Aggregation bias in labour demand equations for the UK economy*

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Introduction

The responsiveness of employment to changes in real wages is an issue of considerable importance, particularly for policy analysis, and over the past decade a number of studies have been devoted to this issue in the UK. Notable examples include the papers by Nickell (1984), Symons (1985), Wren-Lewis (1986), and Burgess (1988) for the manufacturing sector, and by Beenstock and Warburton (1984), Layard and Nickell (1985, 1986) for the private sector and the economy as a whole. In contrast to the earlier work by Godley and Shepherd (1964), Brechling (1965), and Ball and Cyr (1966), these recent studies find a significant and quantitatively important effect for real wages on employment. The point estimates of the long-run wage elasticity obtained in these studies vary widely depending on the coverage of the data (whether the data set used is economy-wide or just manufacturing), and on the specification of the estimated equations. A recent review of these studies by Treasury (1985) concludes that the estimate of long-run wage elasticity most likely falls in the region -0.5 to -1 although, under the influence of Layard and Nickell's important contributions, for the economy as a whole the 'consensus' estimate of this elasticity in the UK currently seems to centre on the figure of -1.[1] All these studies are, however, carried out using highly aggregated data, either at the level of the whole economy or the manufacturing sector, and given the significance of their results for macroeconomic policy it is important that the robustness of their results to the level of aggregation chosen are carefully investigated.

This paper extends the empirical work described in Pesaran et al. (1989) (PPK), and examines the effect of aggregation on the estimates of long-run wage and output elasticities of demand for employment in the UK. The aggregate and the disaggregate employment functions analysed in this paper differ from those in PPK in two respects. First, the functions allow for a longer lagged effect of output on employment. Second, in order to deal with some of the econometric difficulties associated with the use of the time trend as a proxy for technical change in estimating the employment functions,[2] the time trend will be replaced by a measure of embodied technological change based on the current and past movements of *gross* investment, à la Kaldor (1957, 1961). This measure of technological change is both statistically less problematic than a simple time trend and more satisfactory from a theoretical standpoint.

The paper also applies the statistical methods recently developed for the analysis of aggregation by PPK and Lee et al. (1990) (LPP) to employment equations for the UK. Specifically, the aggregation bias in the estimates of the long-run wage and output elasticities will be tested statistically, and the possibility of misspecification of the disaggregate employment equations will be investigated by means of the Durbin-Hausman type test developed in LPP. The adequacy of the aggregate model (relative to

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[1] This consensus estimate is also the same as the figure obtained by Beenstock and Warburton (1984) for their extended data set.

[2] The econometric problems involved in the use of time trends in regression equations containing non-stationary variables are discussed, for example, by Mankiw and Shapiro (1985, 1986), and Durlauf and Phillips (1986).

the disaggregate specification) will also be investigated by means of the goodness-of-fit criteria and the test of perfect aggregation proposed in PPK.

The plan of the paper is as follows. Section 1 sets out the disaggregate employment functions and discusses the theoretical rationale that underlies them. Section 2 motivates the use of a distributed lag function in gross investment as a proxy far technological change. Section 3 reviews the various statistical methods to be applied. Section 4 presents the empirical results, and the final section provides a summary of the main findings of the paper.

1 Industrial employment functions: theoretical considerations

In specifying the employment demand functions we follow the literature on derivation of dynamic factor demand models and suppose that the employment decision is made at the industry level by identical cost minimizing firms operating under uncertainty in an environment where adjustment can be costly. We assume that in the absence of uncertainty and adjustment costs the industry's employment function is given by

$$h_t^* = f(w_t, y_t, a_t) + v_t, \tag{1}$$

where

h_t^* = the desired level of man-hours employment (in logs),
w_t = the real wage rate (in logs),
y_t = the expected level of real demand (in logs),
a_t = an index of technological change,
v_t = mean zero serially uncorrelated productivity shocks.

The actual level of employment, h_t, measured in logarithms of man-hours employed in the industry is then set by solving the following optimisation problem

$$\min_{h_t, h_{t+1}, \dots} \mathrm{E}\left\{ \sum_{\tau=0}^{\infty} \beta^\tau \left[(h_{t+\tau} - h_{t+\tau}^*)^2 + \frac{1}{2}\phi_1(\Delta h_{t+\tau})^2 + \frac{1}{2}\phi_2(\Delta^2 h_{t+\tau})^2 \right] |\Omega_t \right\} \tag{2}$$

where $\Omega_t = (h_t, h_{t-1}, \dots, w_t, w_{t-1}, \dots, y_t, y_{t-1}, \dots, a_t, a_{t-1} \dots, u_t, u_{t-1}, \dots,)$ represents the information set of the firm at time t, Δ is the first difference operator, and $0 \le \beta < 1$ is the real discount factor. The first term in (2) measures the cost of being out of equilibrium, and the second and the third terms stand respectively for the costs of changing the level and the speed with which changes in employment are put into effect. The inclusion of the last term in (2) is proposed in Pesaran (1988) and generalises the familiar adjustment cost-rational expectations models discussed, for example, by Sargent (1978) and Kennan (1979), and is of some interest as it provides a theoretical justification for the inclusion of h_{t-2} in the employment function.[3] In practice, the speed of adjustment coefficients ϕ_1 and ϕ_2 could vary with the state of the labour market as argued, for example, by Smyth (1984) and Burgess (1988). Here, however, we shall assume that they are fixed. The unique solution to the above optimisation problem is derived in Pesaran (1988) and is given by

$$h_t = \psi_1 h_{t-1} + \psi_2 h_{t-2} + \sum_{j=0}^{\infty} \theta_j \, \mathrm{E}(h_{t+j}^* | \Omega_t) \tag{3}$$

where

$$\psi_1 = \mu_1' + \mu_2' > 0, \quad \psi_2 = -\mu_1' \mu_2' < 0, \quad \theta_j = (\mu_1^{-j-1} - \mu_2^{-j-1})/[\phi_2(\mu_2 - \mu_1)]$$

and μ_1, μ_2, μ_1' and μ_2' are the roots of

$$a_2 x^2 + a_1 x + \lambda_1 x^{-1} + \lambda_2 x^{-2} = 1.$$

The reduced-form parameters a_1, a_2, λ_1 and λ_2 are defined in terms of the structural parameters, β, ϕ_1 and ϕ_2 (see, Pesaran (1988)). It is important to note that for plausible values of the structural parameters the theory suggests a negative value for the coefficient of h_{t-2} in (3). Adopting a linear approximation for (1), and assuming that conditional expectations of w_{t+j}, y_{t+j} and a_{t+j} with respect to Ω_t are formed

[3] The inclusion of first or higher order lags of h_t in the employment function can also be justified by appeal to aggregation over different types of labour or firms with different adjustment costs (Nickell (1984)).

rationally on the basis of an rth order vector autoregressive (VAR) system, the decision rule (3) becomes

$$h_t = \text{ intercept } + \psi_1 h_{h-1} + \psi_2 h_{t-2} + \mathbf{c}_{t-1}{}'(L)\mathbf{z}_t + u_t \tag{4}$$

where $u_t = (1-\psi_1-\psi_2)(1-\psi_1/\beta-\psi_2/\beta^2)v_t$, $\mathbf{z}_t = (a_t, y_t, w_t)'$, and $\mathbf{c}_{t-1}(L) = \sum_{i=1}^{r} c_i L^{i-1}$ is a 3×1 vector of lag polynomials of order $r-1$ in the lag operator L. In the case where the variables y_t, w_t and a_t have univariate AR(r_i), $i = y, w, a$ representations, (4) simplifies to

$$h_t = \text{ intercept } + \psi_1 h_{h-1} + \psi_2 h_{t-2} + \left(\sum_{i=1}^{r_y} \gamma_{iy} L^{i-1}\right) y_t + \left(\sum_{i=1}^{r_w} \gamma_{iw} L^{i-1}\right) w_t + \left(\sum_{i=1}^{r_a} \gamma_{ia} L^{i-1}\right) a_t + u_t, \tag{5}$$

which is a generalisation of the aggregate employment function (7.2) in PPK.[4] Under the rational expectations hypothesis (REH), the coefficients c_i in (4), and γ_{iy}, γ_{iw}, γ_{ia} in (5) will be subject to $3r-4$ and $(r_y + r_w + r_a) - 4$ cross-equation restrictions, respectively. However, given our concern with the problem of aggregation, in the present study we do not consider imposing these restrictions, and employ instead the unrestricted version of (5) as our maintained hypothesis.[5] We then choose the orders of the lag polynomials on h_t, y_t, w_t, and a_t empirically. The validity of the RE restrictions at the industry level and the problem of aggregation bias in the context of RE models is beyond the scope of the present paper.

2 Modelling and measurement of technological change

In the empirical analysis of labour demand, technological change, broadly defined to include new scientific, engineering, and electronic discoveries and inventions, is generally assumed to occur exogenously, evolving independently of market conditions and government policy interventions. It is inferred either indirectly as a residual using a production function approach, or is represented by linear, piece-wise linear, or non-linear functions of time. Neither procedure is satisfactory. The former approach, employed, for example, by Layard and Nickell (1985), assumes an *a priori* knowledge of the production possibilities and involves circular reasoning, while the latter is devoid of a satisfactory theoretical rationale and is adopted by most researchers as a 'practical' method of dealing with a very difficult problem (Arrow (1962)).[6]

Ideally, what we need are direct reliable measures of technological change, and there are some data such as expenditure on research and development (R&D) and the number of patents and product designs granted over a given period that can be used. In the absence of suitable direct measures of technological change, here we adopt an indirect approach and following Kaldor (1957, 1961) postulate a distributed lag relationship between the a_t, the technological change index, and the rate of *gross* investment, GI_t,

$$a_t = \text{ intercept } + \sum_{j=0}^{\infty} \lambda_j \log(GI_{t-j}). \tag{6}$$

A static version of this relationship when used in a linear version of (1) yields a log linear approximation to Kaldor's 'technical progress function', which relates the rate of change of productivity per worker to the rate of change of gross investment.[7] According to this model technological progress is 'embodied' in the process of capital accumulation and takes place primarily through gross capital formation by the infusion of new equipment and machines, embodying the most up-to-date technology into the economy. The formulation (6) can also be justified along the lines suggested by Arrow (1962) in his seminal paper on 'learning by doing'. (Arrow, 1962, p. 157) himself uses cumulative gross investment as an index of experience, which is closely related to the distributed lag function in (6).

[4] To derive (7.2) in PPK from (5), let $r_y = r_w = 2$, and notice that when a simple linear trend is used as a proxy for a_t, then $a_t = a_{t-1} + b$, where b is a fixed constant, and

$$\left(\sum_{i=1}^{r_a-1} \gamma_{ia} L^{i-1}\right) a_t = \left(\sum_{i=1}^{r_a-1} \gamma_{ia}\right) a_t - b \sum_{i=1}^{r_a-1} (i-1)\gamma_{ia} = \gamma_a a_t + \text{ constant}.$$

[5] This is similar to the research strategy followed by Nickell (1984) and Burgess (1988).

[6] Notice that the use of time trends in regression equations containing integrated stochastic processes is also subject to important econometric pitfalls and as argued in Mankiw and Shapiro (1985, 1986), and Durlauf and Phillips (1986) can lead to spurious inference.

[7] See in particular (Kaldor and Mirlees, 1962, pp. 176–7). Notice, however, that Kaldor's formulation abstracts from the effect of real wages on labour productivity, while ours does not.

The technological progress function (6) is more than a theoretical postulate. It is also based on direct empirical support. Schmookler (1966) in his pioneering work, using patents as a disaggregate measure of technological change, showed there exist strong positive correlations between gross investment and patents in railroads, petroleum refining, and building industries over the period 1873–1940. He also obtained similar results using cross-section data. While there is some doubt about the direction of causation in Schmookler's findings, there is little dispute about the existence of a close relationship between gross investment and technological change.[8] Since our aim here is not to explain the causes of technological change but to estimate its impact on employment demand, we feel that the controversy over the causality of the investment-patents relationship has little bearing on our analysis.

The coefficients $\lambda_j, j = 1, 2, \ldots$ measure the impact of past investments on the current state of technological advance, and it is reasonable to assume that they are a decreasing function of the lag length, $j = 1, 2, \ldots$. The likely rate of decline of λ_j depends on the importance of the learning-by-doing component of a_t. Under a pure learning story, $\{\lambda_j\}$ will be fixed or show a very slow rate of decline. The rate of decline of $\{\lambda_j\}$ is likely to be much higher if one adopts Kaldor's idea. Here, for the purpose of empirical analysis we assume the following geometrically declining pattern for λ_j

$$\lambda_j = \alpha(1-\lambda)\lambda^j, \quad j = 0, 1, 2, \ldots \quad \alpha, \lambda > 0$$

and write (6) as

$$a_t = \text{ intercept } + \alpha d_t(\lambda) \tag{7}$$

where $d_t(\lambda)$ satisfies the following recursive formula

$$d_t(\lambda) = \lambda d_{t-1}(\lambda) + (1-\lambda)\log(GI_t). \tag{8}$$

Substituting (7) in (5) now yields

$$h_t = \text{ intercept } + \psi_1 h_{t-1} + \psi_2 h_{t-2} + \gamma_y(L)y_t + \gamma_w(L)w_t + \alpha\gamma_a(L)d_t(\lambda) + u_t \tag{9}$$

where $\gamma_y(L)$, $\gamma_w(L)$, and $\gamma_a(L)$ are lag operator polynomials of orders $r_y - 1$, $r_w - 1$ and $r_a - l$, respectively. It is clear that in general α is not identifiable, although the decay coefficient, λ, can in principle be estimated from the data. We shall return to the issue of the estimation of (9) in section 4, but first we briefly review the econometric issues concerning testing for aggregation bias and the relative predictive performance of aggregate and disaggregate models.

3 The aggregation problem: econometric considerations

Suppose that, for a given value of the decay parameter λ, the variables in (9), namely h_t, y_t, w_t, and $d_t(\lambda)$, are observed over the period $t = 1, 2, \ldots, n$ for each of the m firms (industries), $i = 1, 2, \ldots, m$. Then the disaggregate employment equations can be written in matrix notation as

$$H_d: \quad \mathbf{h}_i = \mathbf{X}_i\boldsymbol{\beta}_i + \mathbf{u}_i, \quad i = 1, 2, \ldots, m \tag{10}$$

where $\mathbf{h}_i$ is the $n \times 1$ vector of observations on the log of manhours employment in the ith firm (industry), $\mathbf{X}_i$ is the $n \times k$ $(k = r_y + r_w + r_a + 3)$ matrix of observations on the regressors in (9) for the ith firm (industry). $\boldsymbol{\beta}$ is the $k \times 1$ vector of the coefficients associated with columns of $\mathbf{X}_i$, and $\mathbf{u}_i$ is the $n \times 1$ vector of disturbances for the ith firm (industry). The aggregate equation associated with (9) is given by

$$H_a: \quad \mathbf{h}_a = \mathbf{X}_a\mathbf{b}_a + \mathbf{v} \tag{11}$$

where

$$\mathbf{h}_a = \sum_{i=1}^{m}\mathbf{h}_i. \quad \mathbf{X}_a = \sum_{i=1}^{m}\mathbf{X}_i$$

and $\mathbf{b}_a$ is the $k \times 1$ vector of macro parameters.

The aggregation problem arises when the disaggregate model (10) holds but the investigator decides to base his/her analysis on the aggregate specification (11). The econometric implications of aggregation

[8] For a review of more recent evidence see, for example Beggs (1984) and Baily and Chakrabarti (1985). Notice, however, that Beggs uses wage expenditures as a surrogate for investment data and his results may not be directly comparable to those obtained by Schmookler. On this see the comments by Schankerman (1984) on Beggs's paper.

in linear models have been discussed in the literature in some detail.[9] The principal issues concern the accuracy of predictions and the bias in the parameter estimates. For the analysis of the predictive performance of models (10) and (11), PPK propose using a modified version of the Grunfeld and Griliches criterion which compares the sums of squared errors of predicting $\mathbf{h}_a$ using the aggregate and disaggregate models, adjusting for the differences in the degrees of freedom (see section 4 of PPK). They also propose a test of perfect aggregation which tests the hypothesis that

$$\boldsymbol{\xi} = \sum_{i=1}^{m} \mathbf{X}_i \boldsymbol{\beta}_i - \mathbf{X}_a \mathbf{b} = \mathbf{0}.$$

To test for aggregation bias, two approaches are possible. The first is the method employed in Zellner (1962) and involves testing the micro homogeneity hypothesis

$$H_\beta : \quad \boldsymbol{\beta}_1 = \boldsymbol{\beta}_2 = \cdots = \boldsymbol{\beta}_m.$$

However, as is pointed out in LPP, as a test of aggregation bias this approach is unduly restrictive. Instead they propose testing the hypothesis of zero aggregation bias directly by comparing an average of the estimates of the micro coefficients, or a function thereof, with the aggregate counterpart. In the case of the present study, the parameters of interest are the long-run output and wage elasticities, which, assuming $r_y = r_w = 2$ in (10), are given (in terms of the elements of $\boldsymbol{\beta}_i$) for the ith industry by

$$\epsilon_{iy} = \frac{\beta_{i4} - \beta_{i5}}{1 - \beta i2 - \beta_{i3}}$$

and

$$\epsilon_{iw} = \frac{\beta_{i6} + \beta_{i7}}{1 - \beta i2 - \beta_{i3}}$$

respectively.[10] The null hypothesis we wish to test is that aggregation bias is zero, i.e.

$$\eta_g = \mathbf{g}(\mathbf{b}) = -\frac{1}{m} \sum_{i=1}^{m} \mathbf{g}(\boldsymbol{\beta}_i) = \mathbf{0} \tag{12}$$

where $\mathbf{g}(\boldsymbol{\beta}_i)$ is an $s \times 1$ vector of parameters of interest from the disaggregate model (10) and $\mathbf{g}(\mathbf{b})$ is the corresponding vector from the aggregate model. In the case of our application

$$\mathbf{g}(\boldsymbol{\beta}_i) = (\epsilon_{iy}, \epsilon_{iw})'. \tag{13}$$

Following LPP we distinguish two situations: (i) where $\mathbf{g}(\mathbf{b})$ is given *a priori* (for example by a consensus view) and (ii) where $\mathbf{g}(\mathbf{b})$ is estimated from the aggregate model (11).

Two corresponding statistics are derived

$$q_1^* = \left[\mathbf{g}(\mathbf{b}) - \frac{1}{m} \sum_{i=1}^{m} \mathbf{g}(\widehat{\boldsymbol{\beta}}_i) \right]' \widehat{\boldsymbol{\Omega}}_n^{-1} \left[\mathbf{g}(\mathbf{b}) - \frac{1}{m} \sum_{i=1}^{m} \mathbf{g}(\widehat{\boldsymbol{\beta}}_i) \right] \quad \overset{a}{\sim} \quad \chi_s^2 \tag{14}$$

and

$$q_2^* = n^{-1} \widehat{\boldsymbol{\eta}}_g{}' \widehat{\boldsymbol{\Phi}}_n^{-1} \widehat{\boldsymbol{\eta}}_g \quad \overset{a}{\sim} \quad \chi_s^2 \tag{15}$$

where

$$\widehat{\boldsymbol{\eta}}_g = \mathbf{g}(\widehat{\mathbf{b}}) - \frac{1}{m} \sum_{i=1}^{m} \mathbf{g}(\widehat{\boldsymbol{\beta}}_i) \tag{16}$$

and $\widehat{\boldsymbol{\Omega}}_n$ and$\widehat{\boldsymbol{\Phi}}_n$ are estimated covariance matrices defined in LPP.[11] These tests of aggregation bias assume that the disaggregate model H_d holds and it is important that this assumption is also tested. To this end LPP derive a Durbin-Hausman-type misspecification test which examines the statistical significance of the difference between the estimates of the parameters of the aggregate model based on the disaggregate and aggregate specifications respectively. If this difference turns out to be significant then it is likely that the disaggregate model is misspecified and the aggregation bias tests may be misleading.

[9] See for example Theil (1954), Grunfeld and Griliches (1960), Boot and de Wit (1960), Zellner (1962), Gupta (1971), and Sasaki (1978).

[10] From (5) note that $\boldsymbol{\beta}_i = (\beta_{i1}, \beta_{i2}, \ldots, \beta_{ik})' =$ (intercept, $\psi_{i1}, \psi_{i2}, \gamma_{1y}, \gamma_{2y}, \gamma_{1w}, \gamma_{2w}, \gamma_{1a}, \gamma_{2a}$).

[11] It is recognized that the application of the proposed Wald test may be problematic in finite samples when the restriction set is non-linear since the test is not invariant to the parameterisation of the restrictions. See Gregory and Veall (1985) and LPP.

4 Empirical results

In this section the theoretical considerations on employment functions of sections 1 and 2 and the statistical methods outlined in section 3 are brought together in the estimation of disaggregate and aggregate employment functions for the UK and the analysis of aggregation bias. The data employed are taken from the Cambridge Growth Project Databank, and full details are provided in appendix A. Figures are available annually for the period 1954–84 and, except for some public sector services, the whole of the UK economy is covered, with data provided on a 41-industry basis. As in PPK, industry 4 (mineral oil and natural gas) is excluded from the analysis, and both the disaggregate and the aggregate specifications are based on the remaining 40 industry groups (i.e. $m = 40$). Although our data set starts in 1954, all the equations are estimated over the period 1956–84, and the data for the years 1954 and 1955 are used to generate the lagged values of employment, output, and real wages that are included in the employment function (see equation 9). For the technical change variable $d_t(\lambda)$, we employed the recursive formula given by (8), for $t = 1955, 1956, \ldots, 1984$ and experimented with different methods of initializing the recursive process. We also experimented with different estimates of the decay rate, λ.

4.1 Initialization of the $d_t(\lambda)$ process

We tried two methods for generating the initial value, $d_{1954}(\lambda)$. In one set of experiments we derived $d_{1954}(\lambda)$ assuming that the process generating $\log(GI_t)$ in the pre-1954 period can be characterized by a random walk and that on average $\mathrm{E}[\log(GI_{1954})] = \mathrm{E}[\log(GI_{1953})] = \ldots = \log(\overline{GI})$, where we estimate $\overline{GI}$ by the average of gross investment over the 1954–8 period. Under these assumptions, the estimate of $d_{1954}(\lambda)$, which we denote by $\widehat{d}_{01}$ is given by[12]

$$\widehat{d}_{01} = \log(\overline{GI}). \tag{17}$$

As an alternative procedure we followed the backward forecasting procedure proposed in Pesaran (1973), and derived the following alternative estimate for $d_{1954}(\lambda)$

$$\widehat{d}_{02} = \left\{ \frac{\widehat{\rho}\lambda}{\widehat{\rho} - (1 - \lambda)} \right\} \log(GI_{1954}). \tag{18}$$

This estimate assumes that in the pre-1954 period $\log(GI_t)$ follows the first-order autoregressive process

$$\log(GI_t) = \rho \log(GI_{t-1}) + \epsilon_t, \quad t = 1954, 1953, \ldots$$

and that ρ can be estimated consistently by the OLS method using data over the period 1954–84.

4.2 Estimation of the decay rate parameter, λ

In the initial experiments we assumed a decay rate of $\lambda = 0.10$ and estimated the employment equations under both methods of initializing the $d_t(\lambda)$ process described above. We found that the technological variable, $d_t(\lambda)$ showed significantly in about half of the industries, and of these the majority demonstrated the better fit using $\widehat{d}_{01}$, (i.e. had the larger log likelihood value, LLF) as opposed to $\widehat{d}_{02}$. The difference between LLF obtained in most industries was well below 1, and in only two cases did the difference exceed 2. In both of these $\widehat{d}_{01}$ proved to be the more satisfactory measure. In view of these preliminary results we decided to initialise the $d_t(\lambda)$ process with $\widehat{d}_{01}$. However, we note that, apart from the size of the coefficient on the constant in the estimated equations, there was little qualitative difference between results obtained using either of the two initialization methods.

Using $\widehat{d}_{01}$, we also estimated the industrial employment equations by the grid search method, for values of λ in the range $(0.0, 0.30)$. Again restricting attention to those industries with significant technological change effects, we found for about half of these industries the maximum likelihood estimates of λ fell within this interval, with many of the rest located on the $\lambda = 0.0$ bound. In general, however, we

[12] Notice that

$$d_{1954}(\lambda) = \lambda \sum_{i=0}^{\infty} (1 - \lambda)^i \log(GI_{1954-i})$$

and under $\mathrm{E}[\log(GI_{1954})] = \mathrm{E}[\log(GI_{1953})] = \ldots = \log(\overline{GI})$, we have

$$d_{01} = \mathrm{E}[d_{1954}(\lambda)] = \log(\overline{GI}).$$

found the results to be qualitatively robust to the choice of the decay parameter in the range $(0.0, 0.30)$. In the absence of any strong evidence of a more appropriate estimate of λ, therefore, we decided to maintain our original choice of $\lambda = 0.10$ in the remainder of the empirical work.

4.3 The estimated equations

The most general set of equations that we considered are presented in Table 1. This includes among the explanatory variables two lagged dependent variables, h_{t-1} and h_{t-2}, and current and lagged values of industry output, wages, and technological change (y_t, y_{t-1}, y_{t-2}, w_t, w_{t-1}, d_t, d_{t-1}).[13] This equation follows from the theoretical discussion of sections 1 and 2, by setting $r_y = 3$ and $r_w = r_a = 2$ in (9). Also included in the list of explanatory variables are current and lagged aggregate output measures, $\overline{y}_{ta}$ and $\overline{y}_{t-1,a}$ ($\overline{y}_{ta} = \frac{1}{m}\sum_{i=1}^{m} y_{it}$). These variables were shown to be important in the empirical work of PPK, and it is clearly necessary to consider their influence here also. Their inclusion can be justified on the grounds that agents could use this aggregate information in the formation of their conditional expectations of y_{t+j}, w_{t+j}, which we have shown to be important in explaining current employment. This unrestricted model differs from that in PPK by excluding the time trend, and by including y_{t-2}, d_t and d_{t-1}. Replacing the time trend by d_t and d_{t-1} alone caused a serious deterioration in the performance of many of the industrial equations, and in particular many became unstable. The inclusion of a second lagged output term remedied this in most of the equations, however, and Table 1 represents a satisfactory set of results. The fit of most of the equations is satisfactory, with $\overline{R}^2$ falling below 0.90 only for industry 5 (Petroleum products). Short-run elasticities of employment with respect to wages, employment, and technological change are generally of the expected sign, although as the standard errors of the coefficients (shown in brackets) indicate, the equations are in many cases overparameterised.

For this reason, a specification search was carried out on these equations to obtain a more parsimonious set of results, and these are presented in Tables 2 and 3. Coefficients with t-values less than one (in absolute value) were omitted. Some *a priori* incorrectly signed coefficients were also constrained to zero where the constraints were not violated by the data. Specifically, we expect the coefficients on h_{t-2}, and the long-run wage and technological change effects to be negative. The χ^2 statistic for testing the validity of linear restrictions imposed on the parameters of the unrestricted equations to obtain the results of Table 2 are given in the second column in Table 3. It can be seen that the imposed restrictions are not rejected for any industry, at the conventional levels of significance.

The overall performance of the equations in Table 2 is good and in line with those of PPK. Real wages show up significantly (and negatively) in most industries, with no long-run wage effect found only in industries 22, 33, 37, and 40. The output variable also performed well, showing significantly and positively in all but three industries (6, 20, 38), the last one of which shows a strong positive aggregate output influence. Only fifteen of the industries failed to demonstrate any technological change effects, although there are problem industries (10, 11, 26, 36, and 39) for which the technological change variables are (in sum) incorrectly signed. Other industries with *a priori* implausible parameter estimates include 23, 26, and 31, in which an unexpected positive second lagged dependent variable appears, and industry 25 which is unstable. Industry 20 also remains problematic: the differenced form reported in the PPK paper could not be improved upon, and this equation is retained here.

The histograms in figure 1–3 illustrate the long-run elasticities of employment with respect to industrial output, wages, and technological change as obtained from the results in Table 2. Figure 1 shows the long-run output elasticities for thirty-eight industries, omitting industries 20 and 25; the two industries with incorrectly signed output effects show to the left of the vertical axis, while industry 21 demonstrates an implausibly high positive output elasticity (the equation for this industry has a coefficient on the lagged dependent variable in excess of 0.9). The output elasticities for the bulk of the industries, however, lie within the interval $(0, 1.5)$ and the mean long-run output elasticity is 0.97. The histogram in figure 1 provides a clear illustration of the variability in the responsiveness of employment to output changes across industries, and this is confirmed by a standard deviation around the mean of 0.86. Similar observations can be made on the long-run real wage and technological change elasticities, which have means (standard deviations in brackets), $-0.68(0.66)$, and $-0.41(0.81)$ respectively.

The preferred equations set out in Table 2 show the technological change variable d_t to be an adequate replacement for the time trend in some industries, but not all. Of the twenty-four industrial equations in which a significant time trend was found in PPK, fifteen are improved upon, in terms of the equation standard errors, by their equivalent estimate in Table 2, while nine fit less well in the absence of the

[13] For each industry the technological variable $d_t(\lambda)$, or d_t for short, is computed using (8), with the initial value given by (17) and the decay parameter, $\lambda = 0.10$.

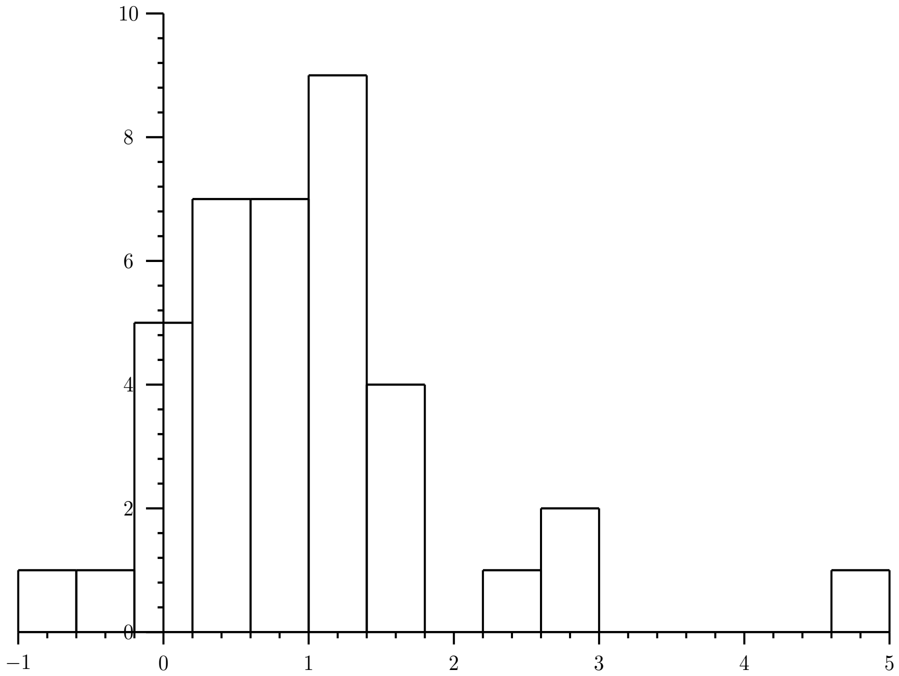

Figure 1: Long-run industry output elasticities from Table 2.

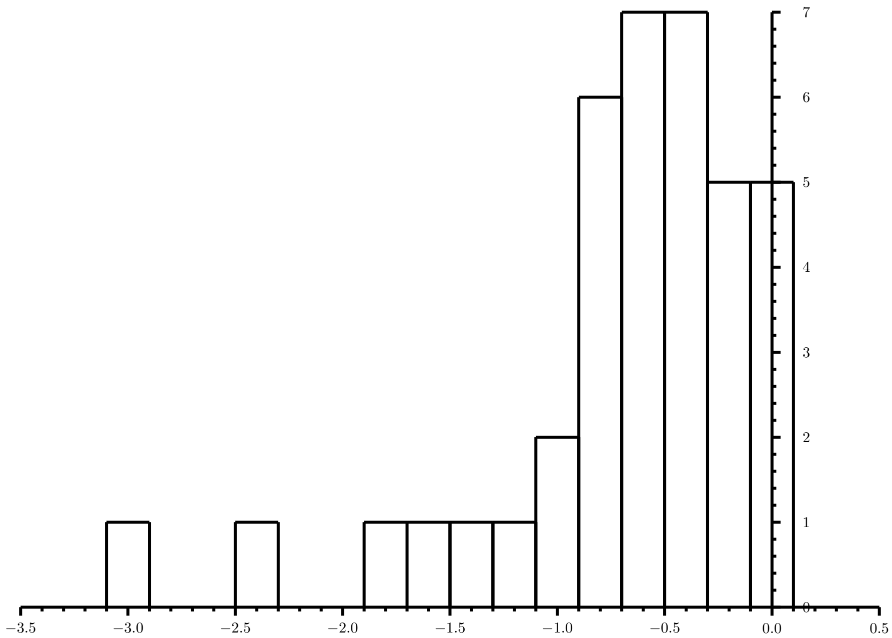

Figure 2: Long-run industry real wage elasticities from Table 2.

time trend. Moreover, there are a further eleven equations which did not previously involve a time trend whose standard error is lower in Table 2 than that in PPK, demonstrating the extra explanatory power of the additional lagged output and technological change variables. Since we prefer to replace a time trend with a variable with a more satisfactory theoretical basis, and given that the fit of this new set of equations is generally higher, these results, taken as a whole, can be seen as an improvement over those obtained previously.

Table 1: Unrestricted industrial labour demand equations

	inpt/40	y_t	y_{t-1}	y_{t-2}	h_{t-1}	h_{t-2}	w_t	w_{t-1}	$\overline{y}_{ta}$	$\overline{y}_{(t-1)a}$	d_t	d_{t-1}	$\overline{R}^2$ (LLF)	$\widehat{\sigma}$
1 Agriculture,etc.	−8.3291	0.3996	0.3135	−0.2215	0.5188	0.0008	−0.5179	0.0399	−0.1477	−0.1409	0.4305	0.3869	0.9982	0.0141
	(101.8650)	(0.1641)	(0.1996)	(0.1442)	(0.2661)	(0.1542)	0.1006	0.1531	(0.1740)	(0.1714)	(0.4127)	(0.3553)	(90.1369)	
2 Coal mining	−99.6098	0.3380	−0.5043	0.1258	1.3944	−0.3702	−0.2331	−0.0772	0.0075	0.1290	−0.4265	0.3679	0.9986	0.0160
	(66.1970)	(0.0499)	(0.0953)	(0.1254)	(0.2044)	(0.2355)	(0.0369)	(0.0777)	(0.1254)	(0.1402)	(0.2022)	(0.2374)	(86.5871)	
3 Coke	−426.9027	0.4256	0.2996	0.1716	0.0496	0.1848	−0.6430	0.0465	0.2449	0.1604	−1.3583	1.8793	09710	0.0906
	(183.1692)	(0.1479)	(0.2329)	(0.2395)	(0.2288)	(0.1285)	(0.1066)	(0.1225)	(0.3889)	(0.4312)	(0.4749)	(0.5582)	(53.1491)	
4 Mineral oil and natural gas														
5 Petroleum	69.7436	0.7333	−0.0163	0.0576	0.6440	−0.0224	−0.4099	0.0223	11.1563	−1.0622	0.5526	−0.6812	0.8841	0.0672
products	(233.7634)	(0.4544)	(0.4349)	(0.2395)	(0.2651)	(0.2815)	(0.1412)	(0.1804)	(0.8680)	(0.8383)	(0.3451)	(0.3579)	(44.8866)	
6 Electricity, etc.	−26.1434	0.0030	0.3339	−0.2057	0.8984	−0.3624	−0.1186	−0.1291	0.0347	0.3182	0.6020	−0.7048	0.9917	0.0155
	(51.5244)	(0.1887)	(0.2605)	(0.1605)	(0.2033)	(0.1964)	(0.0768)	(0.0845)	(01893)	(0.2049)	(0.2725)	(0.2477)	(87.3926)	
7 Public gas	184.9195	−0.1753	0.6582	−0.6325	0.5349	0.0739	−0.3584	0.2904	−0.2904	0.1382	0.2513	−0.1382	0.9779	0.0286
supply	(131.9965)	(0.2299)	(0.2748)	(0.2016)	(0.1630)	(0.2029)	(0.0857)	(0.0858)	(0.2853)	(0.2625)	(0.1922)	(0.2368)	(69.6787)	
8 Water supply	−187.1010	1.0830	0.2506	−0.4169	0.5300	00286	−0.4472	0.3289	−0.0699	0.1324	−2.8566	2.0447	0.9594	0.0309
	(93.4028)	(0.4370)	(0.5354)	(0.4807)	(0.1454)	((1.1480)	(01069)	(0.1258)	(0.3251)	(0.2887)	((1.7126)	(0.5450)	(67.4242)	
9 Minerals and	79.1062	0.2078	−0.0659	−0.1183	0.5591	0.2587	−0.1445	0.0580	−0.5481	0.4380	-0_2124	0.1637	0.9706	0.11351
ores n.e.s.	(171.5604)	(0.1627)	(0.1775)	(0.1319)	(0.2462)	(0.1974)	(0.0952)	(0.1142)	(0.4423)	(0.6235)	(0.3888)	(0.4321)	(63.71109)	
10 Iron and steel	−114.7884	0.3066	0.2143	−0.1191	0.5330	0.1296	−0.1959	−0.0661	0.2340	−0.2408	0.4557	−0.2938	0.9923	0.0284
	(76.2388)	(0.1046)	(0.1108)	(0.1014)	(0.2617)	(0.1655)	(0.1471)	(0.1674)	(0.3665)	(0.3609)	(0.1928)	(0.2185)	(69.8891)	
11 Non-ferrous	−31.6300	0.2543	−0.1371	−0.0952	1.0529	−0.2393	−0.1006	−0.0500	0.6953	−0.6961	0.2762	−0.0547	0.9906	0.0208
metals	(33.2585)	(0.1174)	(0.1294)	(0.1154)	(0.1748)	(0.1712)	(0.0465)	(0.0576)	(0.2225)	(0.1985)	(0.1125)	(0.1306)	(78.8431)	
12 Non-metallic	−412.1530	0.3213	0.0723	−0.1101	0.4784	0.4562	−0.3170	−0.1929	0.5393	0.2921	−0.0472	−0.2831	0.9932	0.0181
mineral products	(163.0320)	(0.1825)	(0.1916)	(0.1668)	(02423)	(0.2947)	(0.1253)	(0.1451)	(0.3488)	(0.4147)	(0.4862)	(0.4049)	(82.9853)	
13 Chemicals and	−185.8193	0.0643	0.0698	−0.0238	0.0445	0.4134	−0.3640	−0.0953	0.3115	0.2586	0.4584	−0.3184	0.9819	0.0146
mm fibres	(45.5295)	(0.1694)	(0.1161)	(0.0925)	(0.2309)	(0.1742)	(0.0978)	(0.1229)	(0.30118)	(0.2523)	(0.2036)	(0.2028)	(89.0752)	
14 Metal goods	54.6916	0.2179	0.0515	−0.1951	0.5656	0.1800	−02192	0.0742	0.1296	−0.2402	1.1805	−1.0864	09893	0.01794
n.e.s.	(125.6380)	(0.1241)	(0.1540)	(01097)	(0.2116)	(0.1728)	(0.1143)	(0.1190)	(0.3236)	(0.3611)	(0.6468)	(0.4716)	(832485)	
15 Mech.	−61.0479	0.4429	−0.2544	0.0449	0.4550	−0.0847	−0.1735	−0.3027	−0.1211	0.4252	0.6855	−0.5910	0.9917	0.0140
engineering	(69.0331)	(0.1756)	(0.1849)	(0.1384)	(0.2231)	(0.2248)	(0.1317)	(0.1531)	(0.1878)	(0.2083)	(0.4794)	(0.5108)	(90.3325)	
16 Office	−469.2709	0.3130	−0.1861	0.2028	1.0064	0.1025	−0.6552	−0.0961	0.4731	0.2497	−0.7454	0.3020	0.9331	0.0272
machinery, etc.	(238.0055)	(0.1262)	(0.1643)	(01074)	(0.2490)	(0.2770)	(0.2125)	(0.2181)	(0.3203)	(0.3034)	(1.1230)	(1.1174)	(71.1734)	
17 Elect.	116.3987	0.3691	−0.0526	0.0530	0.1906	0.1288	−0.2311	0.0905	−0.0759	0.5089	0.5176	−1.3098	0.9894	0.0102
engineering	(26.1750)	(0.0762)	(0.1130)	(0.0950)	(0.1719)	(0.1140)	(0.0838)	(00842)	(0.1322)	(0.1589)	(0.2558)	(0.2954)	(99.4433)	
18 Motor vehicles	−26.1567	0.5670	−0.2497	−0.0747	0.8065	0.0150	0.1033	−0.2076	0.2030	−0.0142	−0.0786	−0.2601	0.9868	0.0191
	(88.6237)	(0.0721)	(0.1452)	(0.1808)	(0.1991)	(0.2676)	(0.1286)	(0.1413)	(0.2125)	(0.2216)	(0.3168)	(0.3650)	(81.3391)	
19 Aerospace	222.3672	0.0106	0.0719	−0.0980	0.8612	−0.3314	−0.0477	−0.1448	−0.2439	02592	−0.0317	−0.6019	0.9837	0.0310
equipment	(112.9182)	(0.0956)	(0.0983)	(0.0900)	(0.2301)	(0.2567)	(0.1001)	(0.1029)	(0.2800)	(0.2864)	(0.5831)	(0.4519)	(67.3423)	
20 Ships and	−234.0763	0.5828	−0.1889	−0.3240	1.0843	0.1554	0.0276	0.0009	0.8235	−0.4509	−0.8088	0.8595	0.9881	0.0261
other vessels	(75.5925)	(0.1078)	(0.1700)	(0.1530)	(0.1868)	(02188)	(0.0654)	(0.0839)	(0.2530)	(0.2490)	(0.5227)	(0.3407)	(72.3533)	
21 Other vehicles	−168.3526	0.2968	0.1114	−0.0248	1.0604	−0.1252	−0.1545	0.1153	0.2878	−0.1187	0.9568	−0.8510	0.9968	0.0262
	(135.2829)	(0.1062)	(0.1206)	(0.1278)	(0.2377)	(0.2950)	(0.0741)	(0.0652)	(0.2332)	(0.2443)	(0.4453)	(0.3900)	(72.1643)	

(continued)

Table 1: Unrestricted industrial labour demand equations (contd.)

	inpt/40	y_t	y_{t-1}	y_{t-2}	h_{t-1}	h_{t-2}	w_t	w_{t-1}	$\overline{y}_{ta}$	$\overline{y}_{(t-1)a}$	d_t	d_{t-1}	$\overline{R}^2$ (LLF)	$\widehat{\sigma}$
22 Instr.	467.8993	0.0551	0.1219	0.3384	0.2943	−0.2474	−0.1954	0.2810	−0.0956	0.1420	0.9770	−2.4352	0.9727	0.0155
engineering	(122.7449)	(0.1390)	(0.1263)	(0.1302)	(0.1752)	(0.1310)	(0.0850)	(0.0897)	(0.2179)	(0.2458)	(0.4345)	(0.5578)	(87.4193)	
23 Manufactured	−96.1864	0.7245	−0.3829	0.1395	0.4446	0.2049	−0.1728	−0.0398	−0.0032	0.2371	0.6892	−1.0381	0.9862	0.0151
food	(138.7636)	(0.3199)	(0.2337)	(0.2045)	(0.1915)	(0.1648)	(0.0757)	(0.1034)	(0.1593)	(0.1614)	(0.4081)	(0.3510)	(88.2687)	
24 Alcoholic	−106.2884	0.4993	0.0207	−0.3969	1.0974	−0.1643	−0.1113	0.0734	0.0755	0.2879	−0.5152	0.2831	0.9033	0.0301
drinks, etc.	(190.7833)	(0.5409)	(0.5076)	(0.5117)	(0.2355)	(0.3246)	(0.1279)	(0.1178)	(0.6244)	(0.4363)	(0.6288)	(0.5310)	(68.1601)	
25 Tobacco	150.5910	1.3370	−0.4851	−0.5259	0.6519	1.0220	0.0061	−0.1805	−2.0127	0.0303	1.6853	−0.6736	0.8996	0.0454
	(238.0243)	(0.4483)	(04499)	(0.4688)	(0.2606)	(0.3253)	(0.0687)	(0.0846)	(0.5811)	(0.5378)	(0.9638)	(0.7384)	(56.2608)	
26 Textiles	−163.5445	0.4008	0.0199	−0.3391	0.3040	0.1939	−0.4269	−0.1452	0.2241	0.1107	−0.1934	0.5008	0.9984	0.0160
	(110.9788)	(0.1809)	(0.1746)	(0.1335)	(0.2162)	(0.1579)	(0.0869)	(0.1585)	(0.2388)	(0.3882)	(0.3831)	(0.3380)	(86.4858)	
27 Clothing and	−50.6793	0.5050	0.0437	−0.0218	0.5797	−0.0361	−0.4216	0.0527	−0.1067	−0.0706	−0.0193	0.1237	0.9980	0.0123
footwear	(62.0796)	(0.1060)	(0.1899)	(0.1111)	(0.2890)	(0.1783)	(0.0871)	(0.1505)	(0.1944)	(0.1993)	(0.3359)	(0.2419)	(94.1785)	
28 Timber and	57.3350	0.2824	0.0633	0.0163	0.3392	0.0730	−0.2734	0.0580	0.0904	−0.0689	0.3085	−0.4176	0.9851	0.0145
furniture	(83.7562)	(0.1185)	(0.1490)	(0.1127)	(0.2469)	(0.1428)	(0.0935)	(0.0981)	(0.2622)	(0.3858)	(0.3788)	(0.3563)	(89.4445)	
29 Paper and	92.5460	0.1240	0.1082	0.0645	0.3571	0.3316	−0.1795	0.1637	0.4807	0.1567	0.1453	−1.5894	0.9942	00171
board	(49.1811)	(0.2041)	(0.1692)	(0.7207)	(0.2419)	(0.1362)	(0.0769)	(0.1279)	(03626)	(0.3013)	(0.4445)	(0.4768)	(84.5039)	
30 Books, etc.	116.8745	0.2547	0.0013	−0.0353	0.8079	−0.2086	−0.0864	−0.0626	−0.1167	−0.2457	0.7865	−0.5611	0.9427	0.0112
	(38.6891)	(0.1161)	(0.1355)	(0.0777)	(0.2747)	(0.2297)	(0.0590)	(0.0617)	(0.1828)	(0.1840)	(0.3149)	(0.2934)	(96.8764)	
31 Rubber and	−114.0693	0.3664	−0.0228	−0.3178	0.4959	0.3564	−0.2941	0.0733	0.0953	0.0950	0.1452	0.0405	0.9795	0.0183
plastic pr.	(68.7654)	(0.2515)	(0.2248)	(0.1387)	(0.2956)	(0.2238)	(0.2183)	(0.1284)	(0.4141)	(0.4318)	(0.7177)	(06053)	(82.5569)	
32 Other	157.9064	0.3169	0.0061	0.0167	0.6974	−0.0339	−0.1025	0.0520	0.1378	−0.6710	0.5953	−0.4945	0.9918	0.0136
manufactures	(71.7964)	(0.0739)	(0.1356)	(0.1194)	((0.1986)	(0.2011)	(0.0938)	(0.0909)	(0.2044)	(0.2084)	(0.2537)	(0.1999)	(91.1621)	
33 Construction	0.1708	03346	−0.4336	0.16*s*0	1.1032	−0.2506	−0.3106	0.4361	0.3935	0.0579	−0.4806	0.1353	0.9804	0.0142
	(72.0577)	(0.1097)	(0.1464)	(0.0958)	(0.1785)	(0.1212)	(0.0893)	(0.1073)	(0.1970)	(0.1980)	(0.3877)	(0.3364)	(89.9104)	
34 Distribution. etc.	165.8094	−0.0730	0.6536	−0.1662	0.7386	−0.2110	−0.1118	−0.0537	−0.0828	−0.5416	0.6452	−0.4648	0.9548	0.0148
	(89.2530)	(0.2295)	(0.3158)	(0.1553)	(0.2320)	(0.1739)	(0.1285)	(0.1296)	(0.1893)	(0.2338)	(0.5798)	(0.4992)	(88.7516)	
35 Hotels and	42.4162	0.3120	0.3603	−0.2291	0.5370	0.0360	−0.3282	0.1610	−0.0757	−0.1791	−0.1462	0.2173	0.8996	0.0218
catering	(100.6322)	(0.2517)	(0.4124)	(0.3271)	(0.3275)	(0.2834)	(0.1593)	(0.1738)	(0.2217)	(0.2135)	(0.3011)	(0.2850)	(77.6065)	
36 Rail transport	120.7537	0.3027	0.4311	−0.0013	0.4013	−0.1819	−0.1381	0.0703	−0.1976	−0.3762	1.1548	−0.7263	0.9979	0.0170
	(103.6322)	(0.1210)	(0.1312)	(0.1354)	(0.1979)	(0.1413)	(0.1133)	(0.1043)	(0.2297)	(0.2246)	(0.2405)	(0.1962)	(84.8173)	
37 Other land	191.4749	−0.0685	0.2417	−0.2581	0.9714	−0.3262	0.0266	0.0380	0.0908	−0.0147	0.3518	−0.4643	0.9740	0.0165
transport	(77.5060)	(0.1657)	(0.1952)	(0.1712)	(0.2405)	(0.2238)	(0.0591)	(0.0650)	(0.1671)	(0.1733)	(0.2886)	(0.2605)	(85.5580)	
38 Sea, air and other	63.4575	0.2006	−0.5254	−0.1053	1.1557	−0.5003	−0.2569	0.2130	−0.0463	0.6873	−0.3834	0.3880	0.9196	0.0224
	(132.3929)	(0.1897)	(0.2355)	(0.1519)	(0.2143)	(0.2906)	(0.1420)	(0.1521)	(0.2573)	(0.3391)	(0.4332)	(0.3686)	(76.7924)	
39 Communications	259.2154	0.5147	−0.4403	−0.2152	0.6941	−0.3138	−0.1371	0.1954	−0.1709	0.1549	0.7280	−0.5472	0.9416	0.0174
	(52.3347)	(0.2695)	(0.4696)	(0.3093)	(0.2071)	(0.2094)	(0.1147)	(01024)	(0.2188)	(0.1711)	((0.3443)	(0.2974)	(84.0346)	
40 Business services	354.3580	0.0441	0.1689	−0.1074	0.3361	−0.1646	0.0769	−0.1400	−0.0283	−0.2971	0.9987	−0.7970	0.9942	0.0125
	(95.7801)	((0.1496)	(0.1514)	(0.1404)	(0.2678)	(0.2481)	(0.0859)	(0.0039)	(0.1137)	(0.1173)	(0.3955)	(0.3127)	(93.5970)	
41 Miscell. services	−248.5543	0.4159	−0.2700	0.2990	1.0218	0.0167	−0.2817	0_1537	0.0955	0.1960	−0.1665	−0.1150	0.9483	0.0229
	(145.5570)	((0.1826)	(0.1973)	(0.1843)	(0.2370)	(0.2849)	(0.1605)	(0.1468)	(0.2302)	(0.2065)	(0.4956)	(0.4013)	(76.1713)	

Notes: $\widehat{\sigma}$ is equation standard error. LLF is the maximized value of log-likelihood function. Standard errors in brackets, $\overline{R}^2$ = is adjusted multiple correlation coefficient. n.e.s. - not elsewhere specified

Table 2: Restricted industrial labour demand equations

	inpt/40	y_t	y_{t-1}	y_{t-2}	h_{t-1}	h_{t-2}	w_t	w_{t-1}	$\overline{y}_{ta}$	$\overline{y}_{(t-1)a}$	d_t	d_{t-1}
1 Agriculture, etc.	5.9025	0.4080	0.3215	−0.1981	0.4782		−0.5134		−0.3886			
	(57.5851)	(0.0338)	(0.1440)	(0.1169)	(0.0669)		(0.0836)		(0.0480)			
2 Coal mining	−24.6379	0.2845	−0.4268	1.3624	−0.4332	−0.2194					−0.1226	
	(10.1993)	(0.0499)	(0.0716))	(0.0957)	(0.1359)	(0.1680)	(0.0297)				(0.0326)	
3 Coke	−81.9147	0.3733	0.5137		0.1876		−0.4294		−0.1354		−14606	1.4606
	(66.9629)	(0.1351)	(0.2122)		(0.1151)		(0.0790)		(0.1158)		(0.4225)	(0.4225)
4 Mineral oil and nat. gas												
5 Petroleum products	−92.6973	0.3475			0.7915		−0.2882				0.3281	−0.5234
	(88.2755)	(0.1847)			(0.1253)		(0.1086)				(0.2698)	(0.2702)
6 Electricity, etc.	42.7381		0.5112	−0.3648	1.1202	−0.4619	−0.1490				0.2793	−0.3007
	(26.8282)		(0.1342)	(0.1475)	(0.1862)	(0.1803)	(0.0746)				(0.2408)	(0.2702)
7 Public gas supply	112.7709		0.4662	−0.5338	0.6934		−0.2975	0.2300				
	(44.4602)		(0.1803)	(0.1653)	(0.1060)		(0.0681)	(0.0774)				
8 Water supply	−167.9418	1.4846			0.4752		−0.4094	0.1846			−3.0775	2.4681
	(62.5607)	(0.3476)			(0.1039)		(0.0976)	(0.1085)			(0.6623)	(0.5508)
9 Minerals and ores nes	172.9158	0.2655			0.6931		−0.1494		−0.5337			
	(79.1246)	(0.1265)			(0.0790)		(0.0622)		(0.2560)			
10 Iron and steel	−155.7089	0.3796	0.1997		0.5533		−0.3402					0.1489
	(20.5070)	(0.0562)	(0.0711)		(0.0854)		(0.0596)					(0.0636)
11 Non-ferrous metals	−21.3448	0.2912	−0.1825		1.0929	−0.3288	−0.1061	−0.0520	0.6320	−0.7019	0.2278	
	(27.8342)	(0.1040)	(0.1138)		(0.1544)	(0.1229)	(0.0439)	(0.0496)	(0.2043)	(0.1920)	(0.0572)	
12 Non-metallic min. pr.	−236.8126	0.3842			0.8437		−0.2505	−0.1262	0.3674			−0.2609
	(65.3042)	(0.1125)			(0.0450)		(0.1029)	(0.1188)	(0.2118)			(0.1336)
13 Chemicals and mm fibres	−99.1032				0.5831		−0.2735		0.5764		0.2720	−0.2720
	(28.1020)				(0.0710)		(0.0329)		(0.0769)		(0.1678)	(0.1678)
14 Metal goods nes	−51.0504	0.2663			0.6006		−0.2335		0.2716		0.4410	−0.6038
	(67.1158)	(0.1006)			(0.0653)		(0.0763)		(0.2663)		(0.3831)	(0.3240)
15 Mech. engineering	−101.2153	0.4909	−0.3408	0.1184	0.5996	−0.2925	−0.1979	−0.3348		0.4802		
	(51.8451)	(0.0750)	(0.1484)	(0.0960)	(0.2087)	(0.1792)	(0.1133)	(0.1163)		(0.1746)		
16 Office machinery etc.	−67.1178			0.2278	0.8571		−0.2389		0.2548		1.0366	−1.5206
	(75.6691)			(0.0600)	(0.0721)		(0.1049)		(0.1399)		(0.5489)	(0.5314)
17 Elect. engineering	106.1219	0.3463			0.3886		−0.2592	0.1351		0.3684	0.2694	−0.9762
	(25.5818)	(0.0462)			(0.0646)		(0.0771)	(0.0637)		(0.1099)	(0.1979)	(0.2051)
18 Motor vehicles	−74.0164	0.5451	−0.2618		0.8395	−0.1165		−0.2102	0.2625		−0.2471	
	(48.8105)	(0.0470)	(0.1197)		(0.1614)	(0.0909)		(0.0666)	(0.1099)		(0.0892)	
19 Aerospace equipment	246.9802				1.1388	−0.6421		−0.1737			−0.6598	
	(75.2084)				(0.1495)	(0.1727)		(0.0720)			(0.2197)	
20 Ships and other vessels	−0.7667	0.4809	−0.4809		1.4717	−0.4717			0.5103	−0.5103		
	(0.3086)	(0.1171)	(0.1171)		(0.1543)	(0.1543)			(0.2000)	(0.2000)		
21 Other vehicles	−165.4705	0.3896			0.9154		−0.1680	0.1064	0.2078		0.7687	−0.7687
	(58.7346)	(0.0706)			(0.0419)		(0.0552)	(0.0564)	(0.1235)		(0.3109)	(0.3109)

(continued)

Table 2: Restricted industrial labour demand equations (contd.)

	inpt/40	y_t	y_{t-1}	y_{t-2}	h_{t-1}	h_{t-2}	w_t	w_{t-1}	$\overline{y}_{ta}$	$\overline{y}_{(t-1)a}$	d_t	d_{t-1}
22 Instr. engineering	423.2630		0.2115	0.3539	0.3177	−0.2486	−0.2377	0.2377			1.2396	−2.6097
	(55.7285)		(0.0825)	(0.0987)	(0.1267)	(0.1064)	(0.0581)	(0.0581)			(0.3043)	(0.3537)
23 Manufactured food	−172.9101	0.5982			0.4844	0.3037	−0.2337				0.6483	−0.8005
	(63.0103)	(0.1660)			(0.1266)	(0.1327)	(0.0498)				(0.3462)	(0.3177)
24 Alcoholic drinks, etc.	−96.0446				1.1312	−0.3072	−0.0956		0.4479			−0.1047
	(69.2247)				(0.1750)	(0.2359)	(0.0705)		(0.1457)			(0.0868)
25 Tobacco	155.5488	1.3459	−0.4827	−0.5240	0.6473	1.0209		−0.1781	−2.0136		1.7244	−0.6987
	(182.3643)	(0.4049)	(0.4058)	(0.3982)	(0.2205)	(0.2796)		(0.0668)	(0.5337)		(0.6965)	(0.6201)
26 Textiles	−69.3333	0.3637		−0.2759	0.5652		−0.4337		0.0882			0.2960
	(39.2933)	(0.0675)		(0.0871)	(0.0657)		(0.0753)		(0.1207)			(0.1265)
27 Clothing and footware	−68.9489	0.4514			0.5364		−0.3756					
	(11.9600)	(0.0372)			(0.0411)		(0.0284)					
28 Timber and furniture	27.5732	0.3925			0.5144		−0.2885	0.1108			−0.1174	
	(13.7004)	(0.0352)			(0.0572)		(0.0595)	(0.0681)			(0.0282)	
29 Paper and board	39.4291	0.4375	0.1880		0.4661		−0.2130					−0.5252
	(31.8083)	(0.0640)	(0.0929)		(0.0659)		(0.0477)					(0.1523)
30 Books, etc.	96.1742	0.4094	−0.2040		1.3273	−0.6121	−0.0578		−0.2125			
	(32.3071)	(0.0946)	(0.0681)		(0.1955)	(0.1602)	(0.0477)		(0.1434)			
31 Rubber and plastic pr.	−81.7005	0.4581		−0.2463	0.5365	0.3160	−0.2692					
	(16.8687)	(0.0427)		(0.0729)	(0.1198)	(0.1195)	(0.0700)					
32 Other manufactures	56.9103	0.2992			0.7367		−0.0805		0.4048	−0.6459		
	(51.0746)	(0.0602)			(0.0902)		(0.0810)		(0.1692)	(0.1125)		
33 Construction	3.3516	0.3475	−0.3710	0.1345	0.9814	−0.2355	−0.3435	0.3435	0.3916		−0.2830	
	(27.4087)	(0.0858)	(0.1167)	(0.0835)	(0.0957)	(0.0955)	(0.0704)	(0.0704)	(0.1500)		(0.0705)	
34 Distribution. etc.	141.2744		0.7842	−0.2726	0.6360		−0.0409			−0.5717		
	(41.2202)		(0.1615)	(0.1207)	(0.0917)		(0.0356)			(0.1527)		
35 Hotels and catering	−58.7494	0.3544			0.7096		−0.3876	0.1959				
	(44.4425)	(0.1150)			(0.1022)		(0.1191)	(0.1094)				
36 Rail transport	−50.9886	0.1307	0.3372		0.5187		−0.2545				0.8608	−0.6958
	(25.3141)	(0.0894)	(0.1055)		(0.0978)		(0.0718)				(0.2211)	(0.1953)
37 Other land transport	118.4359		0.2123	−0.2016	1.003	−0.2638					0.4509	−0.5162
	(34.6439)		(0.1302)	(0.1434)	(0.1803)	(0.1884)					(0.2304)	(0.1937)
38 Sea, air and other	67.2451	0.1608	−0.3506		1.2952	−0.6002	−0.2432	0.1835		0.3148		
	(92.1103)	(0.1269)	(0.1263)		(0.1460)	(0.1863)	(0.1204)	(0.1255)		(0.1521)		
39 Communications	309.7212				0.5777	−0.4744	−0.0937	0.0860			1.0539	−0.9139
	(57.1105)				(0.1677)	(0.1616)	(0.0631)	(0.0664)			(0.2010)	(0.1745)
40 Business services	209.6513	0.3108			0.6781	−0.3104				−0.1633		
	(49.1545)	(0.0718)			(0.1759)	(0.1680)				(0.0486)		
41 Miscell. services	−39.9043	0.2123			0.8264		−0.1408					
	(33.3057)	(0.0790)			(0.0970)		(0.0747)					

Notes: See notes to Table 1.

Table 3: Summary and diagnostic statistics for the restricted employment equations of Table 2

Industry	$\overline{R}^2$	χ^2_r	$\widehat{\sigma}$	$\chi^2_{SC}(1)$	$\chi^2_{FF}(1)$	$\chi^2_N(2)$	$\chi^2_H(1)$
1 Agriculture, etc.	0.9983	5.00 (5)	0.0136	0.08	5.96	0.02	0.06
2 Coal mining	0.9987	4.02 (4)	0.0155	0.00	0.25	1.18	0.32
3 Coke	0.9656	10.10 (5)	0.0551	0.00	13.82	0.50	2.96
4 Mineral oil and nat. gas	—	—	—	—	—	—	—
5 Petroleum products	0.8874	6.94 (6)	0.0663	0.00	1.89	1.93	0.33
6 Electricity, etc.	0.9909	7.59 (4)	0.0163	1.08	1.26	0.22	2.58
7 Public gas supply	0.9773	8.14 (6)	0.0290	4.60	1.11	4.12	5.42
8 Water supply	0.9520	10.06 (5)	0.0336	0.01	0.38	0.71	0.00
9 Minerals and ores nes	0.9760	3.84 (7)	0.0318	1.36	0.16	32.70	0.00
10 Iron and steel	0.9919	8.63 (6)	0.0291	0.20	4.59	2.08	0.77
11 Non-ferrous metals	0.9912	1.31 (2)	0.0202	4.25	2.19	2.75	0.05
12 Non-metallic min. pr.	0.9937	4.82 (5)	0.0174	1.82	4.70	2.09	4.48
13 Chemicals and mm fibres	0.9808	9.67 (7)	0.0151	4.76	3.53	1.65	1.29
14 Metal goods nes	0.9898	5.39 (5)	0.0174	0.21	5.96	1.69	4.74
15 Mech. engineering	0.9916	4.60 (3)	0.0141	0.17	0.21	0.02	1.09
16 Office machinery, etc.	0.9291	7.85 (5)	0.0280	0.38	1.10	0.76	4.48
17 Elect. engineering	0.9893	5.82 (4)	0.0103	1.79	0.01	0.41	1.12
18 Motor vehicles	0.9887	1.43 (4)	0.0176	4.16	0.88	1.55	1.58
19 Aerospace equipment	0.9847	7.20 (7)	0.0301	3.56	1.04	0.06	2.78
20 Ships and other vessels	0.9818	16.13 (8)	0.0323	0.45	0.61	0.40	4.46
21 Other vehicles	0.9972	2.85 (5)	0.0243	0.90	2.10	0.33	2.59
22 Instr. engineering	0.9759	2.44 (4)	0.0146	1.57	1.29	2.14	1.02
23 Manufactured food	0.9856	7.50 (5)	0.0154	0.43	0.48	6.76	2.46
24 Alcoholic drinks, etc.	0.9119	5.49 (6)	0.0288	0.10	1.43	0.71	3.57
25 Tobacco	0.9101	0.02 (2)	0.0430	4.95	16.07	0.09	0.04
26 Textiles	0.9985	5.09 (5)	0.0155	4.21	2.46	2.20	2.03
27 Clothing and footwear	0.9984	4.32 (8)	0.0110	0.36	1.92	0.62	0.03
28 Timber and furniture	0.9873	3.76 (6)	0.0133	0.08	3.73	0.91	0.85
29 Paper and board	0.9932	10.81 (6)	0.0186	5.30	0.14	1.73	6.16
30 Books, etc.	0.9341	9.52 (5)	0.0120	1.76	0.00	0.00	1.13
31 Rubber and plastic pr.	0.9834	2.51 (6)	0.0165	0.14	2.45	0.50	0.01
32 Other manufactures	0.9908	9.82 (6)	0.0144	0.22	0.37	1.11	0.02
33 Construction	0.9819	2.42 (3)	0.0137	0.02	0.10	0.73	0.27
34 Distribution, etc.	0.9603	4.63 (6)	0.0139	0.32	1.96	0.23	2.47
35 Hotels and catering	0.9169	4.17 (7)	0.0198	0.58	1.88	0.45	0.63
36 Rail transport	0.9975	9.84 (5)	0.0183	0.03	0.38	2.66	0.86
37 Other land transport	0.9766	4.12 (5)	0.0157	0.13	0.98	1.02	0.02
38 Sea, air and other	0.9278	2.87 (4)	0.0212	2.23	7.95	1.88	0.91
39 Communications	0.9388	7.59 (5)	0.0178	0.53	1.51	1.16	4.09
40 Business services	0.9940	9.26 (7)	0.0128	0.98	2.01	1.98	0.17
41 Miscell. services	0.9512	8.14 (8)	0.0222	0.06	0.47	0.39	191

Notes:

$\widehat{\sigma}$ is the equation standard error. $\overline{R}^2$ is the adjusted multiple correlation coefficient.

χ^2_r is the chi-squared statistic for the test of r linear restrictions on the parameters of unrestricted employment equations (see Table 1). The value of r is given in brackets after the statistic.

$\chi^2_{SC}(1)$ is the first order LM test of residual serial correlation. $\chi^2_N(2)$ is a test of normality of the errors. $\chi^2_{FF}(1)$ is Ramsey's RESET test of order 1. $\chi^2_H(1)$ is a heteroscedasticity test of order 1.

The underlying regressions and the test statistics reported in this table are computed in the Microfit package. For details of relevant algorithms and references, see Pesaran and Pesaran (1987).

Table 4: Composite restricted industrial labour demand equations

	inpt/40	y_t	y_{t-1}	y_{t-2}	h_{t-1}	h_{t-2}	w_t	w_{t-1}	$\overline{y}_{ta}$	$\overline{y}_{(t-1)a}$	d_t	d_{t-1}	T_t
1 Agriculture, etc.	5.9025	0.4080	0.3215	−0.1981	0.4782		−0.5134		−0.3886				
	(57.5851)	(0.0338)	(0.1440)	(0.1169)	(0.0669)		(0.0836)		(0.0480)				
2 Coal mining	−24.6379	0.2845	−0.4268	1.3624	−0.4332	−0.2194					−0.1226		
	(10.1993)	(0.0499)	(0.0716))	(0.0957)	(0.1359)	(0.1680)	(0.0297)				(0.0326)		
3 Coke	−351.5712		0.6330				−0.3005		1.0448				−1.3100
	(44.6561)		(0.1471)				(0.0418)		(0.1564)				(0.1752)
4 Mineral oil and nat. gas													
5 Petroleum products	−70.7059	0.3640			0.5185		−0.3144						−0.5087
	(71.7711)	(0.1324)			(0.1348)		(0.0869)						(0.1297)
6 Electricity, etc.	42.7381		0.5112	−0.3648	1.1202	−0.4619	−0.1490				0.2793	−0.3007	
	(26.8282)		(0.1342)	(0.1475)	(0.1862)	(0.1803)	(0.0746)				(0.2408)	(0.2702)	
7 Public gas supply	−47.7381		0.0611		0.4191		−0.1507		0.5379				−0.6014
	(97.2188)		(0.0659)		(0.1524)		(0.0496)		(0.1827)			(0.1995)	
8 Water supply	−167.9418	1.4846			0.4752		−0.4094	0.1846			−3.0775	2.4681	
	(62.5607)	(0.3476)			(0.1039)		(0.0976)	(0.1085)			(0.6623)	(0.5508)	
9 Minerals and ores nes	172.9158	0.2655			0.6931		−0.1494		−0.5337				
	(79.1246)	(0.1265)			(0.0790)		(0.0622)	(0.2560)					
10 Iron and steel	−349.9558	0.1083			0.4978		−0.3873		1.1803				−0.9045
	(58.8686)	(0.0893)			(0.0832)		(0.0777)		(0.2928)				(0.2732)
11 Non-ferrous metals	−84.8257	0.1817	−0.3091		1.2461	−0.4796	−0.0756	0.0756	0.5854				−0.5749
	(30.7245)	(0.1286)	(0.1273)		(0.1458)	(0.1229)	(0.0481)	(0.0481)	(0.1789)				(0.1517)
12 Non-metallic min. pr.	−280.5702	0.3101			0.6919		−0.2356	−0.2214	0.5170				−0.3729
	(60.6439)	(0.1511)			(0.0877)		(0.1075)	(0.0959)	(0.2901)				(0.2148)
13 Chemicals and mm fibres	−125.0557				0.6205		−0.2810		0.6049				
	(23.8339)				(0.0693)		(0.0337)		(0.0773)				
14 Metal goods nes	−32.2448	0.4365			0.5798		−0.1671						−0.1231
	(25.5280)	(0.0444)			(0.0542)		(0.0817)						(0.0976)
15 Mech. engineering	−101.2153	0.4909	−0.3408	0.1184	0.5996	−0.2925	−0.1979	−0.3348		0.4802			
	(51.8451)	(0.0750)	(0.1484)	(0.0960)	(0.2087)	(0.1792)	(0.1133)	(0.1163)		(0.1746)			
16 Office machinery etc.	−67.1178			0.2278	0.8571		−0.2389		0.2548		1.0366	−1.5206	
	(75.6691)			(0.0600)	(0.0721)		(0.1049)		(0.1399)		(0.5489)	(0.5314)	
17 Elect. engineering	106.1219	0.3463			0.3886		−0.2592	0.1351		0.3684	0.2694	−0.9762	
	(25.5818)	(0.0462)			(0.0646)		(0.0771)	(0.0637)		(0.1099)	(0.1979)	(0.2051)	
18 Motor vehicles	−74.0164	0.5451	−0.2618		0.8395	−0.1165		−0.2102	0.2625		−0.2471		
	(48.8105)	(0.0470)	(0.1197)		(0.1614)	(0.0909)		(0.0666)	(0.1099)		(0.0892)		
19 Aerospace equipment	200.3920	0.0732			0.7560	−0.4659		−0.1252					−0.6788
	(53.1219)	(0.0654)			(0.1659)	(0.1440)		(0.0674)					(0.1586)
20 Ships and other vessels	−0.7667	0.4809	−0.4809		1.4717	−0.4717			0.5103	−0.5103			
	(0.3086)	(0.1171)	(0.1171)		(0.1543)	(0.1543)			(0.2000)	(0.2000)			
21 Other vehicles	−165.4705	0.3896			0.9154		−0.1680	0.1064	0.2078		0.7687	−0.7687	
	(58.7346)	(0.0706)			(0.0419)		(0.0552)	(0.0564)	(0.1235)		(0.3109)	(0.3109)	

(continued)

Table 4: Composite restricted industrial labour demand equations (contd.)

	inpt/40	y_t	y_{t-1}	y_{t-2}	h_{t-1}	h_{t-2}	w_t	w_{t-1}	$\overline{y}_{ta}$	$\overline{y}_{(t-1)a}$	d_t	d_{t-1}	T_t
22 Instr. engineering	423.2630		0.2115	0.3539	0.3177	−0.2486	−0.2377	0.2377			1.2396	−2.6097	
	(55.7285)		(0.0825)	(0.0987)	(0.1267)	(0.1064)	(0.0581)	(0.0581)			(0.3043)	(0.3537)	
23 Manufactured food	−172.1572	0.6697			0.3177	0.2237	−0.1962			0.1157		−0.4510	
	(76.0517)	(0.1734)			(0.1742)	(0.1560)	(0.0645)			(0.1233)			(0.1973)
24 Alcoholic drinks, etc.	−15.1802	0.2933			0.7283		−0.0945	0.0591					−0.4844
	(73.4889)	(0.1167)			(0.1239)		(0.0919)	(0.0882)					(0.1411)
25 Tobacco	−213.3698	0.7424			0.7367	0.2633							−0.3959
	(80.8449)	(0.2840)			(0.2225)	(0.2225)							(0.1161)
26 Textiles	−69.3333	0.3637		−0.2759	0.5652		−0.4337		0.0882			0.2960	
	(39.2933)	(0.0675)		(0.0871)	(0.0657)		(0.0753)		(0.1207)			(0.1265)	
27 Clothing and footware	−68.9489	0.4514			0.5364		−0.3756						
	(11.9600)	(0.0372)			(0.0411)		(0.0284)						
28 Timber and furniture	27.5732	0.3925			0.5144		−0.2885	0.1108			−0.1174		
	(13.7004)	(0.0352)			(0.0572)		(0.0595)	(0.0681)			(0.0282)		
29 Paper and board	−44.7394	0.4680	0.1585		0.3644		−0.2503						−0.3259
	(13.2869)	(0.0652)	(0.0925)		(0.0842)		(0.0433)						(0.1040)
30 Books, etc.	96.1742	0.4094	−0.2040		1.3273	−0.6121	−0.0578		−0.2125				
	(32.3071)	(0.0946)	(0.0681)		(0.1955)	(0.1602)	(0.0477)		(0.1434)				
31 Rubber and plastic pr.	−64.4432	0.5998	−0.1401		0.6844		−0.1820						−0.3192
	(14.2846)	(0.0588)	(0.0963)		(0.0818)		(0.1007)						(0.1872)
32 Other manufactures	60.3555	0.2345			0.6028				0.4274	−0.4274			−0.3233
	(20.0274)	(0.0435)			(0.0933)				(0.1287)	(0.1287)			(0.0653)
33 Construction	3.3516	0.3475	−0.3710	0.1345	0.9814	−0.2355	−0.3435	0.3435	0.3916		−0.2830		
	(27.4087)	(0.0858)	(0.1167)	(0.0835)	(0.0957)	(0.0955)	(0.0704)	(0.0704)	(0.1500)		(0.0705)		
34 Distribution. etc.	141.2744		0.7842	−0.2726	0.6360		−0.0409			−0.5717			
	(41.2202)		(0.1615)	(0.1207)	(0.0917)		(0.0356)			(0.1527)			
35 Hotels and catering	−58.7494	0.3544			0.7096		−0.3876	0.1959					
	(44.4425)	(0.1150)			(0.1022)		(0.1191)	(0.1094)					
36 Rail transport	−50.9886	0.1307	0.3372		0.5187		−0.2545				0.8608	−0.6958	
	(25.3141)	(0.0894)	(0.1055)		(0.0978)		(0.0718)				(0.2211)	(0.1953)	
37 Other land transport	118.4359		0.2123	−0.2016	1.003	−0.2638					0.4509	−0.5162	
	(34.6439)		(0.1302)	(0.1434)	(0.1803)	(0.1884)					(0.2304)	(0.1937)	
38 Sea, air and other	67.2451	0.1608	−0.3506		1.2952	−0.6002	−0.2432	0.1835		0.3148			
	(92.1103)	(0.1269)	(0.1263)		(0.1460)	(0.1863)	(0.1204)	(0.1255)		(0.1521)			
39 Communications	14.3221	0.9014	−0.4533		0.8261	−0.2785	−0.1686	0.1565					−0.6566
	(41.3966)	(0.1808)	(0.1966)		(0.1727)	(0.1579)	(0.0822)	(0.0807)					(0.2354)
40 Business services	209.6513	0.3108			0.6781	−0.3104				−0.1633			
	(49.1545)	(0.0718)			(0.1759)	(0.1680)				(0.0486)			
41 Miscell. services	−39.9043	0.2123			0.8264		−0.1408						
	(33.3057)	(0.0790)			(0.0970)		(0.0747)						

Notes: See notes to Table 1.

Having made these points, however, closer comparison of the results in Tables 2 and 3 with those in PPK reveals that in some cases the diagnostic test statistics on the new set of equations are less reasonable than those previously found, and in all sixteen industries have a preferable specification in the PPK paper. The superiority of the original equations in so many industries cannot of course be ignored, and for this reason we present a third set of industrial equations in Tables 4 and 5 which are an amalgamation of the results in Table 2 and those in PPK. (The PPK results are labelled *.) These

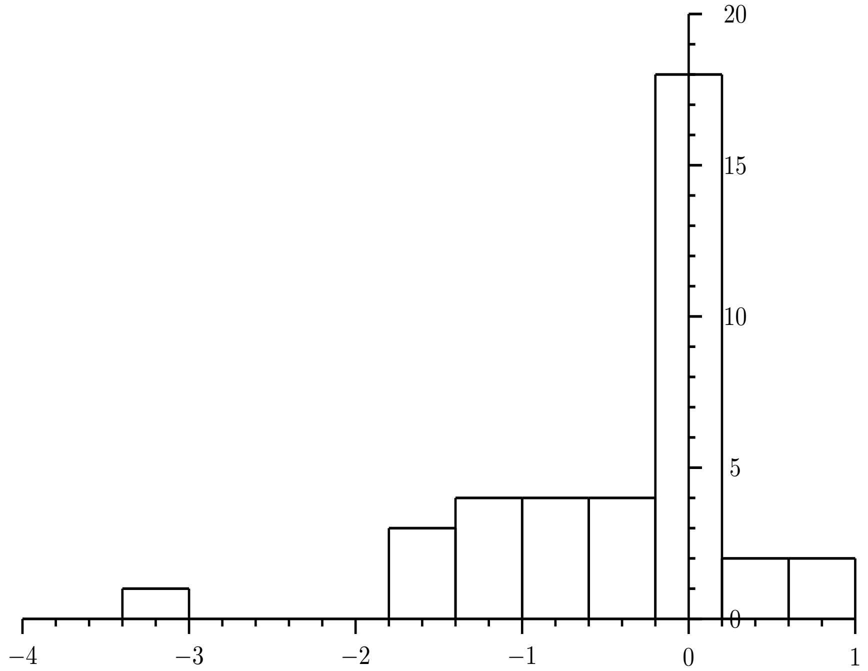

Figure 3: Long-run industry productivity elasticities from Table 2.

results represent the most satisfactory set of equations that we have been able to obtain for explaining employment at the industrial level in the UK. As before, the long-run coefficients are represented diagrammatically in the histograms of figures 4–6. Estimated coefficients are once again largely of the expected sign, and of a reasonable magnitude. The mean and standard deviation (in brackets) of the plotted long-run elasticities are 0.86(0.88), −0.54(0.58), and −0.27(0.72) for output, wages, and technological change respectively, confirming the considerable variability of long-run estimates across the industries and providing a reasonable *a priori* case for the use of disaggregated analysis.

4.4 Comparison with the aggregate relations

The following unrestricted and restricted aggregate employment equations, corresponding to the results discussed above, were also estimated:
Unrestricted aggregate equation

$$\begin{aligned} h_{ta} = {} & \underset{(3.77)}{-137.45} + \underset{(6.39)}{0.49689}\, y_{ta} + \underset{(1.32)}{0.19565}\, y_{(t-1)a} + \underset{(1.03)}{0.11375}\, y_{(t-2)a} \\ & + \underset{(1.48)}{0.33110}\, h_{(t-1)a} + \underset{(1.17)}{0.18986}\, h_{(t-2)a} - \underset{(-5.13)}{0.34110}\, w_{ta} \\ & - \underset{(-1.00)}{0.087043}\, w_{(t-1)a} - \underset{(-0.13)}{0.046365}\, d_{ta} - \underset{(-0.82)}{0.23405}\, d_{(t-1)a} \qquad (19) \\ & \overline{R}^2 = 0.998, \quad \widehat{\sigma} = 0.3316, \quad n = 29 \ (1956\text{–}1984) \\ & \chi^2_{SC}(1) = 3.23, \quad \chi^2_{FF}(1) = 1.27, \quad \chi^2_N(1) = 0.67, \quad \chi^2_H(1) = 3.51. \end{aligned}$$

The figures in brackets are t-ratios, $\widehat{\sigma}$ is the standard error of the regression, $\overline{R}^2$ is the adjusted R^2, n is the number of observations. $\chi^2_{SC}(1)$, $\chi^2_{FF}(1)$, $\chi^2_N(2)$, $\chi^2_H(1)$ are diagnostic statistics distributed

Table 5: Summary and diagnostic statistics for the restricted employment equations of Table 4

Industry	$\overline{R}^2$	χ^2_r	$\widehat{\sigma}$	$\chi^2_{SC}(1)$	$\chi^2_{FF}(1)$	$\chi^2_N(2)$	$\chi^2_H(1)$
1 Agriculture, etc.	0.9983	5.21 (6)	0.0136	0.08	5.96	0.02	0.06
2 Coal mining	0.9987	6.84 (5)	0.0155	0.00	0.25	1.18	0.32
3 Coke (*)	0.9771	10.15 (8)	0.0449	0.24	0.67	0.27	1.87
4 Mineral oil and nat. gas	—	—	—	—	—	—	—
5 Petroleum products (*)	0.9178	13.40 (8)	0.0566	0.48	0.01	1.83	0.85
6 Electricity, etc.	0.9909	14.25 (5)	0.0163	1.08	1.26	0.22	2.58
7 Public gas supply (*)	0.9719	23.36 (7)	0.0322	1.29	0.00	4.86	1.42
8 Water supply	0.9520	10.18 (6)	0.0336	0.01	0.38	0.71	0.00
9 Minerals and ores nes	0.9760	3.90 (8)	0.0318	1.36	0.16	32.70	0.00
10 Iron and steel (*)	0.9933	12.88 (7)	0.0265	0.08	0.19	1.42	0.43
11 Non-ferrous metals (*)	0.9864	13.33 (5)	0.0250	0.01	3.47	0.20	1.89
12 Non-metallic min. pr. (*)	0.9935	12.21 (6)	0.0177	1.11	0.23	0.76	3.15
13 Chemicals and mm fibres (*)	0.9795	11.78 (9)	0.0156	3.51	1.80	0.96	1.14
14 Metal goods nes (*)	0.9877	12.31 (8)	0.0192	0.09	0.27	0.38	1.00
15 Mech. engineering	0.9916	4.63 (4)	0.0141	0.17	0.21	0.02	1.09
16 Office machinery, etc.	0.9291	9.49 (6)	0.0280	0.38	1.10	0.76	4.48
17 Elect. engineering	0.9893	11.58 (5)	0.0103	1.79	0.01	0.41	1.12
18 Motor vehicles	0.9887	4.82 (5)	0.0176	4.16	0.88	1.55	1.58
19 Aerospace equipment (*)	0.9878	6.31 (7)	0.0268	0.90	0.30	1.81	1.30
20 Ships and other vessels	0.9818	16.91 (9)	0.0323	0.45	0.61	0.40	4.46
21 Other vehicles	0.9972	12.07 (6)	0.0243	0.90	2.10	0.33	2.59
22 Instr. engineering	0.9759	2.46 (5)	0.0146	1.57	1.29	2.14	1.02
23 Manufactured food (*)	0.9837	13.89 (6)	0.0164	1.69	2.78	1.33	4.38
24 Alcoholic drinks, etc.	0.9232	15.42 (7)	0.0269	1.32	0.02	0.94	2.06
25 Tobacco (*)	0.8796	16.63 (9)	0.0497	0.25	8.22	0.65	7.62
26 Textiles	0.9985	5.59 (6)	0.0155	4.21	2.46	2.20	2.03
27 Clothing and footwear	0.9984	4.37 (9)	0.0110	0.36	1.92	0.62	0.03
28 Timber and furniture	0.9873	6.05 (7)	0.0133	0.08	3.73	0.91	0.85
29 Paper and board (*)	0.9927	12.00 (7)	0.0192	1.09	1.33	1.74	4.41
30 Books, etc.	0.9341	9.55 (6)	0.0120	1.76	0.00	0.00	1.13
31 Rubber and plastic pr. (*)	0.9818	8.01 (7)	0.0173	0.21	1.59	0.96	1.03
32 Other manufactures (*)	0.9917	13.49 (8)	0.0137	0.37	0.21	1.12	0.00
33 Construction	0.9819	2.58 (4)	0.0137	0.02	0.10	0.73	0.27
34 Distribution, etc.	0.9603	13.35 (7)	0.0139	0.32	1.96	0.23	2.47
35 Hotels and catering	0.9169	5.59 (8)	0.0198	0.58	1.88	0.45	0.63
36 Rail transport	0.9975	11.38 (6)	0.0183	0.03	0.38	2.66	0.86
37 Other land transport	0.9766	8.48 (6)	0.0157	0.13	0.98	1.02	0.02
38 Sea, air and other	0.9278	6.26 (5)	0.0212	2.23	7.95	1.88	0.91
39 Communications (*)	0.9351	8.03 (5)	0.0184	1.56	0.48	0.14	1.81
40 Business services	0.9940	9.33 (8)	0.0128	0.98	2.01	1.98	0.17
41 Miscell. services	0.9512	8.20 (9)	0.0222	0.06	0.47	0.39	191

Notes: See notes to Table 3.

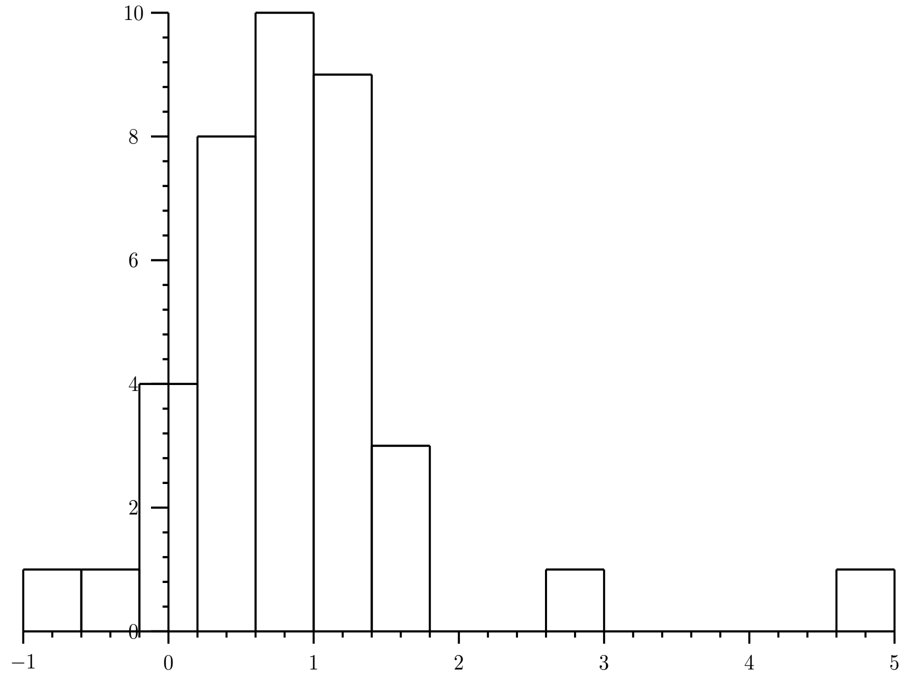

Figure 4: Long-run industry output elasticities from Table 3.

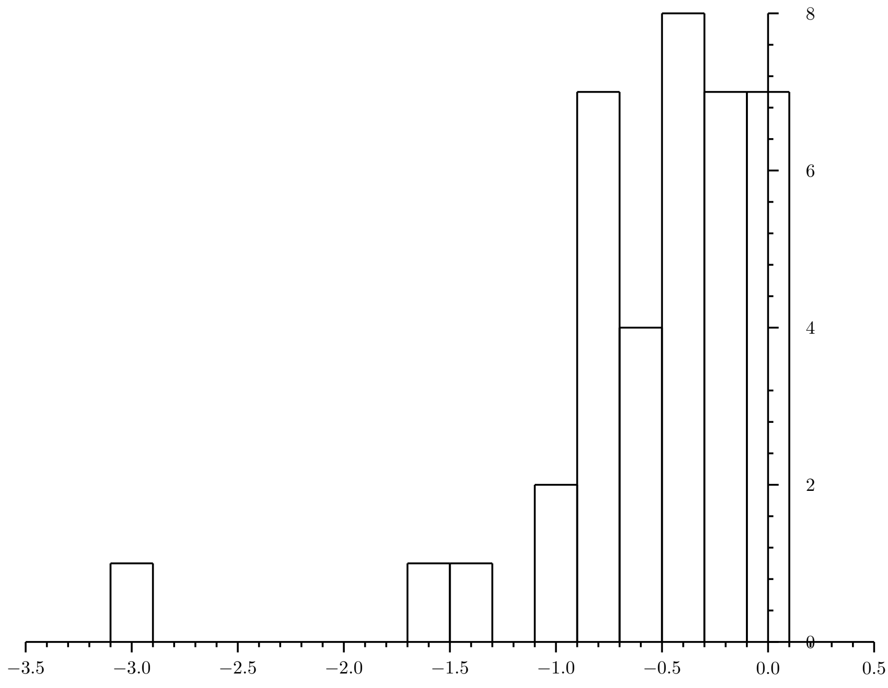

Figure 5: Long-run industry real wage elasticities from Table 3.

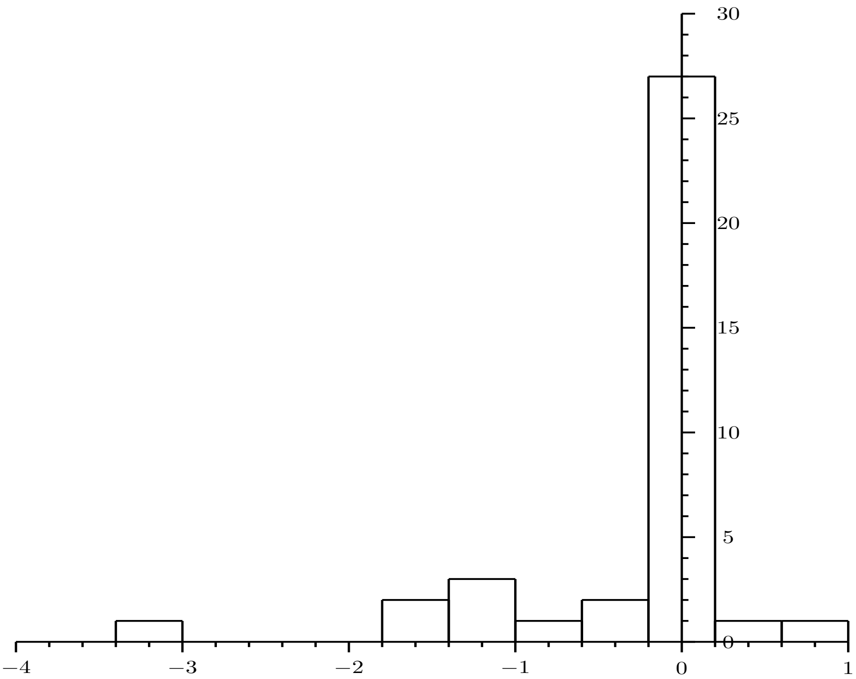

Figure 6: Long-run industry productivity elasticities from Table 3.

approximately as chi-squared variates (with degrees of freedom in parentheses), for tests of residual serial correlation, functional form misspecification, non-normal errors, and heteroscedasticity, respectively. (For more details about these test statistics and their computations see Pesaran and Pesaran (1987).)
Restricted aggregate equation

$$
\begin{aligned}
h_{ta} = &- 99.28 + 0.49854\, y_{ta} + 0.67897\, h_{(t-1)a} \\
&(-4.84) \quad (11.06) \qquad (17.37) \\
&- 0.31216\, w_{ta} - 0.12049\, d_{(t-1)a} \\
&(-7.53) \qquad (-2.33) \\
&\overline{R}^2 = 0.997, \quad \widehat{\sigma} = 0.3209, \quad n = 29 \text{ (1956–1984)} \\
&\chi^2_{SC}(1) = 1.83, \quad \chi^2_{FF}(1) = 2.46, \quad \chi^2_N(1) = 1.68, \quad \chi^2_H(1) = 5.29. \\
&\text{LM test on exclusion of } (y_{(t-1)a}, y_{(t-2)a}, h_{(t-2)a}, w_{(t-1)a}, d_{ta}) = 4.47, \text{ cf } \chi^2(5) \\
&\text{LM test on exclusion of } (y_{(t-1)a}, y_{(t-2)a}, h_{(t-2)a}, w_{(t-1)a}, d_{ta}, T_t) = 5.90, \text{ cf } \chi^2(6)
\end{aligned} \tag{20}
$$

where h_{ta}, w_{ta}, and d_{ta} are the aggregate measures of employment, wages, and technological change derived from the industrial figures, and T_t, is a linear time trend ($T_{1980} = 0$).

To check for the possible effect of the simultaneous determination of output, employment, and real wages on the OLS estimates, we also estimated the restricted aggregate equations using the instrumental variable method. With $\mathbf{z}_t = \{1, h_{(t-1)a}, h_{(t-2)a}, y_{(t-1)a}, y_{(t-2)a}, w_{(t-1)a}, w_{(t-2)a}, d_{(t-1)a}\}$ as instruments, we obtained

$$
\begin{aligned}
h_{ta} = &- 86.86 + 0.4708\, y_{ta} + 0.702\, h_{(t-1)a} \\
&(-3.36) \quad (7.11) \qquad (13.48) \\
&- 0.2783\, w_{ta} - 0.1365\, d_{(t-1)a} \\
&(-4.69) \qquad (-2.21) \\
&\overline{R}^2 = 0.997, \quad \widehat{\sigma} = 0.3258 \\
&\text{Sargan's misspecification statistic } = 4.40 \text{ cf } \chi^2(3) \\
&\chi^2_{SC}(1) = 1.53, \quad \chi^2_{FF}(1) = 0.48, \quad \chi^2_N(1) = 3.83, \quad \chi^2_H(1) = 5.23.
\end{aligned} \tag{21}
$$

These clearly differ only marginally from the OLS results in (20).

The parameter estimates in (19) and (20) imply long-run elasticities with respect to aggregate output, real wages, and technological change of (1.68, −0.89, −0.59) for the unrestricted equation and (1.55, −0.97, −0.38) for the restricted equation.

4.5 Predictive performance and aggregation bias

Table 6 presents the prediction criteria developed in PPK for the aggregate equations (19) and (20) and the disaggregate equations of Tables 1, 2, and 4. In each case the disaggregate model outperforms the aggregate equation. The superiority (in terms of predictive performance) of the specifications in Table 4 over those in Table 2 can also be seen in the estimates presented in Table 6. The computation of the statistic for the test of perfect aggregation also provides evidence in favour of the disaggregate model. In the case of the unrestricted version the value of the test statistic is 89.6 which is approximately distributed as $\chi^2(29)$. This strongly rejects the null hypothesis of perfect aggregation.

Bearing this finding in mind, we applied the tests of aggregation bias discussed in section 3 to the

Table 6: Relative predictive performance of the aggregate and the disaggregate employment functions*

	Unrestricted specifications	Restricted specifications	
	(Table 1)	(Table 2)	(Table 4)
Disaggregate criterion	0.1007	0.0856	0.0737
Aggregate criterion	0.1100^a	0.1030^b	0.1030^b

Notes: *Results exclude industry 4 (Mineral oil and Natural gas).
[a]Corresponds to the unrestricted aggregate equation (19).
[b]Corresponds to the restricted aggregate equation (20).

aggregate and disaggregate employment equations. The results obtained are summarised in Table 7. The first row of this table shows the statistics, q_1^*, for testing the hypothesis that the average of the long-run wage elasticities across industries is equal to −1. As discussed in the introduction, much policy debate has centred around the extent to which aggregate employment in the UK is influenced by real wage levels. The unit long-run wage elasticity has emerged as the consensus view from this debate and it is for this reason that we use this *a priori* value in our test. The average of the estimated long-run wage elasticities obtained on the basis of the disaggregate results in the three Tables 1, 2, and 4 is −0.66, −0.68, and −0.54 respectively, and these were each compared to the consensus value of −1. As is clear,

Table 7: Tests of aggregation bias†

	Unrestricted specifications	Restricted specifications	
	$(\text{Table } 1)^a$	$(\text{Table } 2)^b$	$(\text{Table } 4)^b$
$q_1^*(1)$ [wages]	0.63	5.13	17.20
$q_2^*(1)$ [wages]	0.32	2.46	5.18
$q_2^*(1)$ [output]	0.00	1.68	1.66
$q_2^*(1)$ [technology]	0.07	0.05	0.34

Notes: †Square brackets indicate variables over which restrictions are imposed; figures in round brackets show the number of restrictions imposed, s. Test statistics are compared to $\chi^2(s)$. The $q_1^*$and q_2^* statistics are computed using the results (14) and (15), respectively.
[a]Results compared to unrestricted aggregate equation (19).
[b]Results compared to restricted aggregate equation (20).

the hypothesised unit elasticity is accepted in the case of the unrestricted specifications, but when a more precisely determined set of results are considered, as in Tables 2 and 4, the hypothesis is firmly rejected.

Since the q_1^* statistic does not take account of the sampling variation in the consensus estimate that it uses, a more appropriate test of aggregation bias is that based on the q_2^* statistic (see LPP and section 3). This test is based on a pseudo true aggregate elasticity obtained through estimation of the aggregate relation, and has the advantage that the same data and the same general specification are used in estimating the aggregate and the disaggregate elasticities. Row 2 of Table 7 presents the results of this test for the specifications in Tables 1, 2, and 4. The average wage elasticity across industries in Table 1 is compared to −0.89 (the estimated long-run wage elasticity of equation (19)), while the averages from Tables 2 and 4 are compared to −0.97 (obtained from the restricted aggregate equation (20)). Once again, the poorly determined set of equations in Table 1 provide no evidence of aggregation bias. A similar conclusion is also obtained from the results of Table 2. However, the hypothesis of no aggregation bias based on the more satisfactory estimates in Table 4 is firmly rejected at the 5 per cent level, providing strong evidence in support of the claim that the aggregate relation overstates the responsiveness of employment to changes in wages. Similar tests on aggregation bias are reported in rows 3 and 4, for the long-run output and technological change elasticities in turn. Here, average output elasticities of 1.63, 1.23, and 1.24 are obtained from Tables 1, 2, and 4 respectively, while the corresponding average estimates for the technological change elasticity were −0.46, −0.41, and −0.27. These estimates are compared to long-run output and technological change elasticities of 1.68 and −0.59 from the unrestricted equation (19), and of 1.55 and −0.38 from the restricted aggregate equation (20). In none of these tests is there any evidence of aggregation bias in the estimated coefficients.

Finally, to check the robustness of the above tests to the specification of the disaggregate model, we computed the Durbin-Hausman misspecification test statistic, q_3, as developed in LPP. For the set of unrestricted disaggregated results of Table 1 and the unrestricted aggregate equation (19) we obtained a value of 48.56 which is distributed as a $\chi^2(7)$) since there are three regressors common to the aggregate and the disaggregate specifications (namely the intercept term, y_{ta} and $y_{(t-1)a}$). This result implies strong rejection of the orthogonality of the disaggregate residuals to the aggregate variables and sheds some doubt on the results of the aggregation bias tests. The misspecification of the disaggregate model might be due to the omission of industry-specific variables, measurement errors, functional form, or dynamic misspecification. It is therefore important that further research is carried out on the specification of the disaggregate employment equations and on the importance of aggregation bias in estimating long-run wage and output elasticities for the economy as a whole.

5 Concluding remarks

The application of the statistical methods recently developed by the authors to the study of employment equations in the UK provides some important insights for academics and policy makers alike. The estimated industrial employment equations show that there is a wide diversity in the responsiveness of labour demand to different influences across industries, illustrated most clearly by the histograms discussed in the previous section. In itself, this provides strong support for employing disaggregated analysis rather than aggregate analysis, since the latter cannot capture the structural detail that clearly exists.[14] The result of the test for perfect aggregation confirms that this detail is important even if we are interested only in the prediction of aggregate employment levels, discounting the possibility that errors in disaggregate relations might be offsetting ones. Further, the results of the aggregation bias tests show that the emphasis of policy makers on the importance of wage restraint in attempts to reduce unemployment may be misplaced. These tests confirm the view put forward in PPK that labour demand equations estimated at the aggregate level significantly overstate the extra employment that might be achieved through wage reductions, however these are achieved. In fact, a wage elasticity of around −0.6 is suggested by the disaggregate results, considerably less than the unit elasticity that has become the consensus view in the UK and which is supported by our own aggregate estimates.[15] The results do not, however, provide any evidence of aggregation bias in the long-run estimates of output and technological change elasticities. Taken together, therefore, these results provide an illustration of the gains to be made from disaggregate analysis, and of the dangers involved in aggregation.

[14] Indeed, the relatively poor diagnostic statistics obtained in the case of some of the industrial equations indicate that there is likely to be scope for further structural detail in the form of industry-specific variables, and the use of different functional forms across industries.

[15] Of course, estimated wage elasticities obtained in unconditional labour demand equations would be somewhat higher as reduced wage inflation helps encourage higher output levels.

A Appendix

With the exception of data on industrial investment, the data used in this study are the same as those employed in PPK, and are taken from the Cambridge Growth Project (CGP) Databank. For the sources of the data and the classifications of industry groups see the data appendix and table A in PPK. For convenience, table A is reproduced in this Appendix (Table A1).

Data on industrial investment in vehicles, in plant and machinery, and in buildings are available separately for the period 1954–84, from which total gross investment is constructed. There is not a one-to-one correspondence between the Blue Book (BB) industrial classifications for which the data are published and our own, however. Where the BB data are more disaggregated, this causes no problem, since we simply amalgamate the appropriate industries. There remain six areas in which the BB data are more aggregated than our own. These are listed in Table A2.

In these cases, we have made the simplifying assumption that the investment reported by BB classification can be divided equally over the (more disaggregate) CGP industrial groups. This procedure is satisfactory if the CGP industry groups within the BB classifications show similar investment growths over the 1954–84 period. This is likely to be the case for the Coal and Coke Industries, but is less likely to hold in the case of the BB industry classifications 13 and 17.

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Table A1: Classification of industry groups (in terms of the 1980 standard industrial classification)

Industry groups (CGP classification)	Division, class, or group
1 Agriculture, forestry, and farming	0
2 Coal mining	1113, 1114
3 Coke	1115, 1200
4 Mineral oil and natural gas	1300
5 Petroleum products	140
6 Electricity, etc.	1520, 1610, 1630
7 Public gas supply	1620
8 Water supply	1700
9 Minerals and ores nes	21,23
10 Iron and steel	2210, 2220, 223
11 Non-ferrous metals	224
12 Non-metallic mineral products	24
13 Chemicals and man-made fibres	25,26
14 Metal goods nes	31
15 Mechanical engineering	32
16 Office machinery, etc.	33
17 Electrical engineering	34
18 Motor vehicles	35
19 Aerospace equipment	3640
20 Ships and other vessels	3610
21 Other vehicles	3620, 363, 3650
22 Instrument engineering	37
23 Manufactured food	41, 4200, 421, 422, 4239
24 Alcoholic drinks, etc.	4240, 4267, 4270, 4283
25 Tobacco	4290
26 Textiles	43
27 Clothing and footwear	45
28 Timber and furniture	46
29 Paper and board	4710, 472
30 Books, etc.	475
31 Rubber and plastic products	48
32 Other manufactures	44, 49
33 Construction	5
34 Distribution, etc.	61, 62, 63, 64, 65, 67
35 Hotels and catering	66
36 Rail transport	71
37 Other land transport	72
38 Sea, air, and other	74, 75, 76, 77
39 Communications	79
40 Business services	81, 82, 83, 84, 85
41 Miscellaneous services	94, 98, 923, 95, 96, 97

Table A2: Blue Book and Cambridge Growth Project industrial classifications

CCP classification	BB classification
2 Coal 3 Coke	2 Coal and coke
9 Minerals and ores nes 10 Iron and steel 11 Non-ferrous metals 12 Non-metallic mineral products	8 Metals 9 Other minerals
16 Office machinery 17 Electrical engineering 22 Instrument engineering	13 Electrical and instrument engineering
19 Aerospace equipment 20 Ships 21 Other vehicles	15 Transport, other than motor vehicles
24 Drink 25 Tobacco	17 Drink and tobacco
29 Paper and board 30 Books	21 Paper, printing, and publishing

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