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TRADE, TECHNOLOGY AND U.K. WAGE INEQUALITY

Jonathan Haskel
Matthew J. Slaughter

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ABSTRACT

The U.K. skill premium fell from the 1950s to the late 1970s and then rose very sharply. This paper examines the contributions to these relative wage movements of international trade and technical change. We first measure trade as changes in product prices and technical change as TFP growth. Then we relate price and TFP changes to a set of underlying factors. Among a number of results, we find that changes in prices, not TFP, were the major force behind the rise in inequality in the 1980s. We also find that although increased trade pressure has raised technical change, its effect on wage inequality was not quantitatively significant.

Jonathan E. Haskel
Department of Economics
Queen Mary and Westfield College
University of London
London E1 4NS ENGLAND
j.e.haskel@qmw.ac.uk

Matthew J. Slaughter
Department of Economics
Dartmouth College
309 Rockefeller Hall
Hanover, NH 03755
and NBER
slaughter@dartmouth.edu

1. Introduction

UK skilled wages relative to unskilled wages fell more or less continuously from the end of World War II to the late 1970s. Since then they have risen very sharply: the rise in the last twenty years has undone the fall over the previous thirty-five. This sharp rise has been associated with a range of issues that have risen to the top of the policy agenda: social exclusion, poverty and unemployment.

The leading demand-side causes for these trends, international trade and technical change, have been explored by a number of researchers (see Wood, 1998, for a recent summary). Most studies do not find support for the trade hypothesis. Desjonqueres, Machin, and Van Reenen (1997) and Neven and Wyplosz (1996) analyse changes in U.K. product prices across industries of different skill intensities. Contrary to the intuition of the Stolper-Samuelson theorem, these studies find no evidence that relative prices for unskilled-intensive products fell during the 1980s. As for technology, Machin (1996) and Machin and van Reenen (1998) document the widespread occurrence of skill-biased technical change (SBTC) in a number of industries or establishments over a number of countries; they also show that most economy-wide skill-upgrading has occurred due to skill-upgrading within industries. This evidence suggests that SBTC may have contributed to the rising skill premium.

These studies are suggestive, but they face at least three important limitations. First, in the technology studies, the link between SBTC and relative wages is usually based on a one-sector model, in which technical change must be factor-biased to affect relative wages. But in a multi-sector model the wage effects of technical change often depend on its sector bias, i.e., on what sectors enjoy the most technical progress, independent of any factor bias. Furthermore, in a multi-sector model all kinds of technical change, factor-biased or factor-neutral, can affect relative wages. No U.K. study has considered all kinds of technical change from this multi-sector perspective.[1]

[1] The importance of sector bias is a well-established result in the multi-sector literature, see below for more discussion. Its intuition can be seen from the Stolper-Samuelson theorem, which works via the sector bias of product-price changes altering

Second, the product-price studies have been only loosely linked to the Heckscher-Ohlin (HO) trade framework they commonly invoke. These studies regress changes in industry product prices on the industry skilled/unskilled employment ratio. This specification was used in many early HO studies of U.S. wages, but, as later studies showed and as we show below, it is misspecified relative to HO theory. These results are therefore difficult to interpret.

Third, all these studies assume that prices and technology are exogenous. In linking price changes with international trade, the price studies all assume, explicitly or implicitly, that domestic prices change due to trade forces. But, as Deardorff and Haikura (1994) and Freeman (1995) have argued, evidence is required as to how much domestic-price variation is caused by international trade, such as changes in trade barriers or changes in international product prices.[2] Similarly, one might reasonably ask what forces cause technical change. For example, Wood (1994) has conjectured that trade liberalisation induces technical change (in which case the trade/technology distinction might be inappropriate). Overall, knowing what underlying forces are driving prices and technology may be extremely important for understanding the consequence of policy**,** e.g., trade barriers or R&D incentives.

In this paper we address all these issues by using a single theoretical framework, the production side of HO trade theory, to explore the role of trade and technology in changing U.K. relative wages. The core of this framework is a set of zero-profit conditions linking domestic factor prices to product prices and technology in traded sectors where goods are produced domestically. These conditions help determine national factor demands and thus, when combined with factor supplies, equilibrium factor prices. Importantly, the effect on

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the relative profitability of sectors and so inducing wage changes to restore general equilibrium. Likewise it is the *sector bias* of technology changes that tends to alter sectoral profitability and so relative wages, a result dating back as far as Findlay and Grubert (1959). Haskel and Slaughter (1998) set out a model explaining the roles of sector bias versus factor bias and analyse the sector bias of SBTC for the UK and other countries. SBTC is of course only one type of technical change that can change sectoral profits.

[2] Freeman (1995, p. 29) writes: "Perhaps the biggest problem with these studies is that they ignore potential determinants of changes in sectoral prices and potential reasons for the proportion of unskilled workers in a sector to be correlated with changes in prices, save for trade." Using an approach different from this paper, Harrigan and Balaban (1997) instrument for U.S. tradables prices using foreign labour endowments and trade flows.

wages of changes in product prices and technology tends to depend on the sector bias of these changes. The reason is that any price or technology change which initially increases profits in a particular sector tends to raise the economy-wide wage for factor(s) employed relatively intensively in that sector until zero profits are restored in all sectors.

This theory implies an empirical specification in which a cross-section of changes in sector product prices or total-factor productivity (TFP) are regressed on sector cost shares for various factors of production. We interpret the coefficient estimates on the cost shares as the economy-wide wage changes "mandated" by the sector bias of changes in prices or TFP, i.e., wage changes which maintain zero profits in all sectors following changes in prices or technology. Estimates of these mandated wage changes can then be compared with actual wage changes to see what share of actual changes can be accounted for by various trade and technology forces.

To address the question of whether prices and technology are endogenous, we estimate two sets of mandated-wage regressions based on two different sets of assumptions. First, as a benchmark, we assume that the United Kingdom is a small, open economy, implying that changes in domestic prices are entirely due to international trade, and that TFP growth is exogenous. Here, we simply use price changes or TFP growth in the mandated-wage regressions to estimate trade and technology's wage effects.

Second, we assume that sector price changes and TFP growth are each caused by a set of underlying forces. We model U.K. prices as depending on U.K. import prices from various country groups, and TFP as depending on technology and on product and labour market competition. In a first stage, we can calculate the contribution of each underlying force to changes in prices or TFP. In a second stage, we regress each of these contributions on sector factor-cost shares. The second-stage coefficients we interpret as wage changes mandated by the sector bias of underlying forces working through changes product prices or TFP growth.

Among a number of results, we find that changes in prices, not TFP, were the major force behind the rise in inequality in the 1980s. We are the first study to find significant price effects on UK wage inequality.[3] We also find that although increased pressure of trade has affected technology, its effect on wage inequality was not statistically significant.

We believe that this paper makes a number of contributions to the literature on U.K. wage inequality. First, our work addresses all three concerns raised above in a unified framework. Second, we obtain quantitative estimates of trade and technology's wage impacts rather than just qualitative evidence.[4] Third, our study is the first to apply the mandated-wage methodology to the U.K. case—in fact, the first we are aware of to apply it to a country other than the United States. Fourth, most U.K. studies focus on the 1980s; we analyse the 1960s and 1970s as well.

In addition to these contributions to existing research on the U.K. experience, we think our study also contributes to the recent mandated-wage literature (see Slaughter (1999) for a survey). Only one other study has used the two-stage procedure. Feenstra and Hanson (1998) decompose the sum of US price changes and TFP into components attributable to computer usage and to imported intermediate inputs. We make three contributions to this two-stage approach. First, we are the first mandated-wage study to relate domestic prices to import prices. Second, our TFP decomposition uses a broader set of structural forces suggested by the large industrial-organisation literature on causes of TFP. Third, we are the first mandated-wage study to consider empirically whether import competition induces technical change.[5]

The next section of the paper sets out our mandated wage framework. In section 3 we describe the data. Section 4 presents our empirical work, and section 5 concludes.

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[3] Whilst this paper was being completed were we made aware of Gregory and Zissimos (1998) that uses the mandated wage method for the 1980s. Using input/output data and different skill divisions they also find significant price effects. They do not use a two-stage procedure as we do, nor do they provide evidence for earlier decades.

[4] For example, the finding that SBTC has been widespread does not indicate what share of overall inequality changes SBTC accounts for.

[5] Our findings are consistent with a large literature explaining U.K. TFP. For the role of unions see Metcalf (1989) and Gregg, Machin and Metcalf (1993); for product-market competition see Haskel (1991) and Nickell (1996)). See Lawrence (1999) for an empirical analysis of U.S. TFP growth and foreign competition.

2. Mandated-Wage Methodology

Most researchers have analysed U.K. wage inequality in a supply-and-demand framework. In deriving economy-wide labour demand, almost all U.K. studies have assumed a *one-sector* economy. In this case, firm-level relative labour demand aggregates straightforwardly, so that national relative demand slopes downward in (relative quantity, relative wage) space.

We, too, use a supply-and-demand framework. The key feature of our analysis, however, is we assume there are *many* sectors, not just one. Many fundamental ideas in trade theory require multiple sectors, e.g., comparative advantage. In addition, empirical work on SBTC has documented its pervasiveness across many disaggregated sectors (e.g., Berman, Bound, and Griliches, 1994). It therefore seems appropriate to use a multi-sector model. [6]

Why do multiple sectors matter? Consider an increase in skilled-labour supply to the economy. In a one-sector model, the economy can absorb the extra skilled labour only through wage changes. But in a multi-sector model, sectoral outputs can change as well. A combination of higher output in the skill-intensive sector and lower output in the unskilled-intensive sector can potentially absorb the rise in skilled supply (a Rybczynski effect). Therefore, the economy-wide labour-demand curve, in a multi-sector model, reflects both these output mix changes and relative wage changes.

2a. Economy-Wide Relative Labour Demand in the HO Model

To derive the economy-wide relative labour demand schedule we need to explain how relative labour-supply changes can be absorbed by changing output mixes. To do this, consider a country endowed with J distinct primary factors of production. The country freely trades with the rest of the world but has no influence on product prices. Suppose there are a large number, S, of tradable output sectors in the world. The domestic decentralised optimisation of all profit-maximising firms is equivalent to the country "choosing" the

[6] We do *not* suggest, of course, that one-sector models are always inappropriate. But it is always acknowledged that compositional effects may be important in one sector/representative agent models. Here composition effects are key.

national output mix that maximises GNP subject to the constraints of world product prices, national factor supplies, and national production technology (see, e.g., Dixit and Norman, 1980). This optimal output mix consists of both which sectors are produced and production quantities.

Let this decentralised process result in I different tradable goods that the country optimally produces, each of which requires some combination of J primary factors and I intermediate inputs.[7] Then in each of the I sectors, perfect competition ensures zero profits, i.e., average cost equals price. For each sector i, we write zero-profit condition

$$p_i^G = \sum_{j \in J} a_{ji} w_j + \sum_{i \in I} b_{ii} p_i^G \qquad i = 1 \ldots I \qquad \textbf{(1)}$$

where p_i^G is the domestic gross-output price in sector i; w_j is the unit cost of the jth input; a_{ji} is the employment of input j per unit of output in sector i; and b_{ii} is the amount of intermediate input required to produce a unit of good i. There are I equations in (1), one for each sector where production occurs. There are three points to note about (1). First, for a small open economy, p_i^G is also the world price. Second, because the HO framework assumes perfect factor mobility across sectors, wages w_j in (1) are not indexed by sector i. Third, all a_{ji} and b_{ii} are optimally chosen by profit-maximising firms and so depend on production technology and (assuming substitutability in production) wages and prices.

The I zero-profit conditions in (1) link domestic factor prices to product prices and technology in all traded sectors with positive domestic production. As national factor supplies vary, so might the set of I products produced and thus the set of I zero-profit conditions in (1). This suggests a way to derive national factor-demand schedules: vary factor supplies, and use these endowments plus the zero-profit conditions to trace out the labour demand curve.

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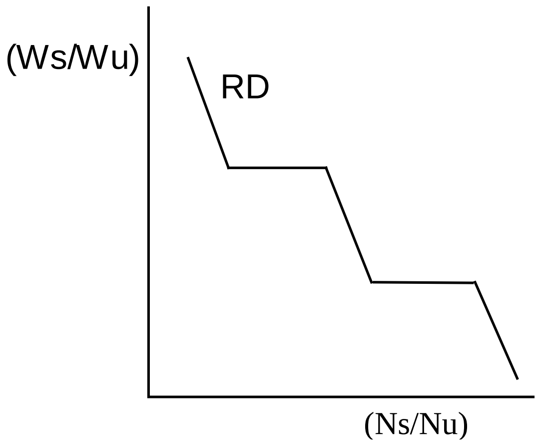
[7]We omit imported intermediate inputs for notational simplicity.

To make this derivation concrete, Figure 1 graphs the national relative factor demand schedule for the case of two factors, skilled and unskilled labour, and three sectors: an unskilled-labour-intensive good, a "middle" factor-intensity good, and a skilled-labour-intensive good (see also Leamer, 1998 and Wood, 1995 for a similar diagram).

Figure 1
National Relative Labour Demand in
The Heckscher-Ohlin Model



Notes: Skilled labour is subscripted "s" and unskilled labour "u".

Consider the leftmost downward-sloping branch, where the relative supply of skilled labour is very low. Given this endowment, the country maximises GNP by producing only one product**,** the unskilled-labour-intensive good. A relatively high quantity of unskilled labour is demanded and since skilled labour is relatively scarce, it earns a high relative wage. Now increase the relative supply of skilled labour, but by a small enough amount that GNP is still maximised by producing only the one product. Since only one product is made, there is no scope for Rybczynski effects and the one-sector intuition holds: to price themselves into employment, skilled workers' relative wages must fall. The relevant zero profit condition in this endowment range is

$$p_1 = a_{s1}w_s + a_{u1}w_u \qquad \textbf{(1′)}$$

where subscripts s and u denote skilled and unskilled labour, respectively. Note that in (1′) there are two endogenously determined national wages, w_s and w_u, but only one equation relating these wages to exogenous product prices and production technology. Prices and technology alone cannot determine wages, so endowments matter as well.

Now increase the supply of skilled labour until the first perfectly-elastic portion is reached. Here, the country maximises GNP by producing both the unskilled-labour-intensive product and the middle product. With two products there is now scope for Rybczynski effects. Additional skilled labour can be completely absorbed with no change in wages by increasing output of the middle good and reducing output of the unskilled-intensive good. This explains why RD has a flat portion where the *same* relative wage is consistent with a range of quantities of relative labour demanded. This result can be seen algebraically by writing the two zero profit conditions

$$\begin{aligned} p_1 &= a_{s1}w_s + a_{u1}w_u \\ p_2 &= a_{s2}w_s + a_{u2}w_u \end{aligned} \qquad \textbf{(1″)}$$

In (1") there are two equations and two unknowns (w_s and w_u). Hence w_s and w_u are completely determined by the prices (p_1 and p_2) and technology (the a_{ji}'s)[8]. For any change in supply wages do not change, so long as the country continues to make these two products. This insensitivity of national wages to national factor supplies Leamer and Levinsohn (1995) call the factor price insensitivity (FPI) theorem.[9]

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[8] With Leontief technology the a_{ji}'s are constants. With substitutability, they depend on relative wages as well. The algebra is more involved, but the results still stands: the two wages are determined by the two output prices and technology parameters.

[9] Note that FPI assumes that the country is sufficiently small that changes in its relative-output mix do not change world product prices. If world prices do change than so, too, do domestic wages. Below we discuss such price changes; for now, note that a change in prices changes (1") and thus wages.

The remaining portions of RD follow the same intuition. Beyond the first perfectly-elastic portion the country switches to producing just the middle good; on the next perfectly-elastic portion it produces both that good and the skill-intensive good; and on the last downward-sloping branch it produces just the skill-intensive good. Note that because a different set of products is made on each elastic part, each has different relative wages.

Our derivation of Figure 1 used an example with 3 goods and 2 factors. But Figure 1 can be re-interpreted for the more general case of J factors and I sectors. With I sectors in the output mix there are I zero-profit equations with J endogenously determined factor prices. If $J \leq I$, then national factor prices are *completely* determined by (1). In this case national factor supplies do *not* influence wages: only exogenous product prices and technology do. If $I<J$ factor supplies do matter because prices and technology are not sufficient to determine wages. Thus in Figure 1, the infinitely-elastic parts of RD are where $J \leq I$ while the downward-sloping parts are where $I<J$.[10]

Given this intuition for the *shape* of RD, it is important to emphasise that its *position* depends on product prices and production technology. Hence, changes in prices or technology shift the position of the relevant parts of RD**,** and given labour supplies, wages change to restore zero profits in all sectors.

To see the adjustment process formally, assume that over some time period an economy produces the same set of $I>J$ goods and therefore remains on a flat portion of RD. Totally differentiating the I zero profit conditions in (1) with respect to time gives (Leamer, 1998)[11]

$$\Delta \log p_{it} + \Delta \log TFP_{it} = \sum_{j \in J} V_{jit} \, \Delta \log w_{jt} \qquad \textbf{(2)}$$

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[10]Two final comments on Figure 1. First, note that when the number of sectors S exceeds the number of factors, output mixes are usually indeterminate. That is, there is no unique optimal output mix that can fully employ all factors in a given endowment. Instead, the range of optimal outputs usually lies in an (S-I) dimensional space. In our derivation of RD in the text, for simplicity we focused on output mixes whose relation to the underlying endowments seems most intuitive. Second, the downward-sloping portions of RD assume flexible production technologies which allow substitutability among factors. If technology were Leontief these portions would become vertical.

[11] This ignores second-order terms, see data appendix.

where $\Delta \log p_{it} = [\Delta \log p_{it}^{G} - \Sigma \nu_{ii} \Delta \log p_{it}^{G}]$ is the change in value added prices[12], V_{jit} is the share of factor *j* in total costs in sector *i* at time *t*; and $\Delta \log TFP_{it}$ is the growth in total-factor productivity for sector *i*. The final term in (2), $\Delta \log w_{jt}$, is the change in the wage of factor *j*, which is of course economy-wide since all factors are mobile across sectors.

Equation (2) shows how $\Delta \log w_{jt}$ responds to any changes in prices ($\Delta \log p_{it}$) or in technology ($\Delta \log TFP_{it}$) to restore zero profits in all sectors. At initial factor prices, any change in product prices or technology means zero profits no longer hold in one or more sectors. Hence producers try to expand output in now-profitable sectors and reduce output in unprofitable sectors. Relative labour demand increases for the factors employed relatively intensively in expanding sectors and reduces for the factors intensive in the contracting sectors. To restore equilibrium, at fixed labour supply, relative wages must adjust in response to the demand shifts until all profit opportunities are arbitraged away.

The key empirical implication of (2) is that the wage effects of changes in product prices and technology tend to depend on their *sector* bias. Any change which initially increases profits in a particular sector tends to raise the economy-wide wage for factor(s) employed relatively intensively in that sector. The Stolper-Samuelson theorem describes how wages tend to rise for factors employed intensively in sectors enjoying rising relative product prices. The same intuition applies to technology: wages tend to rise for factors employed intensively in sectors enjoying relatively large technology gains.[13]

In terms of figure 1, RD shifts up when price and/or TFP growth is concentrated in skill-intensive sectors. RD shifts down when this growth is concentrated in unskilled-intensive sectors. Assuming the economy remains on a flat portion of RD, (2) allows us to quantify

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[12] This nomenclature follows Leamer (1998), although strictly speaking $\Delta \log p_{it}$ is value-added prices multiplied by the share of total value added in production costs.

[13] Wage effects are harder to determine if technology changes also induce product-price changes as well, but sector bias still matters in this case in many circumstances (see Haskel and Slaughter, 1998).

these wage effects of shifts in RD induced by sector-biased changes in prices and technology.[14]

Equation (2) links technical change, prices and relative wages. To use it further, we must make some additional assumptions regarding exogeneity. First, suppose that the UK is a small open economy, i.e. changes in domestic prices are entirely due to international trade, and suppose too that TFP growth is exogenous. In (2), we can use data on prices and outputs and inputs to construct $\Delta \log p_{it}$, $\Delta \log TFP_{it}$ and V_{jit}. The term $\Delta \log w_{jt}$, which is the change in the economy-wide factor price required to maintain zero profits, is of course unknown. To determine technology's effect on wages we estimate

$$\Delta \log TFP_{it} = \sum_{j \in J} V_{jit}\, \beta_{jt} + \varepsilon_{it} \qquad \textbf{(3)}$$

where ε_{it} is an additive error term and the J coefficients β_{jt} are parameters to be estimated. A positive β_{jt} indicates that technical change was larger in sectors in which factor j constitutes a larger share of costs, i.e., in sectors which employ factor j relatively intensively. Our sector-bias intuition suggests that the national wage for factor j should have risen in response to these price changes. Hence, we interpret each β_{jt} as factor j's wage change "mandated" to restore zero profits in all sectors in response to the sector bias of technical change. We can then compare our mandated wage changes with actual wage changes to determine what share of actual changes are accounted for by technology.

For trade we estimate a similar equation given by

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[14] If the economy produces a range of goods such that it is on the downward sloping portion of RD, the zero profit conditions in (2) still hold. But (2) would not fully determine wage changes since factor supplies matter as well. It would clearly be of relevance to know the width of the flat and downward-sloping parts of the RD curve and the details of the change in goods produced. Theory predicts that switching product mixes (i.e. dropping production of unskilled-intensive goods and undertaking production of skilled-intensive goods) as the economy moves from a flat section to a downward-sloping section of RD depends on the interaction production technologies, world product prices and domestic endowments. Empirically, there is very little empirical evidence on changes in product mix over countries or time.

$$\Delta \log p_{it} \;=\; \sum_{j \in J} V_{jit} \gamma_{jt} \;+ \varepsilon_{it} \qquad \textbf{(4)}$$

where ε_{it} is an additive error term. Each estimate γ_{jt} is the zero-profit-restoring change in factor *j*'s wage "mandated" by the sector bias of price changes. We also can compare mandated changes to actual wage changes to see what share of actual changes technology accounts for. Finally, adding together the βs and γs from (3) and (4) for each factor *j* gives the net wage changes mandated by trade plus technology.[15]

By contrast, suppose now that prices and TFP are endogenous. For this case we adopt a two stage approach. In the first stage we regress TFP and price changes each on a set of underlying regressors, Z_{te} and Z_{pr}, which are assumed to drive TFP and price changes respectively over some period *t*. This can be written

$$\Delta \log TFP_{\mathrm{it}} \;=\; \sum_{\mathrm{te} \in \mathrm{S_{te}}} Z_{\mathrm{te,it}} \delta_{\mathrm{te,\,t}} \;+ \varepsilon_{\mathrm{it}} \qquad \textbf{(5)}$$

and

$$\Delta \log p_{\mathrm{it}} \;=\; \sum_{\mathrm{pr} \in \mathrm{S_{pr}}} Z_{\mathrm{pr,it}} \delta_{\mathrm{pr,\,t}} \;+ \varepsilon_{\mathrm{it}} \qquad \textbf{(6)}$$

where S_{pr} and S_{te} are the two sets of underlying variables and each parameter in the vectors δ_{te} and δ_{pr} gives the contribution of its affiliated structural variable to observed TFP and price variation, respectively.

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[15]Three further points on (3) and (4) are worth noting. First, the error term in each equation captures, for example, zero profits not holding exactly in all sectors. Second, note that with our small-economy assumption TFP growth can affect factor prices but not product prices. Third, our mandated-wage regressions might appear odd because the exogenous variable is the regressand rather than the regressor while the dependent variable of interest (factor-price changes) is estimated rather than the regressand. The most important reason a "standard" regression cannot be used is the dimensionality of the data prevents inversion of the (J x I) regressor matrix formed by stacking all I industries in equations (3) or (4). For example, our data used below contain over 100 manufacturing industries but only three primary factors plus intermediate inputs. With more products than factors the regressor matrix is not square and thus cannot be inverted.

In the second stage we regress the predicted values due to each underlying variable on the factor cost shares:

$$\hat{\delta}_{te} Z_{te,\, it} = \sum_{j \in J} V_{jit} \beta_{jt,\, te} + \varepsilon_{it} \qquad \textbf{(7)}$$

and

$$\hat{\delta}_{pr} Z_{pr,\, it} = \sum_{j \in J} V_{jit} \gamma_{jt,\, pr} + \varepsilon_{it} \qquad \textbf{(8)}$$

The share coefficients ($\beta_{jt,\, te}$ and $\gamma_{jt,\, pr}$) give the wage changes mandated by the sector bias of each structural force working through either TFP or prices. For example, if the first-stage equation (5) indicates that increased trade contributes to $\Delta \log TFP_{it}$ then second-stage equation (7) tells how much trade has affected wages through its induced sector bias of changes in TFP.

In sum, we estimate the wage effects of trade and technology under two different assumptions. First we assume prices and technology are exogenous and estimate (3) and (4). Second, we assume prices and technology are endogenous and estimate (5)-(8).

Before finishing the discussion of our HO framework, we contrast our single-stage price regression (4) with the U.K. price regressions, cited in the introduction, which are of the form

$$\Delta \log p_{\mathrm{it}} = \lambda (S/U)_i + \varepsilon_i \qquad \textbf{(9)}$$

where $(S/U)_i$ is the skilled/unskilled employment ratio in industry *i* during the starting period. Equation (9) is estimated with reference to HO trade theory, as in many of the initial product-price studies for the U.S. But (9) does not follow from the HO model as closely as (6) does, so these earlier findings may not be as informative (see Slaughter, 1999).

2b. Other Issues Concerning the HO Model

To address some possible criticisms of the HO model, we note the following. First, it its important to stress the role of factor supplies. FPI does not imply that wages are invariant to factor supplies. As explained earlier, national factor supplies do help determine wage levels in at least two cases. First, when the country chooses a national output mix with fewer produced goods than factors and second, even if FPI initially holds, when labour-supply shocks induce the country to make a different set of products. In our data analysis, for each decade we assume both that FPI holds and that the U.K. product mix did not change. In the absence of information on changes in product mix, every previous mandated-wage study has made these same assumptions. In terms of Figure 1, they mean that we estimate trade and technology-driven shifts up or down for a single flat portion of RD. If our assumptions are correct**,** then our mandated wage changes should match actual wage changes. If the two do not match, one possible reason will be that endowment changes moved the economy to a new part of RD. We return to this issue in Section 4.

A second issue is the role of SBTC. In (2), $\Delta\log TFP_{it}$ embodies *all* kinds of technical change, including SBTC.[16] We consider all types of technical change, since any type of technical progress increases sectoral profitability and thus induces wage changes.

Third, the factor price equalisation (FPE) theorem (Samuelson, 1948) predicts that each factor receives the same wage world-wide. It is important to stress we do not assume FPE or impose it at any stage. Our framework considers the production side of a *single* country. FPE requires at least one other country and restrictive assumptions about cross-country similarities (such as identical production technologies) which we do not impose in any way. Our framework allows FPI, but this is a much less restrictive condition than FPE.

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[16] To see that ΔlnTFP growth embodies all types of technical progress, suppose $Y=A\times F(\alpha S, \beta U)$ where Y is output, S skilled labour, U unskilled labour, A is Hicks-Neutral TC, α is skill-biased TC and β is unskilled biased TC. Taking logs and differentiating with respect to time gives, where Δx denotes change in log x over time, $\Delta\ln TFP \equiv \Delta y - V_s\Delta S - V_u\Delta U = \Delta a + V_s\Delta\alpha + V_u\Delta\beta$ where V_s and V_u are cost shares in output and we have used the first-order conditions for S and U.

The fourth point concerns interindustry wage differentials. Our model assumes perfect interindustry factor mobility such that each factor earns the same wage in all sectors. A large literature has documented sizeable interindustry wage differentials for workers with the same measurable skills (see e.g. Katz and Summers, 1989). Whether or not these differentials exist, what matters here is whether they are stable over time. Since we estimate mandated *changes* in economy-wide wages, the issue is whether actual changes in industry wages are driven mainly by economy-wide changes common to all sectors or by changes in the differentials specific to each sector. To examine this, Table 1 sets out the fraction of actual industry wage changes accounted for by changes in industry-specific differentials for skilled and unskilled labour over three decades.[17]

Table 1
Share of Change in Industry Wages Accounted for By Change in Industry Wage Differentials

	Skilled	**Unskilled**
1960s	0.113	0.087
1970s	0.060	0.043
1980s	0.093	0.080

Source: Authors' calculations based on Oulton and O'Mahony data. See data appendix.

As the table shows, changes in inter-industry wage differentials account for at most 11% of total industry wage changes. This is consistent with the evidence in Katz and Summers (1989) and others that wage differentials are very stable over time. Interindustry wage differentials clearly exist in *levels*, but *changes* in industry wages are driven almost entirely by changes in economy-wide wages. Thus, we think that our mandated-wage analysis is of considerable relevance (algebraically, wage differentials might be fixed effects in (1) that disappear in (2)).

[17] We calculate, for the skilled and unskilled, $\Sigma[\Delta((w_{si}) - (w_s))/(w_s))]$ and $\Sigma[\Delta((w_{ui}) - (w_u))/(w_u))]$ where w_s and w_u are economy-wide averages and we sum over industries. For more information on the data see below.

Fifth, a related issue is imperfectly competitive product markets. For sector bias to drive relative wages we only require a systematic link from prices and technology to wages. Perfect competition delivers this link, but an alternative would be imperfect competition with a constant price-cost mark-up. Like wage differentials, this would change (1) but not (2): some constant extranormal profit would be added to (1) (which might contribute to wage differentials), but this would disappear in (2). Even with imperfect competition, monopolistic competition with entry would give zero equilibrium profits (Helpman and Krugman, 1985).

Sixth, a nontraded sector can easily be incorporated into our framework. If the number of tradable goods at least equals the number of primary factors, national wages are still determined by the zero-profit conditions of the tradable sectors only. This means that nontraded industries need *not* be included in the estimation. Nontradables' product prices are endogenously determined by production technology in the nontraded sector and by wages. Technical progress in nontradables does not affect wages; instead, it lowers nontraded prices.

Finally, our model does not have labour-market institutions, such as unions or centralised wage setting, which might influence wages. Empirically we do consider unions, but through their effect on TFP growth**.** Constructing an estimable general equilibrium model incorporating these wage setting institutions is beyond the scope of this current paper. [18]

3. Data, Measurement and Econometrics

Here we discuss the essential features of the data; details are given in an appendix. Our main data are the U.K. manufacturing data collected by Oulton and O'Mahony (OO, 1994).[19] OO constructed an industry-year panel, based mainly on the *Census of Production*, for around

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[18] For (partial equilibrium) evidence that unions do not seem very important in explaining U.K. wage inequality see Gosling and Machin (1996). It is worth contrasting the role of unionisation here to that usually considered in the literature. Unions are generally seen as narrowing wage inequality for (not well understood) institutional reasons or via unobserved sorting. Our framework measures instead the contribution of unions to wage inequality via technical change. For example, if unions hold up technical change disproportionately in the skill-intensive sectors then they raise the relative profitability of the unskill-intensive sectors. This tends to lower wage inequality. A reduction of union power could therefore raise wage inequality by increasing TFP growth in the skill-intensive sectors.

[19] We are extremely grateful to Nicholas Oulton for providing us with these data and some unpublished data consistent with published data.

135 three-digit U.K. SIC manufacturing industries at roughly five-year intervals.[20] This panel contains information on prices and quantities of output, labour, capital and intermediates.

The labour data are divided into manual and non-manual employees, whom we call unskilled and skilled workers, respectively. Our measure of wage inequality is thus the non-manual/manual wage premium in U.K. manufacturing. This occupational measure is the only skills measure consistently available (a) over a long time period (b) with congruent trade and technology indicators, and (c) at a disaggregated level. On average, non-manuals are more educated than manuals (see Machin (1996) and Haskel and Heden (1998)), so these occupation data do distinguish skill groups.[21] Table 2 shows the fall and then rise of the U.K. skill premium. In addition the 1980s rise, the earlier fall also requires explanation.

Table 2
Wage Inequality in U.K. Manufacturing

Year	Skilled wage (£)	Unskilled wage (£)	Wage inequality
1954	603	410	1.47
1958	747	522	1.43
1963	927	659	1.41
1968	1,256	910	1.38
1973	2,077	1,565	1.33
1976	3,540	2,734	1.30
1979	5,215	4,030	1.29
1982	8,043	5,898	1.36
1986	11,241	7,958	1.41

Notes**:** Skilled and unskilled wages are manufacturing-wide average annual non-manual and manual nominal earnings.
Source**:** Authors' calculations based on Oulton and O'Mahony data, see data appendix.

20 We dropped shipbuilding, vehicles, iron and steel and aerospace since they were (wholly or partly) publicly owned during at least part of the sample period. Our results were robust to their inclusion. We lose a few industries in each decade due to missing observations.

21 Gregory and Zissimos (1998) obtain very similar results to us for the 1980s using a different data set with skill defined by education levels.

We calculated $\Delta \log TFP_{it}$ using our three primary factors (both labour types and capital) and intermediate inputs.[22] We calculated $\Delta \log p_{it}$, changes in value-added prices, as defined earlier. Both $\Delta \log TFP_{it}$ and $\Delta \log p_{it}$ measure decade changes, with endpoints dictated by data availability.[23]. Following Feenstra and Hanson (1998), cost shares in gross output, $V_{jit,}$ are averages between the first and last years of each decade. We assumed that payments to capital equal the value of gross output less the total wage bill and input costs; we do not think we have good enough data to define capital's payments independently.

Table 3a sets out summary statistics for all these variables.

Table 3a
Summary Statistics

	1960s	**1970s**	**1980s**
Change in skilled wage	0.51	1.41	0.77
Change in unskilled wage	0.57	1.51	0.68
$\Delta \log p_{it}$	0.09 (0.10)	0.56 (0.20)	0.25 (0.12)
$\Delta \log TFP_{it}$	0.08 (0.12)	-0.04 (0.17)	0.02 (0.12)
V_s, Skilled share	0.08 (0.04)	0.08 (0.03)	0.09 (0.04)
V_u, Unskilled share	0.19 (0.08)	0.17 (0.08)	0.16 (0.08)
V_k, Capital share	0.18 (0.05)	0.19 (0.05)	0.19 (0.05)

Notes: Cells report employment-weighted means, with standard deviations in parentheses. Wages are manufacturing-wide wages and so have no standard deviation. Prices are value-added prices as defined in the text. Changes are calculated as log changes over 1958-68, 1968-79, and 1979-86. TFP is calculated using manufacturing-wide wages. See data appendix for details.

Source: Author's calculations from OO data.

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[22]In the productivity literature, errors in measuring $\Delta \log TFP_{it}$ are a major concern. We note that the OO data also contain a TFP series constructed using labour and capital disaggregated much more finely; the sample correlation between the two TFP measures was 0.95. We also note that in our analysis $\Delta \log TFP_{it}$ is used as a regressand, not a regressor, so we do not face the problem of estimation bias due to measurement error.

[23] The 1960s change is 1958-68, the 1970s is 1968-79 and the 1980s is 1979-86.

Table 3a shows the absolute wage changes underlying the inequality changes in Table 2. During the high-inflation 1970s wage and price growth were higher while TFP growth was slower; in addition, the standard deviation of price and TFP growth was larger. Capital's average cost share remains roughly constant while the unskilled share falls. There is little change in the standard deviation of any of the shares.

With three factors, in our one-stage analysis the estimating equation for technology is

$$\Delta \log TFP_{it} = \beta_s V_{sit} + \beta_u V_{uit} + \beta_k V_{kit} + \varepsilon_{it} \qquad \textbf{(3')}$$

and for prices is

$$\Delta \log p_{it} = \gamma_s V_{sit} + \gamma_u V_{uit} + \gamma_k V_{kit} + \varepsilon_{it} \qquad \textbf{(4')}$$

where we estimate (3′) and (4′) separately for each decade.

Turning to the two stage approach, our selection of the determinants of $\Delta \log TFP_{it}$ follows the extensive U.K. productivity literature which stresses the role of financial, labour, and product markets (e.g., Haskel (1991), Metcalf (1989), and Nickell (1996)). Unfortunately we do not have satisfactory industry-year financial-market data. For labour markets we use industry union density, (denoted $UNION_{gt}$ where g denotes that the variable is available at two-digit level[24]), and its decade change ($\Delta UNION_{gt}$). In standard effort bargain models $\Delta UNION_{gt}$ reduces $\Delta \log TFP_{it}$, but raises it in "voice" models. $UNION_{gt}$ (in levels) might also affect $\Delta \log TFP_{it}$ through incentives to learn or to introduce new work practices. Our product-market regressor is the share of domestic sales (less imports) accounted for by the five largest firms, $CONC_{it}$, available at the three-digit level.

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24 Unfortunately the only data available over a cross-section and time series is a two-digit measure, but we did enter a three-digit cross-sectional measure of union coverage in 1973 as a partial check and get similar results to the levels data.

Beyond these commonly used determinants of $\Delta\log TFP_{it}$, we consider three others as well. First, it is important to control for cross-sectional differences in $\Delta\log TFP_{it}$ caused by different technical opportunities in different sectors (which may be correlated with *CONC* and *UNION*). To do this we use (two-digit) data on average innovations produced per industry ($INNOV_{gt}$). As Geroski, Machin, and van Reenen (1993) point out, innovation counts have the attractive property of being an output of the research process rather than an input (such as R&D expenditures) and are therefore likely to be helpful indicators of $\Delta\log TFP_{it}$.[25] Second, for the 1980s we also use a measure of changes in computerisation ($\Delta COMPUTER_{gt}$). This is derived from a PSI survey of computerisation and gives the change in the proportion of firms in the (two-digit) industry using computers. We include this variable in light of research suggesting that computers induce SBTC. Finally, to test the hypothesis that international competition induces technical change we include as regressors decade changes in domestic gross-output product prices relative to import prices. To allow different competitive effects from different countries we try three different source-country groups: the OECD, newly industrialised countries (NICs), and the nonOECD rest of the world. Thus, we create three regressors $\Delta\log(p_{UK}/p_{OECD})_{gt}$, $\Delta\log(p_{UK}/p_{NonOECD})_{gt}$ and $\Delta\log(p_{UK}/p_{NICs})_{gt}$. These regressors are available at the two-digit level.

We model $\Delta\log p_{it}$ as depending on changes in prices of competing imports. There is well-documented evidence of persistent price differentials between UK and foreign traded goods (see, e.g., MMC 1984 (compact discs) and Verboven 1996 (automobiles)) that in part reflect trade barriers. Unfortunately, lack of data prevents us from including trade barriers in our analysis. Accordingly, our estimating equation for prices regresses $\Delta\log p_{it}$ on industry changes in U.K. import prices. Using the same country groupings as above we construct changes in import prices $\Delta\log p_{OECD,gt}$, $\Delta\log p_{NonOECD,gt}$, $\Delta\log p_{NIC,gt}$.[26]

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[25] These survey data might be regarded as subjective and/or an incorrect measure of the total number of innovations by industry. For our purposes, however, we need only that these data capture the cross-sectional variation in technical propensity, e.g., how much more innovative the computer sector is than timber.

[26] We are very grateful to Bob Anderton for providing us with these data.

Table 3b sets out summary statistics for these underlying variables.

Table 3b
Further Summary Statistics

	1973-79	1979-86
Innovations	48.4	47.4
	(66.7)	(54.2)
Concentration	0.35	0.32
	(0.40)	(0.23)
Union density	60.7	68.3
	(14.7)	(12.8)
Change in union density	7.20	-15.3
	(10.5)	(3.92)
Change in relative OECD prices	-1.23	-2.20
	(4.41)	(3.770
Change in relative nonOECD prices	2.48	-1.19
	(6.64)	(2.65)
Change in relative NIC prices	-0.05	0.21
	(0.98)	(0.38)
Change in OECD prices	1.57	2.52
	(4.40)	(3.74)
Change in Non-OECD prices	-2.12	1.52
	(6.96)	(2.62)
Change in NIC prices	0.39	0.12
	(0.98)	(0.37)
Change in computer intensity	-	26.6
		(2.84)

Notes: Cells report employment-weighted means, with standard deviations in parentheses. Changes are calculated as log changes between the years indicated. Levels terms here and in the regressions are for the first year of the relevant decade. See data appendix for details.

As the table shows, innovations were fairly constant over the period whilst union density rose in the 1970s and fell in the 1980s. Non-OECD prices fell strongly in the 1970s relative to OECD prices, and in the 1980s NICs prices also fell.

Turning to our estimating equations, our $\Delta\log TFP_{it}$ regression is

$$\Delta\log TFP_{\text{it}} = \delta_1 INNOV_{\text{gt}} + \delta_2 CONC_{\text{it}} + \delta_3 UNION_{gt} + \delta_4 \Delta UNION_{gt} + \delta_5 COMP_{gt} + \delta_6 \Delta\log(p_{gt}/p_{fgt}) + \varepsilon_{it} \qquad \textbf{(5')}$$

where the final term is the group of relative foreign price terms. We have data on the regressors from 1973 onwards, so we estimate (5′) pooling over the two cross-sections 1973-79 and 1979-86 and adding a time dummy; fixed effects were insignificant. For the second stage, as in (7), we take the fitted values of each regressor from (5′) and regress them on the three cost shares (the regressors in (3′)). We do this second stage separately for 1973-79 and 1979-86.

Our estimating equation for $\Delta\log p_{it}$ is

$$\Delta\log p_{it} = \mu_1 \Delta\log p_{OECD,\, gt} + \mu_2 \Delta\log p_{NonOECD,\, gt} + \mu_3 \Delta\log p_{NIC,\, gt} + \varepsilon_{it} \qquad \textbf{(6′)}$$

where we again pool over the cross-sections 1973-79 and 1979-86 and add a time dummy and fixed effects. In the second stage, as in (8), we take the fitted values of each regressor from (6′) and regress them on cost shares separately for 1973-79 and 1979-86. [27]

Concerning the estimation of (3′)-(6′) the following points are worth noting. First, we prefer ten-year differences to five-year differences (which we could construct) because the decade end points generally correspond with turning points in the skill premium. In addition, these endpoints were at roughly similar points in the business cycle, so cost shares should not be too contaminated by labour hoarding. Second, we estimated all our equations by WLS (the panel regressions (5′) and (6′) used LSDV) with sector employment averaged over the decade as weights (unweighted results were very similar). Since the cost shares appear as regressors and are also in $\Delta\log TFP_{it}$, we re-estimated (3′) and (4′) and the second stage of (5′) and (6′) using IV with 1958 cost shares as instruments; we obtained almost identical results. Finally, in (7) and (8) the regressands are generated regressors from (5′) and (6′), and so we correct our coefficient standard errors in (7) and (8) using the method in Feenstra and Hanson (1998).

[27] We estimated equations (5′) and (6′) separately for each decade but the pooling restrictions were accepted. For brevity, we report just the pooled results.

4 Empirical Results

4a. Simple Price Regressions

Table 4 reports estimates of (9).

Table 4
Simple Price Regressions: Estimates of (9)
(dependent variable $\Delta \ln p_{it}$)

Equation Specification	**1960s**	**1970s**	**1980s**
$(N_s/N_u)_{i,\,t-1}$	-0.16 (2.82)	0.09 (0.97)	0.18 (4.32)
Adj. R^2	0.057	-0.005	0.13
# obs	116	121	123

Notes*:* Each column reports estimation of equation (9) for a different decade. For precise years, see Table 3. Equations weighted by average-period employment. Absolute t statistics in parentheses**.**

These regressions suggest that in the 1960s relative prices rose for the unskilled-intensive sectors. This would tend to lower wage inequality, as indeed happened. There is no clear shift in relative prices during the 1970s. In the 1980s price rises were concentrated in the skill-intensive sectors. This would tend to raise inequality, as indeed happened. Our 1980s results are qualitatively similar to Neven and Wyplosz (1996), who find a positive yet insignificant relationship (using gross-output prices). Desjonqueres, et al, (1997) find no significant relation for a sample of 16 sectors. Overall, Table 4 suggests that price changes played a significant role in wage changes during the 1960s and 1980s but not during the 1970s. To quantify the link from prices to wages, however, our mandated-wage analysis is required.

4b. One-Stage Mandated-Wage Regressions

Table 5 reports results for equations (3′) and (4′).

Table 5

One-Stage Mandated-Wage Regressions: Estimates of (3′) and (4′)

(dependent variables: $\Delta \log p_{it}$ and $\Delta \log TFPit$ for each indicated decade)

	1960s		1970s		1980s	
	Δlogp$_{it}$	ΔlogTFP$_{it}$	Δlogp$_{it}$	ΔlogTFP$_{it}$	Δlogp$_{it}$	ΔlogTFP$_{it}$
V_{si}	-0.20	1.18	1.40	0.50	0.92	0.06
	(0.64)	(3.09)	(2.58)	(1.04)	(3.31)	(0.19)
V_{ui}	0.27	0.01	0.36	0.34	-0.16	0.49
	(2.21)	(0.04)	(1.57)	(1.64)	(1.35)	(3.64)
V_{ki}	0.07	-0.26	1.04	0.25	0.94	-0.49
	(0.38)	(1.14)	(2.76)	(0.74)	(4.84)	(2.30)
R^2	0.04	0.08	0.18	0.05	0.30	0.16
Number of Obs.	116	116	121	121	123	123
Mandated % rise	-47	107	104	16	76	-43
in ineq (p value)	(0.20)	(0.01)	(0.40)	(0.76)	(0.001)	(0.23)

Notes: Each column reports estimation results for a specification of either equation (3′) or (4′). Absolute t statistics in parentheses. Mandated inequality changes add the coefficients on Vsi and Vui in each column. The p value for each mandated change shows the probability of accepting the hypothesis that the coefficient on Vsi equals the coefficient on Vui.

To read this table consider the first column which reports coefficient estimates for the regressors V_{si}, V_{ui}, and V_{ki} from (4′) for 1958-68. The coefficient on V_{si}, -0.20, indicates that the sector bias of 1960’s price changes mandated a fall in the skilled wage of 20% to maintain zero profits in all sectors. Similarly, the mandated change in the unskilled wage was a rise of 27% and for capital a rise of 7%. Below these coefficient estimates we report the mandated change in the skill premium, -47% (equal to -0.20 - 0.27), and its p value (0.20) indicating rejection of the null of zero mandated change in inequality at only the 80% significance.

Looking over all decades, the sector bias of price changes mandated an insignificant *decline* in inequality during the 1960s, an insignificant *rise* in inequality during the 1970s, and a significant *rise* in inequality during the 1980s. The 1980s results are the strongest in terms of significance. We regard these 1980s results to be particularly important: this is the first paper in the U.K. literature to find significant price effects during the 1980s (Gregory and Zissimoss, 1998 find a similar result). Turning to the technology regressions, the sector bias of TFP growth mandated a significant *rise* in inequality during the 1960s, a further insignificant *rise* during the 1970s, and an insignificant *decline* in inequality during the 1980s. This suggests that technology, measured as TFP growth, did not contribute to wage inequality in the 1980s.

These results for prices and TFP individually are of interest, but we also want to know their combined wage effects. By comparing the combined "mandated" wage changes with actual changes, we can gauge how well our HO framework performs. Table 6 presents the net mandated wage changes and the actual wage changes.

Table 6
Net Mandated and Actual Wage Changes
(net mandated changes calculated from addition across rows for each decade in table 5)

	1960s	**1970s**	**1980s**
Δw_s mandated	*0.61* 0.98 *1.39*	*1.37* 1.90 *2.44*	*0.63* 0.97 *1.32*
Δw_s actual	0.51	1.41	0.77
Δw_u mandated	*0.14* 0.27 *0.41*	*0.47* 0.70 *0.93*	*0.17* 0.32 *0.48*
Δw_u actual	0.57	1.51	0.68
$\Delta(w_s - w_u)$ mandated	*0.29* 0.70 *1.41*	*0.58* 1.20 *1.83*	*0.24* 0.65 *1.04*
$\Delta(w_s - w_u)$ actual	-0.06	-0.10	0.11

Notes: Italicized numbers adjacent to each mandated change are 95% confidence intervals for that change.

Looking at the top left-hand cell, the 1960s net mandated wage increase was 98% for skilled labour (this equals -20% + 118% from Table 5), with a 95% confidence interval of

61% to 139%. This compares with an actual rise of 51% over the period. The rest of Table 5 reads analogously.

So how well does our HO model perform? Our mandated wage changes for skilled labour are reasonably accurate: within sampling error for the 1970s and 1980s and just outside for the 1960s. For unskilled labour we consistently underpredict the actual wage rise. Because of this underprediction, in all decades our mandated inequality changes exceed actual inequality changes. There are at least two possible reasons for this underprediction. First, our model does not allow unions to raise wages above that consistent with the pressure of labour market competition from workers in other industries. To the extent that unions actually do this, and do this primarily for the less-skilled, one would expect underprediction. Second, our analysis assumes for each decade that any labour-supply shifts induce only Rybczynski product-mix effects. Since the 1960s the relative number of unskilled workers has declined. If these supply shifts have been large enough to have both output-mix and wage effects, they likely have raised less-skilled wages.

4c. Two-Stage Mandated-Wage Regressions

Table 7 reports results for our stage-one estimation of (5′) explaining TFP growth.

Table 7
First-Stage TFP Growth Regressions: Estimates of (5′)
(dependent variable: $\Delta\ln TFP_{it}$)

	1	2	3	4
$INNOV_{g,t}$	0.70	0.66	0.65	0.81
	(4.80)	(3.92)	(4.50)	(2.97)
$CONC_{i,t-1}$	-0.12	-0.11	-0.12	-0.10
	(2.92)	(2.48)	(2.87)	(1.70)
$UNION_{g,t-1}$	-2.31	-2.45	-2.53	-3.01
	(3.19)	(3.19)	(3.48)	(2.75)
$\Delta UNION_{g,t}$	-3.30	-3.05	-3.35	-2.00
	(2.75)	(2.48)	(2.82)	(0.53)
$\Delta\log(p_{UK} - p_{OECD})_{g,t}$		-0.002		
		(1.03)		
$\Delta\log(p_{UK} - p_{Non\text{-}OECD})_{g,t}$		-0.001		
		(0.55)		
$\Delta\log(p_{UK} - p_{NIC})_{g,t}$		0.03	0.02	0.09
		(2.09)	(2.17)	(2.61)
$\Delta COMPUTER_{gt}$				3.71
				(0.82)
R^2	0.28	0.30	0.30	0.31
Number of Obs.	233	233	233	116

Notes: Absolute t statistics in parentheses. Coefficients on $INNOV_{gt}$, $UNION_{gt}$, $\Delta UNION_{gt}$, and $\Delta COMPUTER_{gt}$ are actual coefficients multiplied by 1000. Subscript g indicates the variable available at 2 digit level. Columns (1)-(3) pool differences for 1973-79 and 1979-86 and include a time dummy (fixed effects were insignificant). Column (4) is for 1979-86.

Column (1) of Table 7 reports the estimation of (5′) using just the labour and product-market variables. All four regressors are significant and have signs consistent with previous work. In column (2) we add the three import-price regressors. The basic regressors are still significant**,** but only falls in relative NIC import prices significantly raise $\Delta\log TFP_{it}$. Column (3) includes only relative NIC import and finds the same effect as in column (2). Finally, in column (4) we add computerisation but find an insignificantly positive link with $\Delta\log TFP_{it}$.

Table 8 reports the stage-two estimation results for equation (7) for each of the determinants of ΔlogTFP_{it} in Table 7.

Table 8

Second-Stage Mandated Regressions for Explanatory Variables of ΔlnTFP: estimates of (7)

(dependent variable: predicted ΔlnTFP_{it} from table 7 due to row regressor)

	1970s					1980s					
Regressor:	Innov	CONC	Union	ΔUnion	$\Delta p_{UK}/p_{NICs}$	Innov	CONC	Unio	ΔUnion	$\Delta p_{UK}/p_{NICs}$	ΔComp
$\mathbf{V_s}$	0.61 (5.66)	-0.03 (0.28)	-0.28 (1.80)	-0.24 (1.47)	0.20 (3.14)	0.42 (5.09)	0.10 (2.56)	-0.45 (1.72)	0.20 (1.77)	-0.04 (1.48)	-0.01 NA
$\mathbf{V_u}$	-0.05 (2.48)	0.10 (2.52)	0.18 NA	-0.003 (0.15)	0.04 (1.28)	-0.03 (3.72)	0.06 (3.61)	0.17 NA	-0.01 (1.08)	0.003 (0.53)	0.03 (1.95)
Δ ineq (t)	0.67 (5.36)	-0.13 (1.03)	-0.46 (NA)	-0.24 (1.37)	0.16 (3.14)	0.39 (5.07)	0.04 (0.82)	-.62 (NA)	0.19 (2.18)	-0.04 (1.23)	-0.04 (NA)

Note: Each column reports estimation results for a specification of equation (7) using a different underlying variable multiplied by its coefficient estimate from Table 7. Number of observations are 1973-79=117, 1979-86=121. Number in brackets under V_s and V_u estimates are absolute t statistics corrected for generated regressors, see text. NA denotes cannot calculate standard error due to the generated regressors procedure. Numbers in brackets in final row are absolute t statistics for hypothesis that the rise in inequality is zero. V_k not reported for brevity.

For each underlying variable in each decade we report the mandated change in skilled wages, unskilled wages, and inequality. There are three significant results from Table 8. First, innovations mandated significant rises in inequality over both decades. The intuition is that in both decades the positive effect of innovations on ΔlogTFP_{it} was concentrated in skill-intensive sectors and hence innovations raised inequality. Second, changes in unionisation mandated a significant rise in inequality during the 1980s. The intuition is that the fall in unionisation during the 1980s was concentrated in skill-intensive sectors. This raised ΔlogTFP_{it} in these sectors (from Table 7) and so raised inequality. Third, Δlog(p_{UK}/p_{NIC}) mandated a significant rise in inequality during the 1970s but no significant change during the 1980s. This is somewhat mixed support for the hypothesis that trade-induced TFP growth has raised inequality. Beyond these main results, our other forces had insignificant effects on inequality.

Two other points are worth noting. First, although Table 8 indicates that the sector bias of innovations' effect on $\Delta \log TFP_{it}$ significantly raised inequality during the 1970s and 1980s, Table 5 indicates for these decades that overall $\Delta \log TFP_{it}$ had no significant effect on inequality. These results suggest that other determinants of $\Delta \log TFP_{it}$ outweighed the sector bias of innovations. Second, our results can help think about the consequences of government policy. Policies which influence the determinants of $\Delta \log TFP_{it}$ can contribute to wage changes, e.g., legislation that reduces union power or R&D subsidies which increase innovations. Policies aimed at reducing inequality might need to consider its sectoral effects.

Turning to the price regressions, Table 9 reports stage-one estimates of (6′).

Table 9
First-Stage Regressions for Price Changes: Estimates of (6′)
(dependent variable: $\Delta \ln p_{it}$)

	1	**2**
$\Delta \log p_{OECD}$	-0.001	
	(0.27)	
$\Delta \log p_{\text{Non-OECD}}$	0.0003	
	(0.13)	
$\Delta \log p_{\text{NICS}}$	0.03	0.03
	(2.45)	(2.50)
R^2	0.26	0.49
Number of Obs	256	256

Notes: Both columns pool differences for both 1973-79 and 1979-86 and include a constant, time dummy and fixed effects. Absolute t statistics in brackets. Coefficients on V_k not reported.

Column (1) reports results using all three import-price regressors. As in Table 7, only the NIC import prices have a significant effect: NIC import-price changes are significantly correlated with changes in $\Delta \log p_{it}$. Column (2) omits the other prices and finds the same effect.

Table 10 reports the stage-two estimation results of equation (8) using just NIC import prices as the driving force.

Table 10

Second-Stage Mandated Wage Regressions for Explanatory Variables of Δlog*p*: Estimates of (8)

(dependent variable: predicted $\Delta \ln p_{it}$ from table 9 due to row regressor)

	1970s	**1980s**
Regressand	$\Delta \log p_{NICS}$	$\Delta \log p_{NICS}$
V_s	-0.21	0.07
	(3.57)	(1.38)
V_u	-0.04	0.004
	(1.44)	(0.52)
Mandated Change in Inequality	-0.25	0.07
	(2.69)	(1.21)

Note: Each column reports estimation results for a specification of equation (8) using the a different underlying variable multiplied by its coefficient estimate from Table 9. Number of observations are 1973-79=117, 1979-86=121. Number in brackets under V_s and V_u estimates are absolute t statistics corrected for generated regressors, see text. NA denotes cannot calculate standard error due to the generated regressors procedure. Numbers in brackets in final row are t statistics for hypothesis that the rise in inequality is zero. V_k not reported for brevity.

This table is structured like Table 8, and its message is that the sector bias of import-price changes working through $\Delta \log p_{it}$ mandated a significant decline in inequality during the 1970s but an insignificant rise during the 1980s. Thus, we find some evidence for the 1970s that "trade mattered" through the sector-bias of import-price pressures on domestic prices, but not for the key decade of the 1980s.

4d. Robustness Checks and Discussion of Empirical Results

We carried out a number of robustness checks on the results. First, to explore the role of technical change in inducing price changes, we added $\Delta \log TFP_{it}$ as a regressor in the stage-one price regression (6′) and calculated its implied sector bias in the second stage. Although it was highly significant in explaining prices (coefficient =-.60, t =-11.50) it mandated an insignificant rise in wage inequality in both decades (t=0.27 for the 1970s and 1.55 for the

1980s). This suggests that $\Delta \log TFP_{it}$ did not have significant effects on wage inequality through price changes.

Second, since our data end in 1986 we re-examined the 1980s using a different Census-based data set covering 1980-89 at the three-digit SIC level.[28] We obtained similar results to those above. For the TFP growth equation the estimates (t statistics) on V_s and V_u were 0.22 (0.41) and 0.29 (1.47), which mandates an insignificant fall in inequality (p=0.92). For the price equation, the estimates (t statistics) on V_s and V_u were 0.77 (1.40) and 0.08 (0.40); these mandated rising wage inequality (although insignificantly so, p =0.29).[29]

We also note that our 1980s results are extremely similar to Gregory and Zissimoss (1998). They estimate mandated wage equations for 1979-90 using input-output tables to construct sectors and educational categories to define skills. Like us, they also find that technical change mandated no significant increase in inequality whilst price changes mandated a significant rise. This suggests that our results are robust to our non-manual/manual skills measure.

Haskel and Slaughter (1998) find evidence that SBTC mandated declining U.K. inequality during the 1970s and then rising inequality during the 1980s. The different mandated wage changes for SBTC and $\Delta \log TFP_{it}$ highlight the fact that any observed change in TFP is consistent with many different combinations of factor-biased and factor-neutral technical change. Our SBTC and TFP results suggest that unskilled-biased technical change and/or factor-neutral technical change had different sector biases from SBTC, but more research would be needed to establish this conjecture.[30]

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[28] Because of the major change in SIC codes in 1980, this check addresses both the time span of the 1980s and the concern about measurement error in the OO data introduced by this classification change.

[29] The actual wage change for the skilled is 0.83 which is within the confidence intervals for the net mandated wage change for the skilled is (0.99, 95% confidence intervals 0.68 and 1.31) and for the unskilled the actual change in 0.70 with net mandated 0.36 (0.25, 0.50). It is worth noting that the sector bias of prices mandates a significant rise in inequality 1980-88. Hence over the bulk of the 1980s price changes mandated significant rises in wage inequality.

[30] Desjonques et al (1998) regress $\Delta \log TFP_{it}$ for 16 sectors on *(S/U)* and find no significant relation.

For the United States, Feenstra and Hanson (1998) find that computerisation mandated rising inequality during the 1980s. We do not find any clear wage effect from computers, but we have a much coarser measure than they do. Leamer (1998), reports that U.S. TFP growth mandated rising inequality during the 1960s, 1970s and (less strongly) the 1980s, while price changes mandated rising inequality during the 1970s.

Finally, we should mention that the only regressors in our $\Delta \log p_{it}$ regressions were foreign prices, time dummies and fixed effects. The low R^2 in these regressions suggests they by no means completely explain domestic prices. In future work, we hope to include other trade-related forces such as changes trade barriers.

5. Conclusions

We have attempted to estimate the effects of trade and technology on U.K. wage inequality. To meet the problems in the existing literature we have proposed and implemented a method that (a) calculates the sector bias of prices and technical change, and (b) calculates the parts of prices and technical change due to foreign competition and/or other forces and the contribution of each of these forces to wage inequality.

Our method is based on the production side of Heckscher-Ohlin trade theory. It estimates the wage changes "mandated" by changes in prices and TFP**,** i.e., the wage changes consistent with competitive conditions in the economy. We have a number of findings, but an important result concerning the 1980s was that changes in prices were the major force behind the rise in inequality in the 1980s, not TFP. This result differs from other papers which have not looked at the sector bias of prices and technical change in line with HO underlying theory.

Our results still leave a number of questions unanswered that may provide the basis for future work. First, we have found only a weak link between domestic price changes and international price changes. Without better measures of trade barriers, the extent to which we can ascribe changes in domestic prices as due to some aspect of international trade is still an open question. Second, although our model explains skilled wage changes quite well, we tend to underpredict wage increases of less-skilled workers. This suggests that we need to account better for labour-market institutions and/or the role of supply changes.

Data Appendix

Measurement of technology and prices

Writing out our equations explicitly with our 4 factors of production, N_s, N_u, K and M which are skilled, unskilled labour, capital and materials, TFP is constructed as

$$\Delta \log \boldsymbol{TFP_{it}} = \Delta \log Y_{it} - (\Delta \log \boldsymbol{N_{s,it}} \times V_{s,\, it}) + (\Delta \log \boldsymbol{N_{u,it}} \times V_{u,\, it}) + (\Delta \log \boldsymbol{K_{it}} \times V_{k,\, it}) + (\Delta \log \boldsymbol{M_{m,it}} \times V_{m,it})$$

Second Order Effects

Equation (2) is derived for infinitesimal changes. With discrete changes an extra term appears

$$\Delta \log p_{it} + \Delta \log TFP_{it} = \sum_{j \in J} V_{jit} \Delta \log w_{jt} + \sum_{j \in J} V_{jit} \Delta \log w_{jt} \Delta \log a_{jit}$$

Inserting the extra term into (3) and (4) an re-estimating gives very similar answers to those reported in table 5.

Data from Oulton and O'Mahony (1994)

V_m is the share of intermediate inputs in nominal gross output. N_s and N_u are "administrative, technical and clerical workers" (skilled) and "others", i.e. operatives (unskilled). This corresponds roughly to the US non-production/production split. V_s and V_u are the shares in gross nominal output of each labour group, calculated using the economy-wide skilled and unskilled wage (defined as the cross-sectional average skilled and unskilled wage) times I divided by PY. All shares are average shares by industry over the decade. V_k is calculated as (1-V_s-V_u-V_m) in order that the shares add up to one. To be consistent, K is calculated as V_k*(PY)/p_k where p_k is the capital price deflator from OO. We drop industries from the OO data set outside of manufacturing and those publicly owned for some or all of the period [SIC code and industry: 370 (Shipbuilding), 381 (Motor vehicles), 383 (Aerospace) and 311 (Iron & Steel)]. We do not use OO's TFP data but construct our own for consistency using the formula above; the correlation between the two measures is 0.95.

Other Data

CONC is the five firm concentration ratio, from the Census of Production, various issues. It is multiplied by 1 minus the import penetration ratio (imports/(sales+imports-exports)) with these data from the Census of Production Quarterly Reports. Industries with penetration ratios above 1 were dropped. These are all 3 digit data.

UNION is a two digit measure of union density constructed originally by Bain and Price and updated by Small (1994).

INNOV is a count of significant innovations produced in the sector i, from a survey conducted by the Science Policy Research Unit , for further details see Robson and Townsend (1984) and Geroski et al, (1993). Steve Machin kindly supplied these data. The data was converted to a two digit measure.

Foreign price data are unit value indices of goods supplied to domestic industries by country of origin. These data are on the ISIC basis but there is no official conversion method to UK 1968 SIC basis (which is the OO data). We therefore converted these data to a 2 digit 1968 basis by using the official link to the 1980 UK SIC and then linking the 2 digit 1980 UK SIC to the 2 digit 1968 SIC. We are very grateful to Bob Anderton of the National Institute for kindly supplying us with these data.

ΔCOMPUTER is the change in industry computer intensity derived from a PSI stratified survey of the percentage of establishments replying yes to the question *"are you at present using the new microelectronics technology in your production process?"* PSI publish average use for 10 industries, averaging over sampled establishments, and 1980s difference is computed using changes 1982-87. See Haskel and Heden (1998) for details.

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