brookings Papers,* 1: 327-377.

Krusell, P., et al. (2000). Capital-Skill Complemenatrity and Inequality: A Macroeconomic Analysis. *Econometrica*, 68 (5): 1029-53.

Lawrence, R.Z. and Slaughter, M.J. (1993). International Trade and American Wages in the 1980s: Giant Sucking Sound or Small Hiccup? *Brookings Papers, Microeconomics*, 2: 163-226.

Leamer, E.E. (1998). In Search of Stolper-Samuelson Effects on US Wages. In S. Collins, ed. *Imports, Exports and the American Worker*. Washington D.C.: Brookings Institution Press, 1997: 141-214.

Liu, J. et al. (1998). Disaggregating Labour Payments by Skill Level. In R.A. McDougall, A. Elbehri, and T.P. Truong, (eds.), *Global Trade Assistance and Protection: the GTAP 4 Data Base*. Center for Global Trade Analysis: Purdue University, 1998: Chapter 18.

Office for National Statistics, (1995), *Labour Force Survey Users' Guide*. London: Stationary Office.

Office for National Statistics, (1997a), *Labour Force Survey*. London: Stationary Office.

Office for National Statistics, (1997b), *New Earnings Survey*. London: Stationary Office.

Mincer, J. (1993). Human Capital, Technology and the Wage Structure: What do Time Series Show? In J. Mincer, (ed.), *Studies in Human Capital*. Collected Essays of Jacob Mincer, Vol. I, Cambridge: Edward Elgar, 1993: 366-405.

Rutherford, T.F., and Paltsev, S.V. (2000). GTAPinGAMS and GTAP-EG: Global Datasets for Economic Research and Illustrative Models. University of Colorado.

Sachs, J.D. and Shatz, H.J. (1994). Trade and Jobs in US Manufacturing, *Brookings Papers on Economic Activity*, 1: 1-84.

Slaughter, M.J. (1998). International Trade and Labour Market Outcomes: Results, Questions and Policy Options, *Economic Journal*, Vol. 108: 1452-63.

Slaughter, M.J. (1999). Globalization and Wages: a Tale of Two Perspectives, *The World Economy*, 22 (5): 609-30.

Tyers, R. and Yang, Y. (1997). Trade with Asia and Skill Upgrading: Effects on Factor Markets in the Older Industrial Countries. *Weltwirtschaftliches Archiv*, 133: 383-418.

Tyers, R., and Yang Y. (2000). Capital-Skill Complementarity and Wage Outcomes Following Technical Change in a Global Model. *Oxford Review of Economic Policy*, 16 (3): 23-41.

Winchester, N., and Greenaway D. (2004) "Capital-Skill Complementarity and Rising Wage Inequality," Economics Discussion Paper 0402, University of Otago.

Wood, A. (1994). *North-South Trade, Employment and* I*nequality*. Oxford: Clarendon Press.

Wood, A. (1998). Globalisation and the Rise in Labour Market Inequalities. *Economic Journal*, 108: 1463-1482.

Table 1: *Changes in wage ratios (column / row), 1990-2001 (%)*

	Highly-skilled	Skilled	Semi-skilled	Unskilled
Highly-skilled	-	-9.4	-12.8	-21.4
Skilled	10.4	-	-3.7	-13.2
Semi-skilled	14.6	3.8	-	-9.9
Unskilled	27.2	15.2	11.0	-

Source: Labour types are identified using cluster analysis as described in the text, wage data are taken from the New Earnings Survey.

Table 2: *Employment shares by labour type*

	1990	2001	Change (%)
Highly-skilled	0.106	0.145	3.9
Skilled	0.201	0.218	1.7
Semi-skilled	0.367	0.331	-3.6
Unskilled	0.325	0.305	-2.0

Source: Labour types are identified using cluster analysis as described in the text, employment shares are taken from the New Earnings Survey.

Figure 1: *Value added nest*

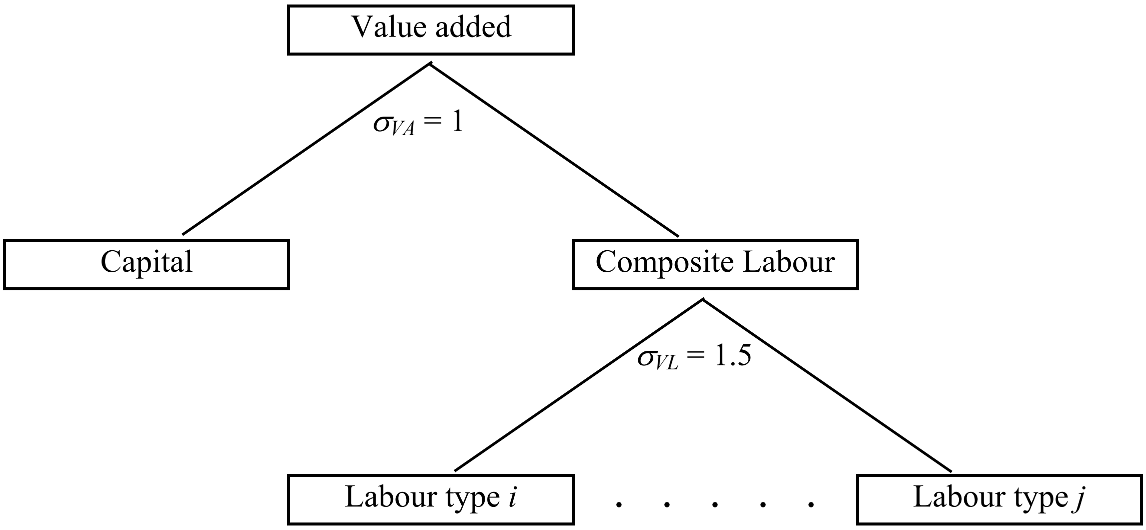


Table 3: *UK labour cost shares in aggregation A.3 (%)*

	H.-skilled	Skilled	Semi-skilled	Unskilled
	Excluding intermediate inputs			
Agriculture	0.133	0.184	0.158	0.525
Skilled manufacturing	0.205	0.283	0.237	0.275
Unskilled manufacturing	0.111	0.180	0.279	0.430
Skilled services	0.349	0.314	0.192	0.145
Unskilled services	0.155	0.161	0.354	0.330
	Including intermediate inputs			
Agriculture	0.169	0.207	0.195	0.429
Skilled manufacturing	0.219	0.265	0.240	0.276
Unskilled manufacturing	0.175	0.216	0.260	0.349
Skilled services	0.322	0.297	0.208	0.172
Unskilled services	0.191	0.197	0.311	0.301

Source: Labour types are identified using cluster analysis as described in the text, and wages shares are calculated using the New Earnings Survey.

Table 4: *Simulated changes in UK wage ratios, 1990-2001 (%)*

	(1)	(2)	(3)		
	$\frac{w_{professional}}{w_{production}}$	$\frac{w_{more\ skiled}}{w_{less\ skilled}}$	$\frac{w_{highly-skiled}}{w_{skilled}}$	$\frac{w_{highly-skilled}}{w_{semi-skilled}}$	$\frac{w_{highly-skilled}}{w_{unskilled}}$
(A)	0.707	0.747	0.534	0.776	1.270
(B)	0.762	0.787	0.455	0.595	1.454

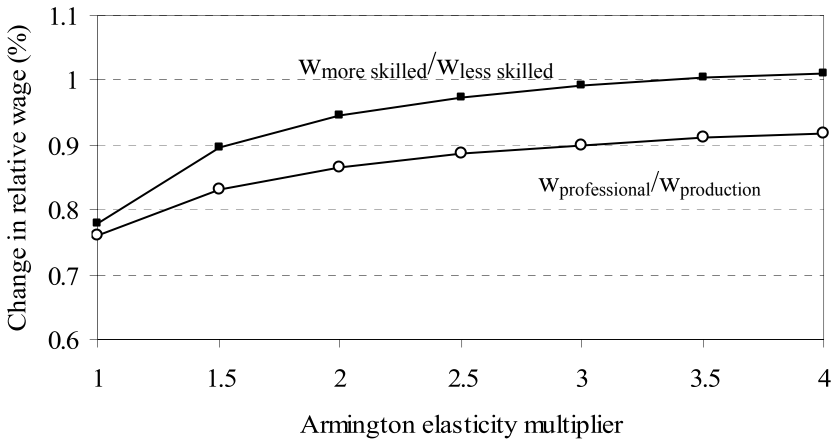
Note: (A) and (B) refer to sectoral aggregations and (1), (2) and (3) describe factor aggregations, as outlined in Box 2.
Source: Backcast simulation described in text.

Table 5: *Simulated changes in UK product prices under sectoral aggregation (A), 1980-2001 (%)*

	(1)	(2)	(3)
Skilled manufacturing	-2.085	-2.084	-2.075
Unskilled manufacturing	-1.509	-1.529	-1.527
Skilled services	0.573	0.576	0.610
Unskilled services	0.016	0.009	0.012

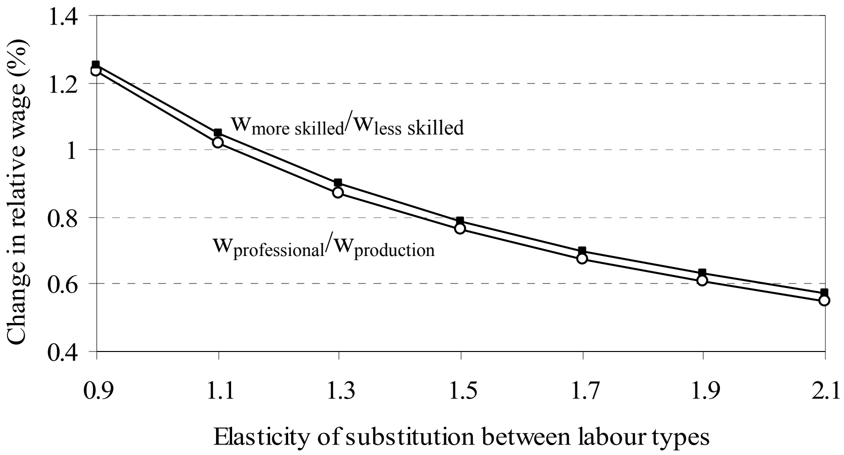
Note: The domestic price of agriculture is chose as the *numeraire*, and (1), (2) and (3) describe factor aggregations, as outlined in Box 2.
Source: Backcast simulation described in text.

Figure 2: *Changes in relative wages under alternative Armington elasticity parameters in aggregations B.1 and B.2*



Note: The Armington elasticity multiplier specifies a scalar by which all elasticities in the Armington nest are multiplied.
Source: Backcast simulation described in text.

Figure 3: *Changes in relative wages under alternative values of the elasticity of substitution between labour types in aggregations B.1 and B.2*



Source: Backcast simulation described in text.

Table A1: *A new labour classification*

SOC	Occupation	Manual/ non-manual	Wage (£ / hour)	NVQ score
	Highly-skilled		**15.07**	**3.67**
10	General managers in government & large companies	NM	16.73	3.30
12	Specialist managers	NM	19.93	3.28
15	Protective service officers	NM	14.97	3.35
20	Natural scientists	NM	12.58	4.18
22	Health professionals	NM	16.95	4.19
23	Teaching professionals	NM	14.04	4.18
24	Legal professionals	NM	15.41	4.07
25	Business & financial professionals	NM	13.76	3.61
33	Ship & aircraft officers, air traffic controllers	NM	15.08	3.08
36	Business & financial associate professionals	NM	15.70	3.15
	Skilled		**10.69**	**3.30**
11	Production managers in manufacturing etc	NM	12.67	3.15
13	Financial institution & office managers etc	NM	12.16	2.90
19	Managers & administrators nec	NM	12.74	2.99
21	Engineers & technologists	NM	12.14	3.59
26	Architects, town planners & surveyors	NM	11.86	3.85
27	Librarians & related professionals	NM	10.31	4.14
29	Professional occupations nec	NM	9.21	3.57
30	Scientific technicians	NM	8.46	3.16
31	Draughtspersons, quantity & other surveyors	NM	9.29	3.50
32	Computer analysts/programmers	NM	11.52	3.48
34	Health associate professionals	NM	8.82	3.84
35	Legal associate professionals	NM	11.64	3.26
37	Social welfare associate professionals	NM	7.81	3.26
38	Literary, artistic & sports professionals	NM	11.11	3.32
39	Associate professional & technical occupations	NM	9.30	3.13
61	Security & protective service occupations	M	8.83	3.11

Continued

Table A1: *A new labour classification*

SOC	Occupation	Manual/ non-manual	Wage (£ / hour)	NVQ score
	Semi-skilled		**7.01**	**2.67**
14	Managers in transport & storing	NM	10.12	2.59
17	Managers & proprietors in service industries	NM	8.42	2.49
40	Administrative/clerical officers & assistants	NM	6.15	2.67
41	Numerical clerks & cashiers	NM	6.87	2.64
42	Filing & records clerks	NM	6.21	2.75
43	Clerks (not otherwise specified)	NM	5.91	2.68
45	Secretaries, personal assistants etc	NM	6.88	2.85
49	Clerical & secretarial occupations nec	NM	7.12	2.73
51	Metal machining & instrument making trades	M	7.83	2.52
52	Electrical/electronic trades	M	7.93	2.76
53	Metal forming, welding & related trades	M	7.11	2.45
54	Vehicle trades	M	6.16	2.54
57	Woodworking trades	M	6.12	2.53
63	Travel attendants & related occupations	M	7.05	2.82
70	Buyers, brokers & related agents	NM	9.90	2.82
71	Sales representatives	NM	9.26	2.75
87	Road transport operatives	M	5.48	2.82
88	Other transport & machinery operatives	M	6.73	2.76
	Unskilled		**5.75**	**2.14**
16	Managers in farming, forestry & fishing	NM	7.83	1.82
44	Stores & despatch clerks, storekeepers	NM	5.75	2.36
46	Receptionists, telephonists and related occupations	NM	5.42	2.46
50	Construction trades	M	6.14	2.17
55	Textiles, garments and related trades	M	4.90	1.52
56	Printing and related trades	M	7.40	2.31
58	Food preparation trades	M	4.92	2.33
59	Other craft and related occupations	M	5.84	2.28
62	Catering occupations	M	4.48	2.41

Table A2: *Model aggregations*

Regions	**Factors**[d]
United Kingdom (UK)	
Western Europe (WE)[a]	*United Kingdom*
Other Developed (OD)[b]	(1)
Rapidly Developing (RD)[c]	Professional labour
Rest of World (RoW)	Production labour
	Capital (including land and resources)
Sectors	
(A)	(2)
Agriculture	More-skilled labour
Skilled manufacturing	Less-skilled labour
Unskilled manufacturing	Capital (including land and resources)
Skilled services	
Unskilled services	(3)
	Highly-skilled labour
(B)	Skilled labour
Agriculture	Semi-skilled labour
Food and beverages	Unskilled labour
Textiles	Capital (including land and resources)
Wearing apparel	
Leather	*Other regions*
Wood products	Professional labour
Paper products & publishing	Production labour
Petroleum and coal products	Capital (including land and resources)
Chemical, rubber & plastic products	
Mineral products nec	
Ferrous metals	
Metals nec	
Motor Vehicles	
Transport equipment nec	
Electronic equipment	
Machinery and equipment nec	
Manufactures nec	
Skilled services	
Unskilled services	

Notes: [a] The EU-15 and the European Free Trade Area. [b] Japan, United States, Canada, Australia, and New Zealand. [c] China, Hong Kong, Taiwan, Korea (Rep.), Indonesia, Malaysia, Philippines, Thailand, Vietnam. [d] Professional and production labour classifications are taken from the GTAP Database, more-skilled labour is the aggregation of highly-skilled and skilled labour, and less-skilled labour is the aggregation of semi-skilled and unskilled labour.

Table A3: *Backcast shocks to import volumes in sectoral aggregation (A) (%)*

	WER	ODV	RDA	RoW
Agriculture	12.4	149.9	107.0	170.7
Skilled manufacturing	-53.4	-37.3	-70.1	-81.2
Unskilled manufacturing	-62.2	-68.8	-92.2	-84.5

Source: GTAP version 6 Database (Dimaranan and McDougall, 2005).