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**The effects of international trade on employment:
heterogeneity among 2-digit ISIC manufacturing industries**

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***Abstract**¹ Most studies of the relationship between international trade and the labour market have been at an aggregate level. If the effects of trade differ among the component firms and disaggregate-level industries on which such studies are based, then the aggregate-level results may tell us little about the partial-equilibrium adjustment of employment to changes in international trade. This study shows that the effects of trade on employment can differ among two-digit ISIC manufacturing industries, and suggests that theoretically more sophisticated disaggregate-level studies may enhance our understanding of the effects of international trade on the labour market.*

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I. Introduction

The majority of empirical studies of the relationship between international trade and the labour market have been at an aggregate level, such as the level of the manufacturing sector or the tradables and non-tradables sectors.¹ It is unlikely, however, that international trade has an identical effect on employment and wages in all of the sub-branches of any aggregate-level industry. Thus, the estimated coefficients of an aggregate-level regression equation based on disaggregate-level data may not accurately describe the adjustment of employment to international trade that occurs at the disaggregate level. Aggregate-level studies may not, therefore, provide useful information for improving our theoretical understanding of the effects of trade on the labour market.²

At least part of the interest of trade-policy makers is in making *ex ante* predictions about the effects of future trade policy changes. If disaggregate level studies can isolate the way in which certain factors influence how trade affects the labour market, then we may be able to make better informed policy decisions. An understanding of these factors, and of the adjustment processes involved, seems particularly important in a world in which trade policy liberalisation in the future is likely to come (at least in part) in a piecemeal form rather than in the form of comprehensive economy-wide liberalisation.

This study shows that the effects of international trade on labour can differ across sub-branches of the manufacturing industry at the two-digit ISIC (International Standardised Industrial Classification) level, and explains the implications of such heterogeneity.³ The structure of the paper is as follows. Section II discusses the data we use and the reasons for choosing the approach we have adopted to measure the effects of international trade on employment. It also examines the possible non-stationarity of the data and tests for the presence of co-integrating relationships among the variables. Section III looks at the diagnostic statistics, and also at the results and their interpretation. Finally, Section IV presents the conclusions of the paper and suggests a direction for further research.

II. The modelling approach and properties of the data

II.1 Theoretical considerations and the form of the relationship

Although the ability of international trade to affect labour market outcomes has been demonstrated empirically (Bound and Johnson, 1992 and Haskel and Slaughter, 2001), disagreement still exists as to what the effects are and through which channels they operate. Moreover, there still seems to be disagreement in the literature regarding what factors drive international trade.

Davis and Weinstein (2001) recently found evidence contradicting the assertion that factor endowments are unimportant for the determination of trade among wealthy countries. Elliot, Greenaway and Hine (2000) have found that the UK SIC headings may group together industries that are not strongly

homogeneous in their relative factor intensities. The implication of this conclusion is that SIC-based measures of intra-industry trade (IIT) can actually include some trade that is driven by factor-endowment differences. Consequently, such measures of IIT may exaggerate the proportion of trade that is intra-industry. Nevertheless, evidence exists to suggest that models of imperfect competition and trade may describe a significant proportion of trade among rich countries.⁴

In addition to the uncertainty about what drives trade, the links between the causes of trade and its effects on the labour market are not always clear. Where models of trade under imperfect competition are considered, there is no clear understanding of the implications of trade for the labour market. This is because, in the presence of imperfectly competitive product markets, the way in which firms will respond to changes in the level of international competition cannot be predicted *a priori* without making restrictive assumptions on firms' behaviour and the exact market structure.

In the perfectly competitive world, the predictions of the Heckscher-Ohlin-Samuelson (HOS) model and the Stolper-Samuelson (SS) theorem regarding wages and inter-industry factor movements are weakened when it is extended beyond the two-dimensional case (Ethier (1984) provides a discussion of higher dimensional issues). Further, Davidson, Martin and Matusz (1999) have recently shown that in a world where search-generated unemployment replaces the usually assumed full employment, SS predicts that the reward to a given factor differs across sectors. Thus, the use of strict HOS assumptions and predictions regarding the relationship between factor rewards and prices to derive an estimable model may be inappropriate even where product markets are perfectly competitive.

Given the above uncertainties about the form of the relationship, and the fact that our interest is in examining whether the effects of trade on employment are different in different industries (rather than in testing a particular theory), we have chosen to use a basic labour demand framework as used by Gaston and Trefler (1993), Konings and Vandenbussche (1995) (KV), Milner and Wright (1998) (MW), and Revenga (1992).⁵

II.2 The data and the long-run equilibrium model

Our study uses annual data for France and Britain on each of seven sub-branches of the manufacturing industry. These data were obtained from the OECD's International Sectoral Database (ISDB). The industries "broadly correspond" (Meyer zu Schlochtern and Meyer zu Schlochtern, 1994) to the two-digit ISIC level. We also examine data on the aggregate manufacturing industry.

The data were pooled across France and Great Britain to raise the number of observations on each industry (the implications of pooling are discussed below). The series cover the period 1970-89 for ISIC number 37, 1970-90 for ISIC number 36, and 1970-91 for ISIC numbers 3, 31, 32, 34, 35 and 38. Data on 33 and

39 were not available for both countries over a long enough period to allow us to work with them. The industry definitions are given in Table 5.⁶

Where the ISDB lacked necessary information, data were also obtained from other sources. The number of industrial disputes (measured at the national level) was obtained from various issues of the International Labour Office's *Yearbook of Labour Statistics* (ILO).⁷ Data on exchange rates (used for conversion of the trade series to a common currency), national consumer price indices (used as deflators), and the public sector bond yield were obtained from the OECD's *Main Economic Indicators* (MEI) database, all at the national level.

By pooling the data, we implicitly assume that the parameters of the OLS regression are identical for the two countries for any given industry. Given that the two countries have been part of "Europe" for much of the period under examination, the assertion that their manufacturing industries would behave similarly, and would face similar international competition and opportunities, may not be unrealistic. Further, pooling the data implicitly assumes that random shocks that would fall into the error term in the "true" model are symmetric across the two countries. It is conceivable that many of the major shocks that are not captured by the explanatory variables were common to all members of the European Community.

The pooled long-run (equilibrium) form of the labour demand equation is specified as follows:

$$\ln L_{i,t} = \ln \beta_0 + \beta_1 \ln W_{i,t} + \beta_2 R_t + \beta_3 \ln Y_{i,t} + \beta_4 \ln K_{i,t} + \beta_5 \ln G_t + \beta_6 \ln ST_t + \beta_7 \ln M_{i,t} + \beta_8 \ln X_{i,t} + \beta_9 DUM + \varepsilon_{i,t} \quad (1)$$

where *i* refers to industry *i* and *t* to time period *t*. *L* is total employment, *W* the real wage rate, and *R* is the real interest rate on long-term public sector bonds expressed as a proportion of 1 (included as a measure of the cost of capital). *Y* denotes real value added, *K* the real gross capital stock (a factor of production), *G* the ratio of government employment to total employment in the national economy, and *ST* the proportion of workers in the national economy who were involved in industrial disputes in a given year. *M* and *X* are the ratios of imports and exports (respectively) to industry value added. *DUM* is a country specific dummy variable (equal to 1 for France and 0 for Great Britain). It is hoped that this dummy will account for the shift in the level of the variables between the last observation on France and the first observation on Great Britain. $\varepsilon_{i,t}$ is a stochastic error term.

With the exception of *R*, all variables are transformed by taking natural logs. Since *R* is already measured as a rate and in some periods is negative, it is not in log form. All series that are measured in currency units (*W*, *Y*, *K*, and the raw imports and exports series) are converted to constant 1990 US dollars PPP for consistency, since the capital stock data were available only in such units.⁸

The wage series is measured with some error, since it is obtained using an hours-per-worker-per-year series that appears to be an average for the national economy. If the difference between the average number of hours in a working week in each two-digit industry and in the national economy is small and random, then the effect of this error should be small and the wage series we use may be a useful instrument for dealing with simultaneity bias. In any case, if the variables are found to be co-integrated then simultaneity bias should hopefully not present major difficulties (since in the presence of non-stationary data, simultaneity bias is a second order problem).⁹

The results for the long-run equation (1) (Table 3) show that the coefficient on the wage variable appears theoretically reasonable in all cases, suggesting that our use of this proxy is justified. Similarly, while value added (Y) may not exactly represent industry output, its estimated coefficients (Table 3) are consistent with our *a priori* expectation of the influence of industry output.¹⁰

The use of imports and exports as shares of some output measure is not new to the literature as a proxy for the degree of foreign competition (see, *inter alia*, Hine and Wright (1998) and Milner and Wright (1998)). It is important, though, that movements in these trade-share series are driven by shifts in exposure to trade (i.e. trade penetration), rather than solely by changes in output over time. Plots of $\ln X$ and $\ln M$ (the trade shares in value added) and $\ln Y$ for each industry were examined prior to estimation and indicated that in many cases $\ln M$ and $\ln X$ trend in the same direction as $\ln Y$ (the denominator of the constructed trade shares) over the period. Indeed, in no case does $\ln Y$ trend in the opposite direction to the trade shares. This suggests that any major inter-temporal variations in the trade-share variables are not dominated by the trend in their denominators, but rather by shifts in the degree of trade penetration.

ST is used as a proxy for the degree of imperfect competition in the labour market, and may also capture the effects of changes to labour market regulations. Since it is measured at the national level its inclusion requires the assumption that the degree of industrial action in two-digit ISIC manufacturing industries closely follows that in the national economy. An analogous assumption is made to justify the inclusion of the government employment variable, G. This attempts to account for any “crowding-out” of private sector activity by government, or any tendency by government to support employment by becoming actively involved in industrial production.

II.3 Testing for unit roots

The data were pre-tested for stationarity using an Augmented Dickey-Fuller (ADF) test on the pooled series, and using the t_{bar} tests and the ψ - t_{bar} tests for unit roots in panel data proposed by Im, Pesaran and Shin (1997) (IPS).¹¹ The panel data tests were undertaken to assess the possibility of working with the data as a panel rather than using pooled data. A summary of the results is given in Table 1 and Table 2.

The lag order in the simple ADF regressions and in those used to obtain the t_{bar} and ψ - t_{bar} statistics was chosen using the general-to-specific criterion discussed by Hall (1994), with an asymptotic 10 per cent critical value used to test for the significance of the last lag in the augmentation process.¹² The longest lag allowed was set to 8 for the ADF test and 6 for the IPS tests (due to the smaller number of useable observations). For the pooled ADF tests the testing strategy suggested by Perron (1988, pp. 314-317) was applied using the asymptotic 10 per cent critical values for each statistic.^{13, 14} For each of the IPS and ADF tests, the first differenced series was examined first to test the null hypothesis that the series was I(2). If a series was found to be I(2), no testing for lower orders of integration was undertaken.

None of the pooled series was found to be I(2). However, the distribution of the ADF statistic in the pooled case is uncertain and so it is possible that type I errors were committed when testing the I(2) null hypothesis against the I(1) alternative. One must bear this fact in mind when considering the results presented in this paper.

The IPS tests found a number of I(2) variables, most commonly lnK and lnL (Table 2). It therefore appeared more sensible (from a co-integration perspective) to work with the data in pooled form, in which case all dependent variables are integrated of order one, and the explanatory variables are all stationary or integrated of order one (with no fewer than four I(1) explanatory variables for any industry).

Intuitively, the idea of using co-integration techniques for pooled series that may have “structural” breaks between countries is unappealing, since this amounts to fitting a trend-line to a broken series. The inclusion of the dummy variables should, however, account for the break. Further, plots of the residual terms from the OLS regressions of the “equilibrium” (long-run) relationship (equation (1)) suggest no apparent break, and in all cases the residual term is very small suggesting that the fit is good for both countries. Also, the apparent insignificance of the heteroscedasticity test statistics for the majority of industries in the long-run relationship (in spite of the fact that the test statistics for that specification can be expected to be spuriously large) (Table 3) and for all industries in the Error Correction Model (ECM) (Table 4) suggests that behaviour in the two countries is similar for most industries.

II.4 Testing for co-integration: methods

Both the residual-based ADF test (t_{DF}) and the Engle-Granger two-step Error Correction Mechanism (t_{ECM}) test were used to ascertain the presence or absence of co-integration. The method for selecting the lag length in the t_{DF} test was the same as that used in the unit root tests (above). In the case of the t_{ECM} test, the lagged residual term (“error correction” term) that was included in the regression was the residual obtained from the long-run equilibrium regressions (equation (1)) whose results are given in Table 3.

For the ADF test, exact sample critical values were obtained from MacKinnon's (1991) response surface estimates for six variables for the cases with both a trend and a constant, and with no trend and a constant.¹⁵ Since MacKinnon does not provide critical values for more than one variable in the case with no constant and no trend, we have used the Engle and Yoo (1987) critical values for 5 variables and 50 observations for that case.¹⁶ As with the unit root tests, there is uncertainty about the actual distribution of the t_{DF} co-integration test statistic when pooled data are used, so care should be taken when interpreting the results of this test.

The t_{ECM} test has the advantage that in small samples it is more powerful than the t_{DF} test for co-integration. Nevertheless, for the t_{ECM} test there is uncertainty regarding the appropriate critical values even with pure time-series data. Conventionally, the asymptotic t distribution was used. Kremers, Ericsson and Dolado (1992) show, though, that depending on the (unknown) values of certain parameters the distribution of the t statistic can either approach that of an asymptotic t distribution or a Dickey-Fuller distribution. Consequently, they suggest using the t_{DF} critical values as a conservative option.¹⁷ Thus, we compare the t statistic on the error-correction term to the critical values from the normal t distribution and to the t_{DF} critical values.¹⁸ The results of the co-integration tests are discussed in section II.6.

II.5 Estimation

The long run relationship (1) was estimated by OLS with all variables included. An ECM relationship was also estimated using OLS, initially with all variables included. The advantage of an ECM so far as interpretation is concerned is that by including dynamic terms it avoids the dynamic misspecification that is likely present when the long-run equilibrium specification (equation (1)) is estimated by OLS.¹⁹ Further, the ECM allows for examination of the dynamic nature of the influences of the explanatory variables on employment, and assuming co-integration is found to be present we may also interpret the t-statistics in the normal way.

Each first-differenced explanatory variable in the ECM was initially included for time periods t, t-1 and t-2. The general form of the ECM is as follows:

$$\Delta L_{i,t} = \sum_{k=1}^2 \beta_{L,i,t-k} \Delta L_{i,t-k} + \sum_{j=1}^8 \beta_{j,i,t} \Delta Z_{j,i,t} + \sum_{j=1}^8 \beta_{j,i,t-1} \Delta Z_{j,i,t-1} + \sum_{j=1}^8 \beta_{j,i,t-2} \Delta Z_{j,i,t-2} + \theta_i RES_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

where j refers to variable j, and the Z_j refer to the explanatory variables associated with β_1, \dots, β_8 (respectively) in equation (1), where the levels of all variables except R are measured in their natural logs. As usual, i denotes industry i (although as discussed earlier, some variables are measured at the national level, and so are identical for each industry). “ Δ ” denotes the first-difference operator. $RES_{i,t-1}$ is the “error

correction” term, and as noted above is the once-lagged residual term from the long-run equation whose results are given in Table 3.

Unlike the long run equation (equation (1)), the ECM (equation (2)) should need no dummy. This is because we are looking at changes in variables rather than the levels of variables, and because when we pool the data we implicitly assume similar behaviour in the two countries. Hence we should not expect a significant difference in the growth rates of employment between France and Great Britain.

Once the ECM had been specified and estimated, variables were then dropped that did not appear to contribute usefully to the model. Since there was uncertainty regarding the order of integration of the error-correction term (RES_{t-1}) and therefore about the distributions of the diagnostic statistics and t and F tests, the decision to drop a variable depended on a number of criteria. Only variables whose removal did not appear to significantly worsen the diagnostic statistics, that had small t statistics, and that did not lead to large and “unreasonable” changes in the magnitude, sign, and apparent significance of the coefficients on other variables, were removed. The trade variables were left in at all lags regardless of their contribution to the model. Where their contribution to the model appeared not to be statistically significant, their inclusion allows us to compare the pattern of the qualitative and quantitative estimated effects of trade on employment over time and across industries.

II.6 Co-integration results

Tables 3 and 4 report the results for the long-run relationship and the ECM respectively. As Table 3 shows, only for ISIC industries 31 and 32 are the variables co-integrated according to the t_{DF} test. The t_{ECM} statistic (the t-statistic on RES_{t-1} in Table 4, where RES_{t-1} is the “error correction term”) should provide a more powerful test however. This test suggests that, according to the conventional finite-sample t critical values, the variables are co-integrated for industries 31, 32, 34, 36, 37, and 38 (since the coefficient on RES_{t-1} is negative and statistically significant). Of these, only for industries 31, 32, 34, and 38 are the variables co-integrated when the t_{ECM} statistic is compared to the t_{DF} critical values.²⁰ If one accepts that the data for 31, 32, 34, 36, 37, and 38 are co-integrated (based on a comparison with the conventional t distribution), then we have six industries to discuss and compare. For the remainder of the paper we shall limit our attention to those six industries.

III. Diagnostic statistics and results

III.1 Diagnostic statistics

Table 3 shows that adjusted R^2 (R_a^2) is high in all industries for the long-run equation as one would expect with non-stationary data. What is notable, however, is that R_a^2 is also large in the ECM regressions, suggesting that the explanatory power of the ECM is high due to the large number of variables included. Given the high R_a^2 for the ECM in industries 31 and 32, where co-integration is supported by both the

conventional and Dickey-Fuller critical values in the ECM and by the residual based ADF test, the latter case appears realistic.²¹

According to conventional critical values the RESET test suggests that the long-run relationship (Table 3) is misspecified in all industries. It is likely that to some extent the omission of any dynamic terms results in autocorrelation that is reflected by the RESET statistic. The “significance” of the RESET test statistics may also suggest that a common factor restriction (discussed by Kremers et al (1992)) imposed by the static specification in equation (1) is invalid. In addition, it is probable that these statistics are spuriously large due to the presence of non-stationary data. Some (or even all) may therefore also be spuriously significant. The RESET statistics are greatly improved in the ECM (Table 4), although of the six industries for whose variables co-integration exists, industries 31, 34 and 38 still show some signs of misspecification.

In the long-run relationship the Breusch-Pagan-Godfrey and Glejser tests suggest heteroscedasticity only in industries 34, 35, and 38 (although as with the RESET test, these test statistics may be spuriously large). It is hoped that in the presence of I(1) variables, an I(0) problem such as heteroscedasticity will be only of second order and will not have a major bearing on the results. In the case of the ECM, heteroscedasticity is not found to be significant in any industry.

The Breusch-Godfrey F test (Kiviet, 1986) for autocorrelation (of order 4 or less in this case) is unsurprisingly, given the absence of dynamic terms, supportive of autocorrelation in the (static) long-run relationship in five industries. As for all of the other test statistics discussed in this section, however, it is conceivable that this test statistic is spuriously large. In the ECM, autocorrelation is found to be present only for industry 32, and then only at the 10 per cent level.

The ECM, then, appears to be quite well specified for most industries, and for those in which co-integration is present the ECM should provide useful insight. As mentioned above, it is hoped that some of the possible specification problems that may exist for the long-run relationship are of second order, and do not interfere with the interpretation of the coefficients in these regressions. Care must be taken however, since the long-run equation may still suffer from the bias to which OLS is prone when used to estimate a co-integrating relationship in a small sample.²²

III.2 Results

Before discussing the effects of trade, we note that the signs on the coefficients in Table 3 (the long-run relationship) are mostly economically sensible. The negative sign on R is somewhat surprising, but could perhaps be explained in one of two ways. First, if value added does not behave in the same way as output, then controlling for value added is not the same as controlling for the level of output. Thus, the negative

sign on R could be explained by the scale effect of a rise in the cost of capital (whereby a rise in the cost of production leads to a fall in output) outweighing the substitution effect (whereby a rise in the cost of capital leads firms to substitute labour for capital).

Another possible explanation can be made if the interest rate is assumed to follow the business cycle, peaking around the top of the cycle and bottoming near the trough. If firms that have difficulty shedding staff operate less efficiently in a downturn than in an upswing, as they employ more labour than is optimal in the downturn and do not increase staff levels as quickly as their output rises during an upswing, then a given level of output would correspond to a higher ratio of employment to output in a downturn than in an upswing. Thus, for a given level of output, higher interest rates would be consistent with lower employment.²³ If neither of the above explanations is valid, then the negative sign on R in the co-integrating relationship should be of some concern, and may suggest that the OLS estimates are biased.

The mixed sign on G across industries fits with the possible effects discussed in section II. The mixed sign on ST may reflect the possibility that greater market power for workers (reflected by an increase in the proportion of workers involved in industrial disputes in a given year) can lead to a push for higher wages at the expense of non-union employment, or agreements to maintain employment at the expense of wages in the face of falling output. The varied sign on the capital stock may merely reflect labour-replacing and labour-augmenting capital in different industries.

The sign on the coefficient on the dummy variable is consistently negative. This suggests that the level of employment in each of the French industries is lower than in the corresponding British industries, and is consistent with the raw data. Finally, the sign and magnitude of the coefficient on the error correction terms suggest that when employment departs from its equilibrium level, it will return to equilibrium but will take more than one year to do so (the coefficients are all negative and less than 1 in absolute value). This is consistent with our expectations of an imperfectly flexible labour market, and would also be consistent with employment contracts that last one or more years.

The coefficients on the trade variables show the effect of trade penetration, holding output constant (where value added, Y, is used as a proxy for output). These coefficients thus reflect the employment effect of trade over and above the effect through output changes. For the long-run relationship, the fact that these trade variables are present in six apparently co-integrated relationships suggests that they may contribute significantly to those relationships.

Table 3 shows that increased import penetration in the long-run relationship has a negative effect on employment in three of the industries of interest (36, 37, and 38) and a positive effect in the other three. Similarly, exports' share in value added has a negative effect on employment in three industries (31, 32,

34) and a positive effect in the other three. The coefficients on the trade variables range (in absolute value) from 0.014 to 0.311, while the values to each side of the median are 0.131 and 0.157.

In the ECM (Table 4) one can again see economically sensible signs on most variables. The negative and significant coefficient on the once-lagged dependent variable in industry 38 is of some concern, however. This perhaps suggests that employment follows a “cobweb” pattern in this industry. Such “cobweb” behaviour sits uncomfortably with one’s intuition, however, given the relative inflexibility of European labour markets.

The contemporaneous change in Y encouragingly has a positive and significant effect in all of the industries. Also of interest is the fact that the twice-lagged first difference of the capital stock was found to be an insignificant contributor in all industries. This suggests that employment can fully adjust to a change in the capital stock within one year of that change. The negative effect of R on labour demand has been discussed above for the long-run relationship. Moreover, in the error correction model the coefficients show dynamic effects rather than equilibrium relationships, and also show a relationship in growth rates rather than levels. Since either a positive or a negative sign can be explained economically on all other variables (as discussed for the long-run relationship) we shall not go into a discussion of these.

Upon examination of the trade variables in the ECM, we see that the coefficient on the contemporaneous growth in import penetration (ΔM) is only statistically significant in industries 32 and 34. Further, the coefficients on ΔM in those two industries are positive and of similar magnitude to each other. The coefficient on ΔM_{t-1} is statistically significant in only three industries (31, 36, and 38), and is positive in all three. For ΔM_{t-2} , the coefficient is negative and significant for 34, and positive and significant for 32, 36, 37 and 38.

The coefficient on ΔX is statistically significant in industries 31 (positive), 32 (negative) and 34 (negative). The absolute values of the coefficient on ΔX for those three industries are of similar magnitude (close to 0.1). For ΔX_{t-1} , the coefficient is negative and significant in 31 and is positive and significant in 32, and is insignificant in all other industries. For ΔX_{t-2} , the coefficient is positive and significant in 34 and 36, and insignificant in all other industries.

The absolute value of the coefficients on the trade variables, where they are statistically significant, is of a fairly consistent magnitude at all lags and in all industries. The smallest statistically significant coefficient in absolute value is 0.065 (for ΔX_{t-1} in industry 32) while the largest absolute value is 0.275 (in industry 38, for ΔM_{t-1}). The larger coefficients, then, suggest economically significant effects of trade on employment, holding Y constant.

Summing the statistically significant coefficients across all lags for each industry gives us an idea of the dynamic effect on employment growth of growth in imports or exports (as opposed to the equilibrium effect, which is demonstrated by the coefficients in equation (1)). For imports, the total dynamic effect ranges from 0.062 to 0.276, while for exports, the magnitude ranges from -0.024 to 0.075.

The above results lead us to believe that the dynamic effect of exports on employment growth, over and above the effect through output, is small in magnitude. It seems that exporting is no better for achieving employment gains than is domestic production (although this says nothing about wages and other conditions of employment). In the long run, however, a higher level of exports in equilibrium can have an economically significant effect on the level of employment beyond the output effect (Table 3). In some industries this effect is positive, while in others it is negative.

In contrast, the short-run effect of a rise in imports on employment growth appears economically significant in some industries, but not in others. In equilibrium the conclusion is much the same as that for exports: the effect on the level of employment beyond the output effect can be economically significant, while the direction of the effect differs across industries (Table 3).

III.3 Interpretation

The results imply that the effect of international trade on employment differs across two digit ISIC industries. The effects differ among industries in terms of direction and magnitude, and in terms of the length and manner of the adjustment process. The long-run equilibrium effect of a change in trade penetration also differs across industries.

In addition, the variables are apparently not co-integrated for the aggregate manufacturing industry (ISIC 3), while they appear to be co-integrated for six of the seven two-digit sub-branches examined. This fact lends support to the assertion that the manufacturing industry cannot be treated as being representative of each of its sub-branches.

An important implication of these results is that any study that pools disaggregate-level data in order to obtain information about the aggregate-level effects of trade cannot then go back and tell us about the adjustment process at the disaggregate level. Thus, such studies cannot be used as a basis for developing partial equilibrium explanations of the relationship between trade and the labour market. They are, rather, empirical examinations of broad historical events.

Since there is an incomplete theoretical understanding of the relationship between trade and the labour market when product and factor markets are not competitive, little can confidently be said *a priori* about the expected partial equilibrium labour market effects of industry-specific trade policy. Although we have

some idea of what product and factor market variables we expect (theoretically) to influence the relationship between trade and the labour market, we do not always know *a priori* how we expect those variables to affect the relationship. The aim should therefore be to control, in a disaggregate level context, for what are considered to be the key variables determining product and factor market behaviour and ascertain how trade affects employment and wages in that context. By doing so we may also obtain estimates of the influence of product and factor market conditions, and so better understand the way in which labour will be affected by changes in trade and trade policy. This would require the use of time series data on disaggregate-level industries, or of panel or pooled data on relatively homogeneous sub-groups of a disaggregate-level industry.²⁴

IV. Conclusions

We have shown that the effects of trade on employment in French and British manufacturing industries differ across two-digit ISIC manufacturing industries. This implies that aggregate level studies of the relationship between trade and the labour market may tell us little about the adjustment processes involved. We suggest therefore that there is a need for more study at a disaggregate level to improve our empirical and theoretical understanding of how international trade affects labour.

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Appendix A: Data

In this appendix, we outline the sources of and construction of the variables used. All series measured in monetary terms have been converted to constant (1990) prices using the Consumers' Price Index (CPI) series from MEI and to US dollars PPP using the 1990 "PPP (GDP)" exchange rates given in the ISDB handbook (OECD, 1996a).

L: The total number of employees at industry level (ISDB).

W: This is calculated as

$$W = (\text{total compensation of employees}) / (L * \text{hours per year})$$

Compensation of employees is the series WSSS from the ISDB. Hours per year is the series HWY from the ISDB and represents the average number of hours worked per person per year in the national economy.

R: The real long-term yield on public sector bonds. This is calculated as

$$R = [(1+(\text{RNOM}/100))/(1+(\text{CPI}/100))]-1$$

RNOM is the nominal long-term rate from MEI. For France, this is the annual yield on public and semi-public long-term bonds (OECD, 1996b). For Britain, this is the yield on long-term government bonds (OECD, 1996b).

Y: This is the industry level value added at market prices series (GDPD) from the ISDB.

K: This is the gross capital stock, KTVD, from the ISDB. This represents the volume of the physical capital assets available. A perpetual inventory method was used to construct the series in the ISDB by simulating the capital accumulation process, along with a linear retirement pattern for existing capital.

G: The ratio

$$G = \text{EEP GS} / \text{EETET}$$

where EEP GS is total government employment in the national economy and EETET is total national employment from ISDB.

ST: This series is calculated as:

$$ST = (\text{Workers in industrial disputes}) / (\text{Total employment})$$

where the numerator is the total number of workers in the national economy involved in industrial disputes in a given year (from ILO) and the denominator is EETET from ISDB.

M, X: These two series are calculated as follows

$$M = \text{Imports} / Y$$

$$X = \text{Exports} / Y$$

where Imports and Exports are based on the series MGS and XGS from ISDB respectively and have been converted to domestic currency from USD using the exchange rate series in MEI to allow the series to be converted US dollars PPP.

Table 1: ADF results for pooled data by industry

	3	31	32	34	35	36	37	38
lnL	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
lnW	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
R¹	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
lnY	I(0)	I(0)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)
lnK	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
lnG¹	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
lnST¹	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
lnM	I(0)	I(0)	I(0)	I(1)	I(0)	I(1)	I(1)	I(1)
lnX	I(0)	I(1)	I(0)	I(0)	I(0)	I(1)	I(1)	I(0)

¹The results for R, G and ST are the same for all industries since these variables are measured at national (and not industry) level.

Table 2: IPS panel results by industry

	3	31	32	34	35	36	37	38
lnL	I(0)	I(1)	I(0)	I(0)	I(0)	I(2)	I(2)	I(0)
lnW	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)
R¹	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
lnY	I(0)	I(1)	I(0)	I(0)	I(1)	I(0)	I(1)	I(0)
lnK	I(2)	I(2)	I(1)	I(2)	I(1)	I(2)	I(2)	I(1)
lnG¹	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
lnST¹	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
lnM	I(2)	I(0)	I(1)	I(0)	I(1)	I(0)	I(0)	I(1)
lnX	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)	I(1)

¹The results for R, G and ST are the same for all industries since these variables are measured at national (and not industry) level.

Table 3: Results for long-run relationships (dependent variable lnL)

	3	31	32	34	35	36	37	38
lnW	-0.858 (-6.497)	-0.7 (-11.5)	-1.378 (-8.295)	-0.578 (-8.96)	-0.582 (-6.815)	-0.641 (-4.653)	-0.723 (-13.32)	-0.009 (-0.045)
R	-0.504 (-2.044)	-0.666 (-3.404)	-0.596 (-1.845)	-0.183 (-1.125)	-0.623 (-2.096)	-0.635 (-2.79)	-1.773 (-3.421)	-0.502 (-1.498)
lnY	0.664 (6.404)	0.751 (4.34)	0.82 (9.294)	0.042 (0.518)	0.226 (1.575)	0.275 (3.068)	0.05 (0.304)	0.478 (3.595)
lnK	0.815 (0.789)	0.277 (1.724)	0.481 (1.046)	0.318 (3.471)	0.508 (1.986)	0.423 (2.099)	0.782 (2.21)	-0.439 (-1.926)
lnG	0.746 (3.97)	0.314 (2.004)	0.272 (1.636)	-0.038 (-0.28)	-0.271 (-1.112)	-0.384 (-1.704)	-1.407 (-2.792)	0.335 (0.933)
lnST	0.038 (3.834)	0.002 (0.172)	-0.006 (-0.481)	0.017 (1.978)	0.002 (0.18)	0.047 (4.192)	0.035 (1.363)	0.033 (1.958)
lnM	-0.347 (-4.013)	0.157 (2.464)	0.131 (1.163)	0.088 (1.478)	-0.178 (-1.43)	-0.103 (-2.789)	-0.231 (-1.828)	-0.311 (-5.256)
lnX	0.285 (2.153)	-0.171 (-2.517)	-0.12 (-1.508)	-0.014 (-0.18)	0.241 (1.758)	0.019 (0.24)	0.186 (0.972)	0.286 (1.903)
Dum	-0.321 (-4.193)	-0.104 (-2.372)	-0.05 (-0.405)	-0.325 (-11.09)	-0.235 (-3.118)	-0.645 (-2.752)	-0.156 (-0.762)	-0.317 (-2.117)
Const	-3.075 (-0.64)	-9.264 (-2.849)	-13.796 (-1.281)	6.172 (1.624)	-3.511 (-0.735)	-2.338 (-0.622)	-7.353 (-0.9224)	14.661 (3.217)
T-k¹	34	34	34	34	34	32	30	34
Diagnostic statistics								
R²_a	0.974	0.973	0.985	0.989	0.908	0.981	0.953	0.956
t_{DF}(1)²	-4.316(2)	-4.766(2) [^]	-5.136(2) [*]	-3.932(0)	-2.448(4)	-2.353(1)	-2.559(8)	-3.416(5)
t_{DF}(2)	-4.292(2)	-4.741(2) [^]	-5.149(2) [*]	-3.903(0)	-2.474(4)	-2.311(1)	-2.496(8)	-3.401(5)
t_{DF}(3)	-4.246(2)	-4.893(2)	-2.06(8)	-3.906(0)	-2.085(8)	-2.251(1)	-2.405(8)	-3.311(5)
R(2)³	1.575	11.87 [#]	1.151	13.94 [#]	27.672 [#]	30.619 [#]	3.615 [*]	0.064
R(3)	2.588 [^]	10.78 [#]	2.594 [^]	6.923 [#]	15.579 [#]	15.265 [#]	14.723 [#]	10.14 [#]
R(4)	-	-	1.681	-	-	10.021 [#]	10.533 [#]	6.632 [#]
BG-F⁴	1.527	3.36 [*]	1.423	4.821 [#]	3.259 [*]	2.526 [^]	0.898	4.767 [#]
BPG⁵	10.303	12.564	9.893	15.73 [^]	13.513	6.514	10.646	17.379 [*]
Glej⁶	10.614	10.784	8.939	21.416 [*]	15.181 [^]	8.267	12.881	17.992 [*]

[^] denotes statistical significance at the 10 per cent level, ^{*} at the 5 per cent level, and [#] at the 1 per cent level (according to the conventionally used critical values; see note 2 for t_{DF} critical values)

¹T is the total number of observations, k is the number of parameters estimated.

²The t_{DF}(1), t_{DF}(2), t_{DF}(3) refer to the residual based Dickey-Fuller t-statistics for co-integration based on regression equations that include: (1) no trend and no constant; (2) no trend and a constant; and (3) a trend and a constant. The numbers in parentheses accompanying the t_{DF} statistics refer to the order of the augmentation process in the Augmented Dickey-Fuller regressions.

³R(2), R(3) and R(4) refer to the RESET test statistics. Each is distributed as F_{s, n-k-s} where s is the number of restrictions being tested, n is the number of observations, and k is the number of parameters in the restricted regression. The bracketed numbers ((2), (3), and (4)) refer to the highest power of the lagged dependent variable that has been included in the unrestricted regression. Thus, (4) implies that the lagged dependent variable raised to each of the second, third, and fourth powers is included. A hyphen is entered when the statistic could not be calculated because the matrix of explanatory variables in the unrestricted RESET regression was not positive definite.

⁴The BG-F statistic is the Breusch-Godfrey test statistic for autocorrelation adjusted for degrees of freedom (Kiviet, 1986), and in this case tests for autocorrelation of up to fourth order. This statistic is approximately distributed as F_{s, n-k-s}.

⁵The BPG statistic is the Breusch-Pagan-Godfrey test statistic for heteroscedasticity, and is distributed as χ^2_{k-1} .

⁶Glej refers to the Glejser test for heteroscedasticity, which is distributed as χ^2_{k-1} .

Table 4: ECM results (dependent variable $\Delta \ln L$)

	3	31	32	34	35	36	37	38
$\Delta \ln L_{t-1}$	-	1.06 [#] (8.105)	0.635 [#] (5.535)	-	0.266 [^] (1.863)	0.477 [#] (4.337)	0.61 [#] (3.534)	-0.447 [#] (-2.957)
$\Delta \ln L_{t-2}$	0.449 [#] (5.784)	-	0.502 [#] (6.269)	-	0.774 [#] (3.669)	-	-	0.554 [#] (3.079)
$\Delta \ln W_t$	-0.181 [#] (-3.222)	-0.444 [#] (-9.977)	-0.627 [#] (-5.715)	-0.254 [#] (-4.617)	-	-0.274 [#] (-5.897)	-0.209 [#] (-3.061)	-
$\Delta \ln W_{t-1}$	-	0.401 [#] (6.293)	0.229 [*] (2.674)	-	-	0.144 [^] (1.975)	0.215 [*] (2.564)	-
$\Delta \ln W_{t-2}$	-0.145 [*] (-2.144)	0.08 [*] (2.319)	0.255 [*] (2.774)	-	-	0.115 [^] (2.122)	0.224 [#] (3.056)	-0.183 [*] (-2.315)
ΔR_t	-	-	-0.757 [#] (-5.799)	-0.211 [#] (-3.646)	-	0.16 [*] (2.17)	-	0.19 (1.464)
ΔR_{t-1}	-	0.296 [#] (3.752)	-	-	-	0.482 [#] (5.442)	1.13 [#] (3.688)	0.439 [#] (3.1)
ΔR_{t-2}	-	0.309 [#] (4.561)	-	0.268 [#] (5.156)	-	0.239 [*] (2.933)	-	-
$\Delta \ln Y_t$	0.246 [#] (5.221)	0.206 [#] (3.88)	0.502 [#] (12.98)	0.145 [#] (4.735)	0.164 [#] (3.004)	0.191 [#] (3.89)	-	-
$\Delta \ln Y_{t-1}$	0.366 [#] (5.179)	-0.392 [#] (-4.653)	-	-	0.191 [#] (3.182)	-0.154 [*] (-2.293)	0.229 [#] (2.881)	0.371 [*] (2.799)
$\Delta \ln Y_{t-2}$	-	-0.342 [#] (-5.216)	-0.6 [#] (-5.107)	0.07 [*] (2.13)	-	-	-	-
$\Delta \ln K_t$	-	-1.867 [#] (-3.297)	1.313 [#] (4.293)	-	2.152 [#] (3.41)	0.719 [#] (3.946)	-	-
$\Delta \ln K_{t-1}$	-	2.323 [#] (4.216)	-1.949 [#] (-6.354)	0.741 [#] (6.799)	-2.486 [#] (-4.573)	-	-	1.96 [#] (2.999)
$\Delta \ln K_{t-2}$	-	-	-	-	-	-	-	-
$\Delta \ln G_t$	-	-0.326 [#] (-3.354)	0.486 [#] (3.064)	0.274 [*] (2.49)	-	-0.871 [#] (-5.813)	-	-
$\Delta \ln G_{t-1}$	-	-	0.199 (1.304)	0.264 [*] (2.215)	-	0.316 [^] (1.887)	-	-
$\Delta \ln G_{t-2}$	0.46 [#] (3.639)	-	-	-	0.498 [#] (3.238)	-	-	-
$\Delta \ln ST_t$	0.008 [*] (2.645)	0.01 [#] (3.207)	0.007 [^] (2.041)	0.01 [#] (3.505)	-	-	-	-
$\Delta \ln ST_{t-1}$	0.01 [#] (3.702)	-0.014 [#] (-4.104)	-	0.009 [#] (2.971)	0.008 [^] (1.957)	-0.019 [#] (-3.817)	-	-
$\Delta \ln ST_{t-2}$	-	0.005 (1.743)	-	-	-	-0.01 [*] (-2.666)	-	-
$\Delta \ln M_t$	0.039 (1.261)	-0.01 (-0.381)	0.189 [#] (4.059)	0.162 [#] (6.761)	0.053 (1.44)	-0.032 (-1.362)	0.028 (0.5484)	-0.02 (-0.405)
$\Delta \ln M_{t-1}$	0.042 (0.975)	0.084 [#] (3.496)	-0.029 (-0.4998)	-0.145 (-0.678)	0.101 [^] (1.918)	0.116 [#] (4.551)	0.066 (1.116)	0.275 [#] (5.863)
$\Delta \ln M_{t-2}$	0.043 (1.665)	-0.037 (-1.427)	0.087 (2.21)	-0.1 [#] (-4.253)	0.046 (1.14)	0.074 [#] (3.488)	0.121 [*] (2.093)	0.155 [#] (3.659)
$\Delta \ln X_t$	-0.026 (-0.8)	0.088 [*] (2.399)	-0.091 [*] (-2.851)	-0.107 [#] (-3.417)	-0.05 (-1.152)	0.015 (0.465)	-0.062 (-0.801)	0.012 (0.22)
$\Delta \ln X_{t-1}$	-0.003 (-0.081)	-0.084 [#] (-3.311)	0.065 [*] (2.113)	0.016 (0.601)	-0.104 (-1.677)	-0.027 (-0.79)	-0.11 (-1.483)	-0.007 (-0.116)
$\Delta \ln X_{t-2}$	0.036 (1.064)	0.035 (1.161)	0.013 (0.392)	0.083 [#] (3.057)	-0.036 (-0.657)	0.075 [^] (2.095)	-0.122 (-1.445)	-0.031 (-0.532)
RES_{t-1}	-0.121 (-1.476)	-0.397 [#] (-4.467)	-0.72 [#] (-8.162)	-0.653 [#] (-5.283)	-0.093 (-1.159)	-0.348 [#] (-4.291)	-0.402 [*] (-2.723)	-0.518 [#] (-4.606)
Const	-0.158 [#] (-4.702)	-0.007 (-1.075)	-0.002 (-0.334)	-0.031 [#] (-6.384)	-0.007 (-0.668)	-0.037 [#] (-7.644)	0.001 (0.11)	-0.094 [#] (-4.366)

Table 4 (continued)

Diagnostic statistics								
	3	31	32	34	35	36	37	38
T-k¹	22	15	17	19	22	14	19	23
R_a²	0.926	0.914	0.9489	0.921	0.845	0.952	0.72	0.81
R(2)³	9.267 [#]	4.455 [^]	0.738	1.66	2.437	0.067	1.683	0.805
R(3)	4.518 [*]	3.298 [^]	0.414	0.919	1.18	0.057	1.245	2.854 [^]
R(4)	3.159 [*]	2.053	0.444	3.3 [^]	0.872	0.064	1.15	2.175
BG-F⁴	0.226	1.536	2.576 [^]	0.573	0.065	0.099	0.104	1.8
BPG⁵	5.403	18.954	14.041	8.345	8.723	18.668	13.495	20.951
Glej⁶	8.254	13.939	17.016	5.975	12.274	22.906	12.838	19.85

Notes are the same as for Table 3. Cells in Table 4 containing only a hyphen refer to variables that were dropped during the general to specific modelling process. “Δ” is the first difference operator.

Table 5: Industry definitions

ISIC number	Industry
3	Manufacturing
31	Manufacture of food, beverages and tobacco
32	Textiles, wearing apparel and leather industries
33	Manufacture of wood and wood products, including furniture
34	Manufacture of paper and paper products, printing and publishing
35	Manufacture of chemicals and chemical petroleum, coal, rubber and plastic products
36	Manufacture of non-metallic mineral products, except products of petroleum and coal
37	Basic metal industries
38	Manufacture of fabricated metal products, machinery, and equipment
39	Other manufacturing industries

Endnotes

¹ See *inter alia* Gaston and Trefler (1993), Haskel and Slaughter (2001), Hine and Wright (1998), Konings and Vandebussche (1995), Milner and Wright (1998), and Revenga (1992).

² It should be noted at this point that we do not intend to disparage the value of aggregate-level studies. Indeed, such studies have provided useful insight about how international trade has contributed to the labour market outcomes we see today. We merely argue that a greater understanding of the partial equilibrium adjustment process would be valuable for assessing the likely impacts of future trade changes, and that disaggregate-level studies can help to achieve such an understanding.

³ Grossman (1987) has found that the effects of import prices on employment differ across a sample of U.S. three-digit and four-digit SIC industries. However, his interest was not in the implications of these differences for the interpretation of aggregate evidence.

⁴ Davis and Weinstein (2001) also conclude that non-factor-endowment based trade is still important among rich countries. Domowitz, Hubbard and Petersen (1988) find evidence that there are positive price/marginal-cost mark-ups in two-digit ISIC US manufacturing industries. This lends support to the assertion that trade in manufactured goods is not explainable by Heckscher-Ohlin (HO) forces. Lending further support to that assertion, Levinsohn (1993) finds that the “imports-as-market-discipline-hypothesis” appears to hold empirically, using data on Turkish manufacturing industries.

⁵ In contrast to KV and MW, however, we have not derived our labour demand equation by duality via an assumed-form production function. This is partly because duality does not always hold empirically (Bairam and Kahya, 1998) and partly because the appropriate form of the production function is unknown.

⁶ The industry definitions are those of ISIC revision 2. See Appendix A and Meyer zu Schlochtern and Meyer zu Schlochtern (1994) for a detailed discussion of the data and their construction.

⁷ A series at one-digit or two-digit level was not available for the entire period.

⁸ PPP exchange rates were obtained from the ISDB.

⁹ The wage series for French industry ISIC 36 (W_{ILO}) was obtained for the period 1972-1991 from the ILO’s LABORSTA database (no other 2 digit series was available for more than 9 years) and converted to units consistent with our wage series. The difference between the log of this series and of our wage series ($W_{ILO} - W$) was found to have a unit root and when plotted showed a strong downward movement over time. This suggests that the difference between the series is not random. For British industries 31, 33, and 34 (the only other two-digit series available from ILO) the difference between the ILO’s wage series (appropriately converted) and ours was plotted for the nine years in which the series overlapped (1983-91) and looked potentially stationary in each case. Drawing definitive conclusions on the basis of nine plotted observations is not usually, however, considered to be exemplary of statistical rigour.

¹⁰ No output series was provided in the ISDB, hence the use of value added.

¹¹ The Ψ - t_{bar} test is used when the lag order in the ADF regression is greater than zero. Since Im *et al* suggest that the power of the t_{bar} test goes to zero when the lag order is incorrectly set to zero, we examined both the Ψ - t_{bar} and the t_{bar} statistics whenever we found that the lag order was zero. In no case did the two statistics lead to conflicting conclusions. Whether or not to include a trend in the ADF regression was decided by eyeballing plots of the series. A trend was included in the ADF regression when there appeared to be one in the series. When this process led to no obvious conclusion regarding the inclusion of a trend we checked both the trend and no trend statistics and found that they agreed in all cases.

¹² It is important to note that wherever we have used differenced and lagged terms in this study, we have taken the lags and differences in a spreadsheet application and then ensured that none of the terms erroneously takes the difference across the break between countries and none of the lagged variables for one country is actually an observation from the other. In this study, the French data were entered first and then the British, so we had to ensure that none of the lagged or differenced terms for the UK included any French information.

¹³ This testing strategy cannot be applied to the IPS tests as there are no tabulated distributions for the joint tests for panel data.

¹⁴ In two cases the various statistics available led to conflicting conclusions regarding the I(1) versus I(0) test. However, we can work with either an I(1) or an I(0) explanatory variable when there is an I(1) dependent variable and at least one other I(1) explanatory variable present, and so this ambiguity should not disrupt the conclusions of the paper.

¹⁵ Six is the greatest number of variables for which MacKinnon provides response surface estimates.

¹⁶ Inspection of plots of the residuals from equation (1) suggests that these residuals have a mean that may well be zero, and so the no-constant case should be considered.

¹⁷ Banerjee, Dolado and Mestre (1998) provide critical values for the t_{ECM} test, but the use of their tables requires the inclusion of leads as well as lags of the first differenced variables in the regression equation. Given the small number of observations available to us, we were unable to do this.

¹⁸ In table 4, the statistic is compared only to finite-sample t values, but we note in the text which industries stand up to the Dickey-Fuller critical values. The use of finite sample critical t values is a slightly more conservative option than would be the use of asymptotic values, since the finite sample critical values are larger in absolute value.

¹⁹ In spite of the fact that OLS is a super-consistent estimator of equation (1) (when the variables are co-integrated), it may still be biased in small samples due partly to the omission of dynamic terms.

²⁰ The t_{DF} critical values to which the t_{ECM} statistic is compared are the 10 per cent critical values for 50 observations and 5 variables from Engle and Yoo (1987). The variables for industries 32 and 34 are co-integrated even when the t_{ECM} statistic is compared to the 1 per cent critical value.

²¹ If all variables in the ECM (equation (2)) other than RES_{t-1} are stationary (since they are $I(1)$ in their log-levels), an $I(1)$ RES_{t-1} term would not be spuriously correlated with any other variables, and we would not expect a spuriously large R^2 .

²² Unfortunately, the small number of observations available to us prevented the use of a Bewley transformation. Such a transformation would have allowed us to examine the long-run levels relationship together with the dynamic adjustment process, and by including the dynamic terms would also have helped to minimise any dynamic misspecification in equation (1). Bewley transformations (using an instrumental variables approach) also allow for asymptotically valid interpretation of the t -statistics on the explanatory variables' coefficients. Patterson (2000, chapter 8) provides a useful explanation of the Bewley transformation.

²³ The inclusion of some measure of the national output gaps as explanatory variables would perhaps control for this problem, as may the use of hours worked in place of total employment. Some control for productivity may also correct for this problem. The Total Factor Productivity (TFP) series from ISDB could not be used, however, because of its calculation via the ratio of value added to the shares of labour and capital in value added (Meyer zu Schloctern and Meyer zu Schloctern, 1994). Thus, a labour demand equation in logs, using $\ln Y$, $\ln K$ and $\ln TFP$ as explanatory variables is close to being a re-arrangement of the equation used to calculate TFP, and so the right-hand side of the labour demand equation will be close to an identity for employment (the fact that the identity will not be exact is due to the use of standardised, rather than industry- and country-specific, factor weights in the TFP calculation).

²⁴ It seems more likely that the 4-digit sub-branches of a given 3-digit industry will be homogeneous in their behaviour than will the 2-digit sub-branches of a given 1-digit industry. Thus, aggregating to a 2-digit or 3-digit level may be more justifiable than aggregating to a 1-digit level or national level.