TRADE, INCOME AND THE EXCHANGE RATE IN THE OECD: ELASTICITIES IN A PANEL OF INDUSTRIES

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Abstract. How big are cross-country and cross-sector differences in import and export behaviour? A panel of manufacturing industries in several developed countries reveals that there is substantial variation across sectors, in the response of trade to changes in prices and incomes. Ignoring this heterogeneity can render conventional results biased and inconsistent, so a number of robust methods are used to obtain reliable estimates of long-run and short-run trade relationships. The findings point to common behaviour across sectors, which could be due to similarities in technology.

How responsive are imports and exports to changes in relative prices and income? On a country-wide level, there is a large literature that answers the question. However, given differences among the kind of sectors that make up an economy, it seems likely that such a broad picture will disguise substantial heterogeneity in the trading behaviour of individual industries. The aim of this paper, therefore, is to explore the price and income elasticities of imports and exports in a disaggregated panel of industries across a number of countries in the Organisation for Economic Co-operation and Development (OECD).

Using a dataset covering thirteen manufacturing industries in eleven countries, similarities in the behaviour of sectors across countries are exploited to obtain estimates of long-run trade relationships. The broad picture that emerges from this analysis is that there is significant variation in elasticities across industries.

The motivation for studying this topic at an industry level comes from the models of innovation, trade and growth developed by Cameron, Proudman and Redding (2005) and Redding (2002), amongst others. They emphasise that trade performance is related to the level of technological progress in an economy, and that countries can develop competitive trading advantages over competing economies by innovating enough to develop a technological lead over rivales. This raises two issues. First, there is no reason to assume that all the industries in an economy are at the same level of technological leadership, relative to others; thus the UK could be a leader in pharmaceutical products, for example, but not in furniture making. As a result, policies aimed at raising innovation expenditure, and ultimately improving long-run growth, might be more effective in some industries than others.

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Secondly, temporary shocks in trade performance – due to the exchange rate, for instance – might have a long-term impact on some sectors, if expenditure on innovation and future technological improvements are affected.

A disaggregated analysis of trade performance across industries is relevant to these issues because it can quantify differences in industry behaviour, in the face of changes in prices, income and other factors (such as innovation). It also offers a framework to study the long-run impact of short-run shocks.[1] Since there is relatively little existing work on this level of disaggregation, using the OECD database discussed here, the analysis in this paper represents the beginning of a wider research agenda. The scope of empirical work is restricted to examining only price and income elasticities, for a subset of manufacturing industries, over a short period of time. With this assessment accomplished, work can then proceed on the wider issues discussed above.

1. Econometric context

Of the range of questions that emerge from the empirical trade literature, the first important consideration in this paper is the degree of heterogeneity allowed for across the sectors in the economy.[2] Starting from a whole-economy viewpoint as the highest level of aggregation, a first step towards disaggregation could be according to broad commodity group (e.g. agricultural trade, raw materials, manufactures, etc), or by trade partner. This approach is taken by Houthakker and Magee (1969), who analyse trade elasticities by looking first at country-specific elasticities, then bilateral trade flows between the US and major partners, and finally US elasticities for five commodity groups.

The resulting set of equations that comprise a general imperfect substitutes model is presented by Goldstein and Khan (1985, p. 1045), and so the focus here is on the key relationships that underpin the econometric modelling strategy below. They can be expressed generically as:

$$\mathsf{X}_i = f(\mathsf{RPX}_i, \mathsf{YF}_i) \tag{1a}$$

$$\mathsf{M}_i = g(\mathsf{RPM}_i, \mathsf{YD}_i), \tag{1b}$$

for some functions $f(\cdot)$ and $g(\cdot)$, where for country i: X_i and M_i are real exports and imports respectively; RPX_i and RPM_i are the relative prices of exports and imports against an index of the prices of substitute goods; and YD_i and YF_i represent domestic and foreign income respectively.

It is worth highlighting two aspects of a disaggregated picture, as they are relevant to the later sections in this paper. First is the ability to allow for heterogeneity in the trade flows across sectors in the economy, which recognises the fact that two sectors – say textiles and IT – might not share the same trading partners. This could be important, as the appropriate relative price and income measures for each sector need not be the same in this case: if the bilateral exchange rate with the domestic textile sector's major partner appreciated, whilst that of the IT sector depreciated, then relative prices could diverge. Similarly, income shocks affecting one sector's trading partners more than another's could generate the same kind of asymmetry with regard to income.

Secondly, it is possible that the import and export functions themselves might vary by sector and country. In practice this would probably be manifest in heterogeneity

[1]In the trade literature, these phenomena are studied in models of hysteresis: see Baldwin (1988) and Baldwin and Lyons (1994).

[2]Further issues are discussed in greater detail by Fawcett (2008, Chapter 2).

across price and income elasticities, rather than a completely different functional form, but the differences could still be significant.

Besides hetereogeneity across sectors and countries, another consideration is the effect of non-stationarity on any modelling strategy. A criticism of this early literature is that its treatment of non-stationarity in empirical models was poor. Whilst the stationarity of all variables was implicitly assumed, when they were included in *level* form in models, in reality this assumption later turned out to be invalid. As discussed below, tests for the presence of unit roots suggest that the variables in trade equations are, in most cases, $\mathsf{I}(1)$, yielding potentially spurious results from a simple linear regression model including only the levels of each.[3]

The major methodological development that offered a solution to this problem came, of course, with the theory of cointegration in papers by Granger (1981) and Engle and Granger (1987) amongst others. One popular way to use this theory has been to incorporate potential cointegrating relationships within a vector equilibrium-correction (VECM) model, which has two principal attractions. First, it allows for potential endogeneity in the variables in a trade system, and secondly it allows for more than one cointegrating vector. In this specification, the long-run relationship between each trade flow and its price and income drivers can be captured in terms of levels, whilst the short-run elasticities are given by the response of trade growth to changes in price and income.

These existing studies use a VECM comprising a trade flow variable, relative price measure, and income term. Thus, for example, the system for imports is expressed as:[4]

$$\Delta \mathbf{z}_{mt} = \boldsymbol{\kappa}_m + \sum_{j=1}^{n} \boldsymbol{\Gamma}_{mj} \Delta \mathbf{z}_{m,t-j} + \boldsymbol{\Pi}_m \mathbf{z}_{m,t-1} + \boldsymbol{\epsilon}_{mt} \tag{2}$$

where $\boldsymbol{\epsilon}_{mt} \sim \mathsf{IN}(0, \boldsymbol{\Omega}_m)$, $\mathbf{z}_{mt} = (\mathsf{m}_t, \mathsf{rpm}_t, \mathsf{yd}_t)'$ (lower case denoting logs of variables), $\boldsymbol{\kappa}_m$ is an intercept vector (possibly constrained to lie in the cointegration space), $\boldsymbol{\Gamma}_{mj}$ are the short-run feedback coefficients and $\boldsymbol{\Pi}_m$ combines the cointegrating combinations and their loadings, such that $\boldsymbol{\Pi}_m = \boldsymbol{\alpha}_m \boldsymbol{\beta}'_m$. Thus in a cointegrated system, $\boldsymbol{\alpha}_m, \boldsymbol{\beta}_m \in \mathbb{R}^{3\times r}$ where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are of full rank $0 < r < 3$, where r represents the number of cointegrating relationships, and $\boldsymbol{\Pi}_m$ has reduced rank $(3 - r)$. The corresponding equation for exports comprises $\mathbf{z}_{xt} = (\mathsf{x}_t, \mathsf{rpx}_t, \mathsf{yf}_t)'$ with analogues $\boldsymbol{\epsilon}_{xt}$, $\boldsymbol{\kappa}_x$, $\boldsymbol{\Gamma}_x$ and $\boldsymbol{\Pi}_x$ elements. In this framework, the parameters of interest are contained in the $\boldsymbol{\beta}'$ matrix, as shown in the example above (where subscripts have been omitted for notational simplicity), which are the long-run relationships between the variables in $\mathbf{z}_t$. Using (2) and its export equivalent, Hooper *et al.* (2000) derive estimates for trade elasticities for the G7 countries based on aggregate data across several decades (depending on country, for the mid-1950s/70s to 1994), and these are presented in Tables 1 and 2.

Despite the sophistication of this approach in dealing with non-stationarity, however, problems still remain, as the existing literature has largely focused on an aggregate picture, which not only precludes an assessment of trade behaviour by sector, but could also affect the validity of any elasticity estimates obtained, in a

[3]If the variables in a regression in levels are cointegrated, then superconsistency properties of a coefficient estimator might provide meaningful point estimates of the coefficients, but standard errors, and associated inference procedures, could still be affected.

[4]This corresponds to equation (2) of Hooper, Johnson and Marquez (2000), with the export equation given by their equation (1). Fawcett (2003) uses their framework for his estimation exercise, and the statistical theory underlying the VECM approach used, is due to Johansen (1995).

Table 1: TRADE ELASTICITIES IN THE LITERATURE: IMPORTS

		HJM		HM		Krugman	
		Price	Income	Price	Income	Price	Income
Belgium	*LR*			−1.02*	1.94*	−0.53*	1.99*
	SR						
Canada	*LR*	−0.9*	1.4*	−1.46*	1.20*	−1.45	1.66*
	SR	−0.1	1.3*				
Denmark	*LR*			−1.66*	1.31*		
	SR						
France	*LR*	−0.4*	1.6*	0.17	1.66*		
	SR	−0.1	1.7*				
Germany	*LR*	−0.06*	1.5*	−0.24†	1.80*†	−0.09†	2.83*†
	SR	−0.2*	1.0*				
Italy	*LR*	−0.4*	1.4*	−0.13	2.19*	−0.68*	3.65*
	SR	−0.0	1.0*				
Japan	*LR*	−0.3*	0.9*	−0.72*	1.23*	−0.42	0.80
	SR	−0.1	1.0*				
Netherlands	*LR*			0.23	1.89*	−0.22	2.66*
	SR						
Norway	*LR*			−0.78*	1.40*		
	SR						
UK	*LR*	−0.6	2.2*	0.22	1.66*	0.99*	−0.20*
	SR	−0.0	1.0*				
US	*LR*	−0.3*	1.8*	−0.54	1.51*	−0.93*	1.31*
	SR	−0.6	2.3*				
Estimation method		VECM-MLE (LR), OLS (SR)		OLS in levels		OLS in levels	
Data span and frequency		Quarterly, 1950/70-1994		Annual, 1951-1966		Annual, 1971-1986	

NOTES: *LR* and *SR* relate to estimates of long-run and short-run elasticities, where papers distinguish between the two; otherwise it is assumed that papers report long-run parameter estimates. An * denotes statistical significance at the 5% level. Data for Germany denoted † relate to West German estimates. HJM represents Hooper, Johnson and Marquez (2000); HM is Houthakker and Magee (1969); Krugman is his (1989) paper.

Table 2: TRADE ELASTICITIES IN THE LITERATURE: EXPORTS

		HJM		HM		Krugman	
		Price	Income	Price	Income	Price	Income
Belgium	*LR*			0.42	1.83*	−0.19*	1.24*
	SR						
Canada	*LR*	−0.9*	1.1*	−0.59*	1.41*	0.8*	2.87*
	SR	−0.5*	1.1*				
Denmark	*LR*			−0.56	1.69*		
	SR						
France	*LR*	−0.2	1.5*	−2.27*	1.53*		
	SR	−0.1	1.8*				
Germany	*LR*	−0.3	1.4*	1.70†	2.08*†	−0.55†	2.15*†
	SR	−0.1	0.5				
Italy	*LR*	−0.9*	1.6*	−0.03	2.95*	−0.23	2.41*
	SR	−0.3*	2.3*				
Japan	*LR*	−1.0*	1.1*	−0.80	3.55*	−0.88*	1.65*
	SR	−0.5*	0.6				
Netherlands	*LR*			−0.82	1.88*	−0.76	3.86*
	SR						
Norway	*LR*			0.20	1.59*		
	SR						
UK	*LR*	−1.6*	1.1*	−0.44	0.86*	−0.54	1.30*
	SR	−0.2*	1.1*				
US	*LR*	−1.5*	0.8*	−1.51*	0.99*	−1.42*	1.70*
	SR	−0.5*	1.8*				
Estimation method		VECM-MLE (LR), OLS (SR)		OLS in levels		OLS in levels	
Data span and frequency		Quarterly, 1950/70-1994		Annual, 1951-1966		Annual, 1971-1986	

NOTES: See notes for Table 1.

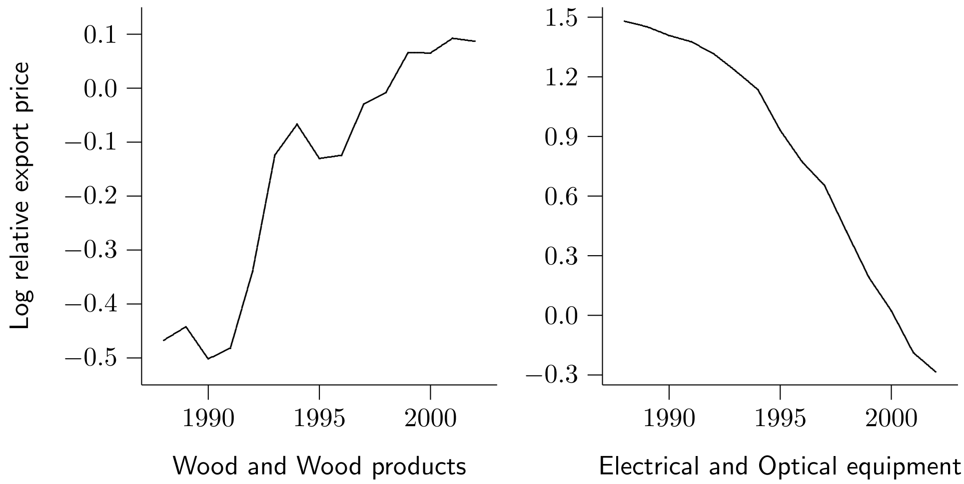
reasonably wide range of situations. Thus the following section introduces the main empirical work of this paper, which seeks to estimate disaggregated elasticities for a number of sectors in a panel of countries.

2. Building a panel model to estimate trade elasticities

The choice of a panel dataset, and associated estimation techniques, is motivated by two considerations:

- First, it can be used to obtain sector-by-sector trade elasticities even when the number of time periods available is quite small, by exploiting similarities in industries across countries (thereby holding an advantage over a conventional time-series approach using disaggregated data), and;
- Secondly, even if the focus is purely on an economy-wide picture of trade performance, panel data methods applied to disaggregated data can offer more reliable estimates in a wide range of situations.

Figure 1: HETEROGENEITY IN US RELATIVE EXPORT PRICES



SOURCE: Author's calculations, using data for two manufacturing sectors in the US, from the OECD Structural Analysis (STAN) database (ISIC codes provided in Appendix 5.A). Log relative export prices are calculated by a trade-weighted export price series for each sector, divided by the price of domestic output from the same sector.

More concretely, there are a number of advantages of a panel approach.

First, with regard to data on trade flows, relative prices, and income, it is quite likely that aggregate data disguises significant heterogeneity in the same series, when they are compared on a sectoral level. To see this more clearly, Figure 1 compares the relative price of exports from two US manufacturing sectors over the same period of time. The remarkable difference in behaviour across each sector is explained by differences in trade flows, in addition to conventional differences in the actual producer price of output. Thus whilst over 95% of US exports of wood and wood products were destined for Canada, only approximately 15% of electrical and optical equipment (including IT) were, with Japan instead being the major destination (receiving 65% of exports).[5] Over the period shown, the US dollar consistently appreciated against the Canadian dollar, whilst the bilateral exchange rate with the Yen was more volatile, with a sharp depreciation over the first five years of the sample, followed by an appreciation. Thus even in this simple comparison it is evident that there is important time-series variation in the disaggregated explanatory variables, and this may be lost by averaging in the disaggregated series. As a result, an aggregate estimate of, say, US trade elasticities, might be unbiased in an econometric sense as a measure of 'average' economy-wide trade behaviour, but it could disguise significant variation in the response across a more disaggregated picture. Of course, there are more than two sectors in the US economy, and so a more systematic treatment of cross-sector variation in the variables of interest is presented below, for a number of countries.

Besides differences in the *variables*, an important source of variability lies in the *parameters* themselves. It could well be the case that the trade *elasticities* for wood and IT sectors differ, and this would not, of course, be detected in an aggregate study. In the presence of parameter heterogeneity across sectors, though, there

[5]Based on 1995 trade figures.

could be problems if aggregated data are used to obtain a set of 'average' trade elasticities. Pesaran and Smith (1995) show that in dynamic models, using an aggregating procedure can give inconsistent parameter estimates, even if the number of sectors and time periods is large. To see why, consider a simple heterogeneous dynamic model such as:[6]

$$y_{it} = \alpha_i y_{i,t-1} + \boldsymbol{\beta}_i' \mathbf{x}_{it} + \epsilon_{it} \qquad \begin{array}{l} i = 1, 2, \ldots, N \\ t = 1, 2, \ldots, T \\ \epsilon_{it} \sim \mathsf{IN}\left(0, \sigma_i^2\right) \end{array} \tag{3}$$

for some $\mathsf{I}(0)$ stochastic $(y, \mathbf{x}')'$, with coefficients α_i and $\boldsymbol{\beta}_i$ given by a random coefficients model so that

$$\alpha_i = \alpha + \eta_{1i} \tag{4a}$$

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \boldsymbol{\eta}_{2i} \tag{4b}$$

where η_{1i} and $\boldsymbol{\eta}_{2i}$ have zero means and constant covariances. Then, Pesaran and Smith show that using the group (i.e. cross-section) averages of y_{it} and $\mathbf{x}_{it}$, denoted $\overline{y}_t$ and $\overline{\mathbf{x}}_t$, the aggregate time-series regression is given by

$$\overline{y}_t = \alpha \overline{y}_{t-1} + \boldsymbol{\beta}' \overline{\mathbf{x}}_t + \overline{v}_t \tag{5}$$

where

$$\overline{v}_t = \overline{\epsilon}_t + \frac{1}{N} \sum_{i=1}^{N} (\eta_{1i} y_{i,t-1} + \boldsymbol{\eta}_{2i}' \mathbf{x}_{it}).$$

Thus estimation of (5) via OLS will yield inconsistent estimates if the $\mathbf{x}_{it}$ are serially correlated, and traditional responses to this via instrumental variables estimation will also fail, since anything correlated with lagged values of $\mathbf{x}_{it}$ will also be correlated with $\overline{v}_t$.[7] Further, since the variables in each trade equation are measured in log form, aggregation bias can emerge since the sum of logged terms is not equal to the log of aggregated series.

As later sections explore, alternative panel techniques can produce more reliable estimates of the $\boldsymbol{\beta}_i$, and examine the possibility that $\boldsymbol{\beta}_i = \boldsymbol{\beta}$ for all i (i.e. the case of complete homogeneity) amongst other cases. Further, the panel dimension is attractive even if there is homogeneity across groups in the $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ parameters, or at least, homogeneity in subsets of groups, as it offers an avenue away from the problem of low statistical power in small samples that affects the Johansen cointegration estimator. If some degree of parameter homogeneity is assumed, then meaningful estimates of long-run relationships can be obtained even for relatively small time-dimension datasets, provided that the number of individuals in the panel is large enough.[8]

This last point suggests an interesting role for two different cross-section dimensions in the empirical problem discussed here. On one hand, the foregoing discussion has considered a disaggregated view within a country, in which total output is decomposed into its sectoral origins, for example. However, there is another dimension available, which looks at the same industry – such as wood and wood products – across several countries. Examining *several* sectors across *multiple* countries raises the possibility of an N-S-T panel where N represents the number of countries, S the number of sectors, and T the time dimension. Although conventionally this might be treated as an $NS \times T$-dimension panel in which all

[6] This draws on Pesaran and Smith (1995) equations (2.1), (2.2) and (2.12).

[7] See Pesaran and Smith (1995, p. 86).

[8] In this sense, individuals refers to distinct groups, whether countries, sectors, firms etc.

country-industry combinations are separate individuals, the time span of the dataset here is too short for estimators or procedures that require a large number of time observations. Thus out of pragmatic considerations, there is an appeal in exploiting the N/S distinction here. For example, when making assumptions about the degree of homogeneity across individuals in the panel, there could be an argument for pooling data across countries, and thereby allowing heterogeneity across industries. The rationale for this is that similarities in the behaviour of each industry across countries – due to common technology and product characteristics, say – would suggest that there is a greater likelihood of elasticities being common to industries, rather than countries. Thus for example, whilst it may be plausible that the elasticities for textiles are the same in the US and the UK, it might not be so for US textiles compared to US IT.

2.1. **The panel dataset.** The data used in this paper comes primarily from the OECD Structural Analysis database, known as STAN (OECD 2005),[9] and covers the period 1988 – 2002. STAN includes data on nearly 50 separate industry groupings (including services), across all OECD member countries. However, as Appendix 5.A explains, the coverage across countries and industries is variable, so that a subset of the data is studied here, covering 13 sectors in 11 countries in a balanced panel for all 15 years. This leaves an N-S-T data 'cube' of nearly equal proportions on each side, and has implications for the choice of panel estimator, since not all behave in the same way for given individual and time dimensions.

2.2. **Approaches to dynamic panel estimation.** The role of heterogeneity in industry and country elasticities can be shown explicitly in two 'stylized' trade equations:

$$\mathsf{m}_{ist} = \beta_{mis}\mathsf{rpm}_{ist} + \gamma_{mis}\mathsf{yd}_{ist} \tag{6}$$

$$\mathsf{x}_{ist} = \beta_{xis}\mathsf{rpx}_{ist} + \gamma_{xis}\mathsf{yf}_{ist} \tag{7}$$

$$i = 1, \dots, N; \quad s = 1, \dots, S; \quad t = 1, \dots, T$$

using the same variable definitions as equation 1. Clearly these do not represent regression equations that one might estimate directly, as they miss obvious elements (such as error specifications) and do not specify the nature of any dynamics. However, (6) and (7) are useful in that they show how each country and sector pairing can be treated, and how this relates to the question of heterogeneity in parameters, and the dependent and independent variables.

The is subscript on all three variables in each equation demonstrates that they can all be country and sector specific in this framework. As Figure 1 shows in the case of rpx for the US wood and electrical equipment industries, this is a valuable advantage of the model, over a more aggregated case. Another point is that assumptions about the behaviour of the parameters β and γ can be varied. Based on the discussion above with regard to the extent to which the data can be pooled, there are four main hypotheses that can be considered in an empirical modelling strategy:[10]

[9] Available from http://www.oecd.org/sti/stan.

[10] In a full specification with dynamics and error terms these restrictions would apply to all parameters, of course, but for now these four scenarios convey the central point.

$$
\begin{array}{lll}
\mathsf{H}_{\text{HET}}: & \textsf{Complete Heterogeneity} & \begin{array}{l}\beta_{is} = \beta_{is} \\ \gamma_{is} = \gamma_{is}\end{array} \\[2ex]
\mathsf{H}_{\text{NOHET}}: & \textsf{No Heterogeneity} & \left.\begin{array}{l}\beta_{is} = \beta \\ \gamma_{is} = \gamma\end{array}\right\} \text{for all } i, s \\[2ex]
\mathsf{H}_{\text{I}}: & \begin{array}{l}\textsf{Industry Heterogeneity} \\ \textsf{(Country homogeneity)}\end{array} & \left.\begin{array}{l}\beta_{is} = \beta_s \\ \gamma_{is} = \gamma_s\end{array}\right\} \text{for all } i \\[2ex]
\mathsf{H}_{\text{C}}: & \begin{array}{l}\textsf{Country Heterogeneity} \\ \textsf{(Industry homogeneity)}\end{array} & \left.\begin{array}{l}\beta_{is} = \beta_i \\ \gamma_{is} = \gamma_i\end{array}\right\} \text{for all } s
\end{array}
$$

A number of observations follow from these four cases. H_{HET} essentially treats the data on country-industry pairs as separate time series, so there are NS estimates of β and γ, each corresponding to the relevant *is* individual. In contrast, $\mathsf{H}_{\text{NOHET}}$ assumes the opposite, allowing the data to be treated as a panel with NS individuals, yielding one estimate of β and γ from the panel dataset. The intermediate cases H_{I} and H_{C} are a feature of the N/S distinction in the cross-section dimension of the data, and offer an attractive compromise in the choice between assuming complete heterogeneity (and thereby losing some of the benefits of the panel approach) and making the potentially restrictive assumption of complete homogeneity. In either intermediate case, data is pooled across countries (for H_{I}) or industries (for H_{C}), to get either S estimates of β and γ in the former case, or N country-specific coefficients in the latter. As observed above, if a homogeneity assumption must be imposed (due to the poor performance of estimators or tests in small-T samples, say) then there could be an argument in favour of hypothesis H_{I}, on the grounds that there might be significant similarity in the same industry across countries. However, Tables 1 and 2 both report that on an aggregate level, at least, there are significant cross-country differences, and it might be dangerous to ignore these *ex ante*.

Thus the estimation strategy pursued here follows a hybrid approach, by exploiting the distinction between the long-run cointegrating relationship that exists for each country-sector individual unit, and short-run changes in the variables in (7) and (6). Imposing an intermediate level of homogeneity in the long-run relationship and allowing for different degrees of heterogeneity in the short-run responses offers a suitable compromise to the trade-off set out above.

In order to understand how such a hybrid approach fits in the literature on dynamic panel models with possibly heterogeneous coefficients, a starting point is the analysis of Pesaran and Smith (1995), which was discussed above. In their baseline model, given earlier in equations (3) and (4), they study a single-equation dynamic model with additional explanatory variables (given by $\mathbf{x}_{it}$), where the slope coefficients on the lagged dependent variable and the $\mathbf{x}_{it}$s, denoted α_i and $\boldsymbol{\beta}_i$, differ randomly across individuals i. In this setting, Pesaran and Smith show that some common panel estimators, including the pooling approach, and aggregating procedure outlined above, deliver biased estimates if there is genuine parameter heterogeneity and the x_{it}s are serially correlated.[11] The underlying cause of this bias is serial correlation in the disturbance, which is evident in (5) when using aggregate data; in the pooling case the model is given by:[12]

$$y_{it} = \delta_i + \alpha y_{i,t-1} + \boldsymbol{\beta}'\mathbf{x}_{it} + v_{it}$$

[11]These concerns would almost certainly apply to the trade equations here.

[12]These equations correspond to Pesaran and Smith (1995) equations (2.4) and (2.5).

where

$$v_{it} = \epsilon_{it} + \eta_{1i} y_{i,t-1} + \boldsymbol{\eta}'_{2i}\mathbf{x}_{it}.$$

As Pesaran and Smith show, for $\mathsf{I}(0)$ series the correlation between the x_{it} and v_{it} render the usual pooled estimators of α and β inconsistent, even for large T and/or N. Thus the choice of pooling assumption $\mathsf{H}_{\text{NOHET}}$, H_{I} or H_{C} could be all the more important, since an incorrect choice introduces *econometric* problems, in addition to the *economic* judgment over which assumption is more plausible.

In the specification given by (3), Pesaran and Smith consider the 'long-run' effect of $\mathbf{x}$ on y, defining $\overline{\boldsymbol{\theta}}$ to be the appropriate measure of the average, where

$$\boldsymbol{\theta}_i = \frac{\boldsymbol{\beta}_i}{1-\alpha_i}; \quad \overline{\theta} = \frac{1}{N}\sum_{i=1}^{N}\theta_i; \quad i = 1,\ldots,N$$

If y and $\mathbf{x}$ are cointegrated, then this long-run relationship corresponds to a cointegrating vector (assuming that $r=1$) equal to $(1, -\boldsymbol{\theta}_i)'$. As an alternative to the aggregating and pooling methods, they also consider running N separate time-series regressions of (3) for $i = 1,\ldots,N$ and then taking the average of the estimated coefficients (this is known as the Mean Group estimator). They also evaluate the cross-section approach using time-averages of all the variables, and then running a cross-section regression. For very short time spans, small-sample bias might render the latter approach unreliable, but in a parsimonious model there could be scope for using the Mean Group method to get an impression of the distribution of parameter estimates, before comparing them to results from pooled alternatives.

In the context of the hybrid homogeneity assumption, Pesaran, Shin and Smith (1999) distinguish between heterogeneity assumptions in the short-run and long-run coefficients in a model. Their Pooled Mean Group approach allows α_i and $\boldsymbol{\beta}_i$ to be heterogeneous across individuals, whilst it restricts $\boldsymbol{\theta}$ to be common. In a cointegrated $\mathsf{I}(1)$ setting, this is analogous to allowing short-run coefficients and equilibrium-correction loadings to be heterogeneous, whilst imposing a common long-run cointegrating vector. Their rationale for this is that "budget or solvency constraints, arbitrage conditions or common technologies" may influence all groups in similar ways in the long run, but in the short run it is less obvious that this will be the case.[13] This distinction raises the question of how to obtain estimates of long- and short-run coefficients in a panel context. The earlier discussion on the existing trade literature showed that modern time series-based studies use cointegration theory as the statistical backdrop for estimation, and so it would seem reasonable the try and implement this in the panel.

2.2.1. *Long-run estimation in cointegrated panel models.* How do time-series considerations of nonstationarity and cointegration translate to the panel setting? In several respects the two literatures share common concerns;[14] first, the variables included in a model must be tested for their order of integration, and then estimation and testing of any cointegrating vectors takes place, either in a single-equation framework, or in a system. However, with the panel dimension comes a number of new issues to resolve, revolving around some key themes. The effects of parameter heterogeneity that were discussed above, are also relevant here; and there is a further concern relating to the interpretation of test results, such that even only slight heterogeneity (in the parameters in a unit-root test, for instance) can lead to incorrect rejection

[13]Pesaran *et al.* (1999, p. 621).

[14]A comprehensive overview of panel time series is provided by Smith and Fuertes (2007), whilst unit roots and cointegration in panels are specifically considered by Breitung and Pesaran (2008).

of hypotheses during testing. Secondly, the dimension of the panel is important, as some approaches are best suited to large T datasets, whilst others work with small T but large N. Finally, an important assumption made in some procedures is that the individuals in the panel are independent, so that a shock in one will not affect another; clearly in the case of country/sector data this is a difficult assumption to justify, and so methods robust to some form of cross-section dependence will be necessary.

A simple model considered by Pesaran *et al.* (1999) can illustrate how some of these factors come into play, and leads on to alternative estimation strategies. This assumes that the variables considered are actually $\mathsf{I}(1)$, and that there is a cointegrating relationship between them; testing that this is true is, of course, vital, and so this section finishes by examining some relevant panel unit root tests.

Using a reparameterized ARDL $(p, q, q, \ldots, q)$ model, the data generating process that Pesaran *et al.* (1999) use can be written as:[15]

$$\Delta y_{it} = \phi_i y_{i,t-1} + \boldsymbol{\beta}_i' \mathbf{x}_{it} + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \boldsymbol{\delta}_{ij}^{*\prime} \Delta \mathbf{x}_{i,t-j} + \mu_i + \epsilon_{it} \tag{8}$$
$$i = 1, 2, \ldots, N \quad t = 1, 2, \ldots, T$$

where y_{it} is the dependent variable, $\mathbf{x}_{it}$ is a $k \times 1$ vector of explanatory variables, μ_i are individual-specific fixed effects, ϕ_i, $\boldsymbol{\beta}_i$, λ_{ij}^* and $\boldsymbol{\delta}_{ij}^{*\prime}$ are parameters which in turn are functions of the parameters in the benchmark ARDL representation (see equation (1) in Pesaran *et al.* (1999)). This corresponds to a single-equation equilibrium-correction representation in the case where there is only one cointegrating vector. If there are enough time periods to run separate Pooled Mean Group regressions for each i, they then stack the time-series observations and then derive a maximum likelihood estimator for the parameters of interest, based on several assumptions, of which three are of particular note here. First, they assume that the error ϵ_{it} in (8) is independently distributed across i, with mean zero and variance σ_i^2. Secondly, the underlying roots of the ARDL model are stable, such that $\phi_i < 0$, ensuring that there is a long-run relationship between y_{it} and $\mathbf{x}_{it}$ given by $y_{it} = (\boldsymbol{\beta}_i'/\phi_i)\mathbf{x}_{it} + \eta_{it}$ for each i, with η_{it} being a stationary error. Finally, defining $\boldsymbol{\theta}_i = (\boldsymbol{\beta}_i'/\phi_i)$, they assume homogeneity of long-run coefficients across groups, such that $\boldsymbol{\theta}_i = \boldsymbol{\theta}$ for all i.

With a further assumption that the errors ϵ_{it} are normally distributed, the joint concentrated log-likelihood for all individuals over time can be derived by taking the product of each individual i log-likelihood, which highlights the importance of the independence assumption, and also identifies a major problem with using the approach in this paper. Since the independence assumption is almost certainly violated here, due to country-specific shocks affecting all industries, for instance, the joint likelihood cannot be derived as the product of the individual likelihoods. Further, given that the independence violation occurs over *individuals* rather than across *time*, and the exact nature of dependence is unknown, a possible route of taking the conditional model to construct the joint likelihood is unavailable.

For similar reasons, other panel estimators such as the Fully-Modified (FMOLS) method are likely to be inappropriate. The FMOLS estimator (see Pedroni (1995, 2000) or Phillips and Moon (1999)) corrects for long-run endogeneity in the regressors, and allows for heterogeneous short-run dynamics. However, since Pedroni (2000), Assumption 1.2 (p. 99) requires cross-sectional independence, it is unsuitable for the kind of data used here. Further, some correction mechanisms that Pedroni (2000)

[15]This corresponds to their equation (2).

suggests, such as estimating a full set of cross-section dependencies and using them to premultiply the errors, require significantly larger T dimension than is available here. Even on the level of the convergence theorems that underlie the asymptotic properties of the FMOLS estimator, Breitung (2005) points out that "Phillips and Moon (1999, p. 1092) state that '... when there are strong correlations in a cross-section (as there will be in the face of global shocks) we can expect failures in the strong laws and central limit theory arising from the nonergodicity' " (p. 160).

Whilst contemporaneous correlation causes problems for some estimators, there are alternatives that are robust to it, and of these, three are prominent, all of which allow for multiple cointegrating vectors, in contrast to earlier techniques which assumed only one long-run relationship. The first two seek to extend the time-series VECM model of Johansen (1995) into a panel dimension, building on a likelihood-based framework for estimation. Thus both Larsson and Lyhagen (1999) and Groen and Kleibergen (2003) start with an underlying panel VECM representation, which is based on a VAR(m) model for a p-dimensional random vector $\mathbf{Y}_{it}$, where for individuals $i = 1, \ldots, N$, there are $0 < r_i < p$ cointegrating relationships. Stacking the $\mathbf{Y}_{it}$ vectors across all individuals, yields a familiar representation in the form of:

$$\Delta \mathbf{Y}_t = \mathbf{A}\mathbf{B}'\mathbf{Y}_{t-1} + \sum_{k=1}^{m-1} \mathbf{\Gamma}_k \Delta \mathbf{Y}_{t-k} + \boldsymbol{\epsilon}_{it} \tag{9}$$

where $\mathbf{A}$ is an $Np \times \sum_i r_i$ matrix of short-run coefficients, $\mathbf{B}$ is an $Np \times \sum_i r_i$ matrix of long-run cointegrating vectors, the $\mathbf{\Gamma}_k$ are a set (for $k = 1, \ldots, m-1$) of feedback coefficients, and the error $\boldsymbol{\epsilon}_t$ has a multivariate normal density given by $\boldsymbol{\epsilon}_t \sim \mathsf{N}(\mathbf{0}, \mathbf{\Omega})$, where $\mathbf{\Omega}$ is an $Np \times Np$ covariance matrix with, crucially, an off-diagonal structure.

In the face of this rather compact representation of the models both papers use, it is perhaps helpful to highlight their important features. First, whilst both models allow for multiple cointegrating vectors, in the Groen and Kleibergen (2003) case, it is assumed that $r_i = r$ for all i, such that all individuals in the panel share the *same* set of cointegrating vectors $\mathbf{B}$.[16] Further, in both cases it is assumed that off-diagonal elements in the block $\mathbf{B}$ are zero, ruling out between-group cointegration.[17] The papers differ in their treatment of the short-run error correction parameters in $\mathbf{A}$, as Larsson and Lyhagen (1999) allow for non-zero off-diagonal elements, whilst Groen and Kleibergen (2003) assumes a diagonal structure. Similarly, the former allow for a non-diagonal set of $\mathbf{\Gamma}_k$ matrices, whilst the latter does not. Perhaps most importantly, given the context of this discussion, is the fact that *both* approaches allow for a non-diagonal error covariance matrix $\mathbf{\Omega}$, which means that contemporaneous correlation is allowed in the model, thereby allaying one of the chief concerns of the earlier estimation methods.

In order to derive estimates of the long-run $\mathbf{B}$ parameters, the approach of Larsson and Lyhagen (1999) is to obtain a preliminary estimate of the diagonal elements of $\mathbf{B}$ (by running N standard time-series cointegrating regressions), and then using these to estimate $\mathbf{A}$ and $\mathbf{\Omega}$, switching back and forth from updated estimates of $\mathbf{B}$, and $\mathbf{A}$ and $\mathbf{\Omega}$ until there is no further increase in the likelihood. In contrast, Groen and Kleibergen (2003) show that there is a relationship between the maximum likelihood estimator, which has an unknown analytical expression in the panel setting,

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[16] Larsson and Lyhagen (1999) also discuss a variant of their own model in which homogeneity in cointegrating vectors is imposed.

[17] Banerjee, Marcellino and Osbat (2004) emphasise some of the problems that can arise when between-group cointegration is ignored.

and a GMM estimator, and then use iterated GMM estimation to obtain maximum likelihood estimates for the coefficients.

Whilst both of these approaches are attractive, in that they allow for multiple cointegrating vectors, and contemporaneous correlation in disturbances across individuals, they suffer from the need for a relatively large number of time observations. Thus for example, in order to estimate (9) for a three-variable trade model across all 143 individuals (using assumption $\mathsf{H}_{\text{NOHET}}$), Larsson and Lyhagen (1999) require at least $T = NSp + 2 = 431$ time periods, whilst the asymptotic results of Groen and Kleibergen (2003) rely on large T. In the context of our panel dataset, where $T = 15$, it is clear that such requirements will not be satisfied.

In response to the small-sample limitations of the these models, Breitung (2005) proposes an alternative method that is possible to implement even with a sample size of 15, and that also allows for contemporaneous correlation in disturbances. In a simple cointegrated VAR(1) model such as:

$$\Delta \mathbf{y}_{it} = \boldsymbol{\alpha}_i \boldsymbol{\beta}' \mathbf{y}_{i,t-1} + \boldsymbol{\epsilon}_{it} \tag{10}$$

$$i = 1, \ldots, N \quad t = 1, \ldots, T \quad \mathsf{E}[\boldsymbol{\epsilon}_{it}] = \mathbf{0} \quad \boldsymbol{\Sigma}_i = \mathsf{E}[\boldsymbol{\epsilon}_{it}\boldsymbol{\epsilon}_{it}']$$

his approach, which seeks to estimate the long-run cointegrating vector $\boldsymbol{\beta}$ (which is common to all i), splits the estimation process into two steps. First, consistent estimates of $\boldsymbol{\alpha}_i$ and $\boldsymbol{\Sigma}_i$ are obtained (denoted $\widehat{\boldsymbol{\alpha}}_i$ and $\widehat{\boldsymbol{\Sigma}}_i$), either via the Johansen (1995) maximum likelihood estimator in the case of multiple cointegrating vectors, or the Engle-Granger two-step method if there is only one such vector.[18] Then, Breitung shows that the $\boldsymbol{\beta}$ matrix can be estimated by a pooled OLS regression of:[19]

$$\widehat{\mathbf{z}}_{it} = \boldsymbol{\beta}' \mathbf{y}_{i,t-1} + \widehat{\mathbf{v}}_{it}$$

$$i = 1, \ldots, N \quad t = 1, \ldots, T$$

where $\widehat{\mathbf{z}}_{it} = (\widehat{\boldsymbol{\alpha}}_i' \widehat{\boldsymbol{\Sigma}}_i^{-1} \widehat{\boldsymbol{\alpha}}_i)^{-1} \widehat{\boldsymbol{\alpha}}_i' \widehat{\boldsymbol{\Sigma}}_i^{-1} \Delta \mathbf{y}_{it}$ and $\widehat{\mathbf{v}}_{it} = (\widehat{\boldsymbol{\alpha}}_i' \widehat{\boldsymbol{\Sigma}}_i^{-1} \widehat{\boldsymbol{\alpha}}_i)^{-1} \widehat{\boldsymbol{\alpha}}_i' \widehat{\boldsymbol{\Sigma}}_i^{-1} \boldsymbol{\epsilon}_{it}$. By normalising the cointegrating vectors such that $\boldsymbol{\beta} = [\mathbf{I}_r, \mathbf{B}]'$,[20] and dividing the vector $\mathbf{y}_{it}$ into two subvectors, $\mathbf{y}_{it}^{(1)}$ which is $r \times 1$ and $\mathbf{y}_{it}^{(2)}$ which is $(k - r) \times 1$, so $\mathbf{y}_{it} = [\mathbf{y}_{it}^{(1)\prime}, \mathbf{y}_{it}^{(2)\prime}]'$, the OLS regression can be written as:[21]

$$\widehat{\mathbf{z}}_{it}^{+} = \mathbf{B} \mathbf{y}_{i,t-1}^{(2)} + \widehat{\mathbf{v}}_{it} \tag{11}$$

where now $\widehat{\mathbf{z}}_{it}^{+} = (\widehat{\boldsymbol{\alpha}}_i' \widehat{\boldsymbol{\Sigma}}_i^{-1} \widehat{\boldsymbol{\alpha}}_i)^{-1} \widehat{\boldsymbol{\alpha}}_i' \widehat{\boldsymbol{\Sigma}}_i^{-1} \Delta \mathbf{y}_{it} - \mathbf{y}_{i,t-1}^{(1)}$. Breitung then proves that this estimator has an asymptotic normal distribution. Besides extending the simple model above to more general VAR(p) models with deterministic terms, such as constant, trend and dummy variables, the Breitung (2005) procedure is more robust to contemporaneous correlation across individuals. It uses the panel-corrected standard errors suggested by Breitung and Das (2005), which correct for any effect of cross-section dependence on standard errors, whilst the estimator itself remains consistent (as T and $N \to \infty$) in the presence of such dependence. In Monte-Carlo studies, both Breitung (2005) and Wagner and Hlouskova (2007) find that this two-step estimator performs better than alternatives such as FMOLS, and the cross-sectional average of conventional cointegrated time-series estimates, when the T dimension of the panel is small (at least $T = 15$ in the former and $T = 25$ in the latter).

[18] These estimates are consistent as $T \to \infty$.

[19] This corresponds to Breitung (2005) equation (4), p. 156.

[20] Note that this $\mathbf{B}$ is not the same as $\mathbf{B}$ in equation 9. As Breitung and Pesaran (2008) note, other exact-identifying restrictions can be used without affecting the result.

[21] cf. *op. cit.* equation (6), p. 156.

Thus it would seem that the Breitung two-step estimator offers an attractive solution to the question of estimating long-run cointegrating vectors. First, it makes it possible to exploit the panel dimension for the long-run coefficients only, whilst allowing heterogeneity in other coefficients such as the error-correction feedback, variance and deterministic terms, which is in the same spirit as the Pooled Mean Group approach taken by Pesaran *et al.* (1999). Secondly, it allows for contemporaneous correlation across the individuals in the panel, which is an essential feature given the nature of the dataset. Finally, the method has been shown to work well with the time and individual dimensions of this panel. Consequently, this estimator is used in the empirical work below.

Panel unit root tests. Having established how to derive estimates of long-run relationships in a panel setting, this section finishes by considering how to test for the nonstationarity that underpins the theory of cointegration. As the earlier discussion of time-series techniques for unit root testing noted, a common strategy is to use an Augmented Dickey-Fuller (ADF) test to establish the order of integration of a series. Extending this to panel models, Breitung and Pesaran (2008) distinguish between first and second generation unit root tests, on the basis that only the latter set have started to allow for cross-section dependence, characterising a similar split in approach that was observed above for cointegration methods. They set out a basic unit root test using a simple autoregressive model for y_{it}:[22]

$$\begin{aligned} y_{it} =& (1-\alpha_i)\mu_i + \alpha_i y_{i,t-1} + \epsilon_{it} \\ & i = 1, \dots, N \quad t = 0, \dots, T \end{aligned} \tag{12}$$

with $\epsilon_{it} \sim \mathsf{IID}\,(0, \sigma_i^2)$, $\mathsf{E}\,(\epsilon_{it}^4) < \infty$ and initial values y_{i0} given. By defining $\phi_i = (\alpha_i - 1)$ and $\widetilde{y}_{it} = y_{it} - \mu_i$, the resulting regression

$$\Delta\widetilde{y}_{it} = \phi_i \widetilde{y}_{i,t-1} + \epsilon_{it} \tag{13}$$

now has a familiar Dickey-Fuller form, and Breitung and Pesaran highlight the null (H_0) and alternative (H_{1a}, H_{1b}) hypotheses that are of interest:

$$\mathsf{H}_0 \;:\quad \phi_1 = \cdots = \phi_N = 0$$

against

$$\begin{aligned} \mathsf{H}_{1a} &:\quad \phi_1 = \cdots = \phi_N \equiv \phi \quad \text{and } \phi < 0 \\ \mathsf{H}_{1b} &:\quad \phi_1 < 0, \dots, \phi_{N_0} < 0, \quad N_0 \leq N \end{aligned}$$

In terms of alternative hypotheses permitted under the various tests available, it is evident that H_{1a} imposes homogeneity on the alternatives, whilst H_{1b} allows for greater heterogeneity in a set of N_0 of the N individuals.

The extent of the present interest in unit root test methods is constrained, by the likely presence of contemporaneous correlation in the dataset, to the second-generation test literature, and so the reader interested in earlier tests is directed to Breitung and Pesaran (2008) and Hlouskova and Wagner (2006) for comprehensive reviews. The literature on second-generation tests is still growing (see the introductory discussion of the former study), but three distinct approaches are emerging, and they build on a general representation of (12) or (13), in which:[23]

$$\Delta\mathbf{y}_t = \mathbf{a} + \boldsymbol{\phi}\mathbf{y}_{t-1} + \boldsymbol{\epsilon}_t \tag{14}$$

[22]See *op. cit.* pp. 4-5.

[23]This presentation draws on Breitung and Pesaran (2008, p. 20).

where the individuals from (12) are stacked vertically, and an arbitrary element a_i of $\mathbf{a}$ is equal to $-\phi\mu_i$. In this specification, the covariance matrix of the errors $\boldsymbol{\epsilon}_t$ is non-diagonal, so $\boldsymbol{\Omega} = \mathsf{E}\left(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t'\right)$ for all t, thereby allowing for cross-section dependence.

The first strategy is to treat (14) as a set of seemingly unrelated regressions (SUR) and then use a generalised least squares (GLS) estimator based on an estimate of the covariance matrix $\widehat{\boldsymbol{\Omega}}$. However, this requires that $T > N$, or else $\boldsymbol{\Omega}$ is singular, as Breitung and Das (2005) point out, which renders the method invalid for the full panel of 143 individuals across 15 time periods.

However, an alternative method developed by Jönsson (2005) and Breitung and Das (2005) tests H_0 against H_{1a} using OLS, with panel-corrected standard errors, which are essentially standard errors robust to cross-section correlation over the individuals (see Jönsson (2005, Section V)). With this approach, the test on ϕ has a robust t statistic, and Breitung and Das (2005) show that it has a standard normal limiting distribution under the null hypothesis H_0.

The third theme in second-generation tests builds on the presence of one or more common factors in the errors ϵ_{it}. In the simple case of one factor, the error in (13) might be expressed as

$$\epsilon_{it} = \lambda_i f_t + v_{it}$$

where f_t is an *unobserved* effect common to *all* individuals, but varying across time, and v_{it} is an individual idiosyncratic error. In this situation, Pesaran (2007) argues that f_t can be proxied by the cross-section mean of y_{it}, and its lagged values. In the case of serially uncorrelated ϵ_{it}, H_0 is based on a test of b_i in the *cross-section* augmented Dickey-Fuller regression (CADF):[24]

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \overline{y}_{t-1} + d_i \Delta\overline{y}_t + e_{it},$$

where e_{it} is white noise, and $\bar{\cdot}$ denotes a cross-section average.[25] Pesaran shows that this test, applied to the average of the t-ratios of the estimates $\left\{\widehat{b}_i\right\}_{i=1}^{N}$ allows for heterogeneity under the alternative hypothesis H_{1b}. Thus if it is the case that the contemporaneous dependence comes into the panel through a common factor, the CADF test has an advantage over the Breitung and Das method, since the panel-consistent standard errors break down, as Breitung and Pesaran (2008) observe. However, since it is not known *ex ante* how any cross-section dependence arises, it would seem pragmatic to adopt an eclectic approach and use both methods, since they are compatible with the T dimension of our panel.

In summary, this section has identified the elements of a long-run modeling strategy for the panel dataset. Bearing in mind that the individuals in the panel are likely to be contemporaneously dependent, the discussion has shown a role for unit root tests and cointegration estimators that are robust to this, and techniques that are suitable to the N and T dimensions available. Thus the following section considers how to complete the modeling strategy by exploring methods of estimating the short-run error-correction representation of the trade equations.

2.2.2. *Short-run estimation in dynamic panels.* Why might it be interesting to explore short-run dynamics using the panel dataset? On a general level, the rationale for doing so mirrors that of the time-series case, in which there is a distinction between long-run and short-run trade elasticities. There are good reasons why there might be differences between the two: whilst the long-run relationship is determined

[24] See Pesaran (2007), equation (6).
[25] For example, $\overline{y}_{t-1} = \frac{1}{N}\sum_{i=1}^{N} y_{i,t-1}$.

by more 'structural' factors such as the development of technology and tastes, the short-run relationship captures dynamic adjustment towards the long run, in the face of shocks to the explanatory variables, or to the error term. Thus there is no obvious reason to expect the elasticities across each time frame to be the same, and there is a further question of how much homogeneity exists in the dynamics across countries or sectors in the short run, versus the long run. As discussed above, the panel dimension of the dataset can be used to impose or test various homogeneity restrictions on parameters, in order to overcome some of the problems associated with a small-T sample. Exploiting similarities in technology within particular industries, for instance, could suggest imposing assumption H_{I} and pooling data across countries, allowing for heterogeneity across industries. However, whilst this might be justified when examining long-run responses, where (as Pesaran *et al.* (1999) point out) there is enough time for, say, common technology to be implemented across countries, it is possible that there is more idiosyncrasy in short-run responses. More concretely, H_{I} could determine the long-run elasticities, whilst H_{HET} governs the short-run dynamics.

How might this be implemented empirically? The answer can be found by considering the bearing of the estimated long-run parameters from the previous section, on approaches to short-run estimation. In a single-equation environment, one option (abstracting from concerns about cross-section dependence) is to embed the long-run relationship in a reparameterised ARDL model, as done by Pesaran *et al.* (1999) in (8), but in view of the earlier discussion of methods to estimate long-run cointegrating vectors, an alternative avenue is one in which the long-run estimates are obtained first, and then inserted into a short-run representation. This follows the spirit of a panel implementation of an Engle and Granger (1987) two-step procedure based on an error-correction model, which gives an $\mathsf{I}(0)$ representation of the $\mathsf{I}(1)$ cointegrated variables. In a panel setting, the process would amount to deriving estimators of the long-run cointegrating vectors (e.g. $\widehat{\boldsymbol{\beta}}$ from equation (10)), and then estimating a regression with $\mathsf{I}(0)$ variables.[26]

A single-equation model can demonstrate how each trade equation can be estimated in practice. For notational simplicity, y_{ist} is defined as as either imports (m_{ist}) or exports (x_{ist}), and the equation conditions on a vector $\mathbf{x}_{ist}$ where $\mathbf{x}_{ist} = (\mathsf{rpm}_{ist}, \mathsf{yd}_{ist})'$ or $\mathbf{x}_{ist} = (\mathsf{rpx}_{ist}, \mathsf{yf}_{ist})'$ as appropriate, with the vector $\mathbf{z}_{ist} = (y_{ist}, \mathbf{x}'_{ist})'$. Then, the parameters in the regression below should strictly have additional m or x subscripts to signify whether they relate to imports or exports, but in the interest of clarity these are omitted; since the estimation exercise for imports is identical to that of exports, there is no loss of understanding from doing this. The general $\mathsf{I}(0)$ specification can therefore be written as:

$$\Delta y_{ist} = \mu_{is} + \sum_{j=1}^{p} \delta_{isj} \Delta y_{is,t-j} + \sum_{j=0}^{q} \boldsymbol{\lambda}'_{isj} \Delta \mathbf{x}_{is,t-j} + \alpha_{is} \widehat{\boldsymbol{\beta}}' \mathbf{z}_{is,t-1} + v_{ist} \tag{15}$$
$$i = 1, \ldots, N \quad s = 1, \ldots, S \qquad t = \max(p, q) + 1, \ldots, T$$

where $\mathsf{E}(v_{ist}) = 0$, $\mathsf{E}(v_{ist}^2) = \sigma_{is}^2 < \infty$, and α_{is}, μ_{is}, $\boldsymbol{\lambda}_{isj}$ and δ_{isj} can vary across individuals. In this case, $\widehat{\boldsymbol{\beta}}' \mathbf{z}_{is,t-1}$ is the error-correction component, so that α_{is} captures the individual-specific disequilibrium feedback. Different assumptions about

[26]The particular way of obtaining estimates of $\boldsymbol{\beta}$ determines how close this approach lies to the Engle and Granger procedure. Thus, for instance, a pure panel Engle-Granger (PEG) method would pool all data and estimate the long-run parameters from an equation in levels. The favoured approach here, though, uses the Breitung method to obtain $\widehat{\boldsymbol{\beta}}$, although the empirical discussion below does compare results to the PEG case.

homogeneity in short-run parameters amount, in this setting, to restrictions on μ_{is}, δ_{isj}, $\boldsymbol{\lambda}_{isj}$, and α_{is}, and are quite distinct from assumptions governing the estimate $\widehat{\boldsymbol{\beta}}$ from the earlier $\mathsf{I}(1)$ analysis.

Besides this question of homogeneity, two main econometric issues are relevant to the choice of estimator. The first is the presence of individual-specific unobserved fixed effects in (15) in the case where homogeneity is imposed on the μ_{is} terms, so $\mu_{is} = \mu$ for all i, s. It follows from this restriction, that the error term v_{ist} can be decomposed into error components:

$$v_{ist} = \eta_{is} + e_{ist}$$

where e_{ist} is an IID error with zero mean and constant variance. If there is correlation between the individual effect η_{is} and either $\Delta\mathbf{x}_{ist}$ (and its lags) or $\mathbf{z}_{is,t-1}$, then an OLS estimator could be inconsistent. Secondly, looking at the error v_{ist} from a different perspective can reveal a different set of problems, if there is cross-sectional dependence in the panel. As Phillips and Sul (2003) comment, in this case "the pooled ordinary least squares estimator provides little gain in precision compared with single equation OLS when cross sectional dependence occurs but is ignored in the panel regression."

All of these problems – heterogeneity, cross-section dependence and fixed effects – have been addressed in the literature, so the next step is to review how they are dealt with in the set of estimators used in the empirical modeling exercise in Section 3.[27] This discussion is structured according to whether there is an assumption of complete heterogeneity in the short-run coefficients, against an alternative of complete (or partial) homogeneity.

In a heterogeneous world, one obvious method, given the earlier discussion of long-run approaches, is the Mean Group (MG) OLS estimator that Pesaran and Smith (1995) demonstrate to be consistent in the presence of genuine parameter heterogeneity. In practice, the basic mean group approach entails estimating (15) separately across all NS individuals, and then taking the cross-sectional average of each coefficient, although in view of the short time span of data, the median of estimates, which is less vulnerable to extreme observations, might also be of interest. As Pesaran and Smith show, this approach gives a meaningful value for the average effect of each independent variable on Δy_{is}. Further, differences across groups – such as countries or sectors – can be explored by calculating separate means across N and S individuals. This would correspond to pursuing the H_{I} and H_{C} hypotheses respectively, and could be useful in giving a more disaggregated impression of average effects, whilst still allowing for heterogeneity on an N-S individual level.

Although the straightforward MG estimator for (15) will work well if the error v_{ist} is a simple IID process as specified, it will encounter problems if there is cross-section dependence. One approach to this has been to use factor models to account for unobserved factors that vary over time, but are common to all individuals in the panel, in the same spirit as Pesaran (2007)'s CADF method for unit roots. Thus Pesaran (2006) proposes a Common Correlated Effects (CCE) estimator, which works by including the cross-section average of *all* variables, including the dependent variable, as extra regressors in (15), to act as proxies for the unobserved factors. This elegant solution works for multiple unobserved factors, and has the attractive property of being straightforward to implement. The resulting CCE-mean group (CCEMG) estimator is still given by the cross-section average of the estimated

[27] Phillips and Sul (2003) provide an elegant approach that deals jointly with both heterogeneity and cross-section dependence, but it is only valid with larger T-dimension sample sizes.

parameters, as before, but the regression is simply augmented with cross-section means of Δy_{ist}, $\Delta \mathbf{x}_{ist}$ and $\widehat{\boldsymbol{\beta}}' \mathbf{z}_{is,t-1}$.

Under the assumption of complete homogeneity, the simplest estimator is the pooled OLS (POLS) approach which, in contrast to the MG estimator, stacks all NS country-sector individuals vertically, and then estimates a common set of short-run parameters via OLS. This basic approach, though, is vulnerable to both unobserved individual-specific fixed effects, and cross-section dependence across individual errors. In response to the latter, Pesaran (2006) develops a pooled CCE (or CCEP), which estimates a pooled OLS regression including the same cross-section means as in the CCEMG case, as further regressors. This offers an attractive solution to the problem of cross-section dependence in situations where alternatives might not exist – for example, if $N > T$, where a feasible GLS estimator is not available, since the estimated covariance matrix is not invertible.

Unfortunately, both the CCEP and CCEMG estimators are not robust to individual-specific unobserved heterogeneity in the form of a fixed effect, η_{is}, in the composite error v_{ist}. One solution is the within group estimator (WG), in which variables are measured in terms of their deviations from time averages. Letting $\widetilde{\cdot}$ denote this transformation, the transformed regression is:[28]

$$\Delta \widetilde{y}_{ist} = \sum_{j=1}^{p} \delta \Delta \widetilde{y}_{is,t-j} + \sum_{j=0}^{q} \boldsymbol{\lambda} \Delta \widetilde{\mathbf{x}}_{is,t-j} + \alpha(\widehat{\boldsymbol{\beta}}' \widetilde{\mathbf{z}}_{is,t-1}) + \widetilde{v}_{ist} \tag{16}$$

This case allows for an individual (i.e. country-sector) specific fixed effect η_{is}, which is eliminated by expressing variables in deviations from time means. However, the price of this is that some degree of homogeneity is imposed on δ, $\boldsymbol{\lambda}$ and α. In (16) as it stands, the parameters are assumed to be fixed across all NS individuals. However, it would be simple to allow for heterogeneity across countries or sectors, by running $N = 11$ or $S = 13$ separate pooled WG regressions, respectively.

One issue in a within group model, is the possibility that the presence of lagged dependent variables (either through lagged Δy_{is}s or the inclusion of $y_{is,t-1}$ in $\widehat{\boldsymbol{\beta}}' \mathbf{z}_{is,t-1}$) could introduce bias for small/fixed T, as explored by Nickell (1981). If this were the case then the α_{is} estimates would be biased downwards, but given $T = 13$ (using one lagged Δy_{is} or $\Delta \mathbf{x}_{is}$) it seems unlikely that such bias will be significant here. More likely as a concern is the presence of cross-section dependence, which can be addressed via the Pesaran (2006) CCE estimator, augmenting the WG regression (16) with cross-section averages, this time adjusted for individual-specific effects.

3. Empirical Modeling

The empirical results presented below suggest that there is a long-run relationship between the variables in each trade flow. Cointegration tests indicate that this relationship is strongest across industry groups, which supports the H_{I} hypothesis that long-run elasticities are common to industries across countries. In contrast, the evidence for homogeneity *within* countries is weaker, whilst the most restrictive case of complete homogeneity across all country-industry pairs is rejected.

Using industry-by-industry estimates of the long-run relationship, the short-run analysis also finds that group-by-group regressions, and the more flexible Mean Group estimator, deliver more robust estimates than the fully pooled regressions.

[28]Thus for example, when $p = 1$ and $q \leq 1$, $\Delta \widetilde{y}_{ist} = \Delta y_{ist} - \frac{1}{T-1} \sum_{j=2}^{T} \Delta y_{isj}$.

3.1. **Testing for integration and cointegration.** The earlier discussion of panel unit root tests highlighted the need for robustness to potential cross-section dependence, so this section uses both the Breitung and Das (2005) test of a homogeneous unit root against an alternative homogeneous stable root, and the approach developed by Pesaran (2007) which tests the same null hypothesis against a heterogeneous alternative. For reference, these results are compared to those from an earlier vintage of unit root tests (which were not robust to cross-section dependence), via the method of Im, Pesaran and Shin (2003).

Table 11 in Appendix 6.A presents persuasive evidence in favour of all the variables having a homogeneous unit root. With one exception (foreign income in the CADF(1) test), all the test statistics for the robust CADF and BD tests suggest that the data are $\mathsf{I}(1)$, and the importance of accounting for cross-section dependence is underlined by the contrast with column 3, which reports the IPS test statistics. With this method, a unit root is unanimously rejected for half the series considered.

An obvious next step is to test for the presence of *co*integration between the variables, and the results from Breitung (2005)'s rank test on $\mathbf{\Pi}_i = \boldsymbol{\alpha}_i \boldsymbol{\beta}'$ in (10) are presented in Table 12 in Appendix 6.A. The rank test is based on the standardised average of individual-specific LM test statistics, with a null hypothesis of up to r cointegrating relationships, against an alternative of no cointegration (i.e. $r = 0$). Since this is a 'sequential' test, if a null hypothesis (of, say, $r = 1$) is accepted, then that value of r represents the true number of cointegrating relationships, so no further tests are necessary.

Table 12 is divided into three panels, each of which reflects a different pooling assumption: Panel (a) refers to the common elasticities case ($\mathsf{H}_{\text{NOHET}}$), (b) refers to H_{C}, and (c) refers to H_{I}. The first of these suggests that the hypothesis of one cointegrating vector for each trade flow across the whole sample is rejected. By imposing the same relationship on all country-industry pairs, the heterogeneity that seems to exist across groups is forced into the unobserved error term in the pooled cointegrating regression. The evidence in panel (b) is less clear-cut, as whilst there is support for one cointegrating vector in a number of countries, there is also evidence of no cointegration in 6 out of the 22 tests. Against this picture, panel (c) is nearly unanimous in indicating that there is one long-run relationship in each of the industries tested, with the null hypothesis rejected only twice, and in one of these, only marginally.

Taken together, these results point to the existence of one cointegrating vector in each sector, which is consistent with the theoretical justification discussed earlier, relating to similarities in production functions and technology across industries.

3.2. **Long-run elasticities.** The main empirical results of this paper are the long-run elasticities presented in Tables 3 to 5, which correspond to the three homogeneity restrictions $\mathsf{H}_{\text{NOHET}}$, H_{C} and H_{I}, respectively. The first theme that emerges from these results is that the aggregate approach embodied in the common elasticities in Table 3 disguises considerable heterogeneity in the group-by-group analysis in the remaining two tables. As the latter report, the standard deviations of all trade elasticities are substantial, although the mean and median estimates are reasonably close to the common pooled figures.

Thinking about the wider purpose of this paper, these estimates can be compared to the selected estimates in Tables 1 and 2, to see what additional insight is gained from the panel approach.

On a country-by-country basis, the panel-based estimates show greater consistency, in the sense that the estimates are all significant (with the sole exception of

Table 3: LONG-RUN TRADE ELASTICITIES: HOMOGENEOUS CASE

Sample	Exports (x)		Imports (m)	
	Price (rpx)	Income (yf)	Price (rpm)	Income (yd)
Common elasticities	−0.927	1.509	−0.861	1.715
	(0.027)	(0.037)	(0.028)	(0.032)

NOTES: Estimation period is 1988-2002 using annual data. Estimates obtained via the Breitung two-step estimator in (11), with long-run coefficients normalised on exports (x) or imports (m) as appropriate. Figures in $(\cdot)$ denote standard errors. In the case of complete pooling, data have been pooled across all $NS = 143$ country-sector individual units, for $T = 15$ time periods. *GAUSS code:* `pan2step.src` (kindly provided by Joerg Breitung); *Ox code:* `DataOverview.ox`.

Norway's export price elasticity), of plausible magnitude, and have signs consistent with economic theory; in contrast, many of the earlier estimates are insignificant (especially for price elasticities) and several have incorrect signs. The comparison with more recent VECM-based estimates from Hooper *et al.* (2000) is more favourable, with similar patterns in price elasticities, although the panel-based income coefficients seem to be higher in many cases.

However, a more fundamental comparison to make is between the country-by-country and industry-by-industry results, as the latter point to significant variation in elasticities within the sectors in a country. Irrespective of whether the former are consistent with existing estimates in the literature, it is inadvisable to ignore potential within-country variation.

Looking at Table 5, it is worth picking out some patterns in the evidence. Starting with outlying estimates, it is interesting that both Chemical products and Machinery and equipment (and the sub-group within this, of Electrical and optical equipment) have by far the highest income elasticities of all industries. These sectors fall under the broad definition from the OECD of 'hi-tech' industries, so the difference between these estimates and those of, say, Basic metal products (where the scope for technological improvements in the latter may be lower) could be related to inputs such as research and development activity. The distinction is less clear-cut with regard to price elasticities, though, since Chemicals imports have one of the lowest estimates, and Electrical and optical equipment the highest.

Whilst the scope of this study is limited to establishing whether there *are* differences in elasticities across industries, and not *why* such differences might exist, it is clear that there is an exciting research agenda in the making. Some studies (such as Driver and Wren-Lewis (2005)) have started to look at the impact of product quality and its role in country-wide trade performance, but a wider industry-level study could explore in more detail the factors behind the patterns in Table 5.

The theoretical rationale for revisiting the topic of trade elasticities with industry-level panel data was that aggregate and pooled studies might disguise the existence of substantial variation within countries, whilst also affecting the statistical validity of estimated relationships. As these results show, the empirical picture supports this theoretical position. Tests using a completely pooled sample reject the hypothesis of cointegration, and whilst there is more success on a country-specific level, there are nonetheless problems. On an industry-by-industry basis, though, the evidence for cointegration is overwhelming, and the long-run elasticities are consistent with

Table 4: LONG-RUN TRADE ELASTICITIES: COUNTRY HETEROGENEITY

Sample	Exports (x)		Imports (m)	
	Price (rpx)	Income (yf)	Price (rpm)	Income (yd)
Belgium	−0.693	1.850	−0.624	2.226
	(0.060)	(0.087)	(0.133)	(0.114)
Canada	−0.948	2.696	−0.979	2.058
	(0.091)	(0.096)	(0.048)	(0.070)
Denmark	−0.564	1.166	−0.742	1.902
	(0.067)	(0.085)	(0.081)	(0.075)
Finland	−0.906	2.120	−0.853	2.010
	(0.149)	(0.313)	(0.065)	(0.086)
Germany	−0.854	1.063	−1.300	1.979
	(0.059)	(0.072)	(0.121)	(0.126)
Italy	−0.610	2.003	−0.854	3.220
	(0.093)	(0.147)	(0.053)	(0.103)
Japan	−0.952	0.530	−1.152	3.667
	(0.066)	(0.082)	(0.076)	(0.232)
Netherlands	−0.577	1.188	−2.126	1.150
	(0.131)	(0.161)	(0.121)	(0.076)
Norway	−0.252	0.783	−1.068	0.533
	(0.154)	(0.112)	(0.113)	(0.075)
UK	−1.038	1.690	−1.178	0.929
	(0.088)	(0.092)	(0.068)	(0.096)
US	−1.192	2.209	−0.856	2.396
	(0.055)	(0.096)	(0.063)	(0.056)
Unweighted Average	−0.781	1.573	−1.066	2.006
(standard deviation)	(0.256)	(0.642)	(0.386)	(0.880)
Median	−0.854	1.690	−0.979	2.010

NOTES: Estimation period is 1988-2002 using annual data. Estimates obtained via the Breitung two-step estimator in (11), with long-run coefficients normalised on exports (x) or imports (m) as appropriate. Figures in (·) denote standard errors. For the country-specific estimates, separate regressions have been run for each country, using data pooled across all $S = 13$ industries, across $T = 15$ time periods. *GAUSS code:* `pan2step.src` (kindly provided by Joerg Breitung); *Ox code:* `DataOverview.ox`.

Table 5: LONG-RUN TRADE ELASTICITIES: INDUSTRY HETEROGENEITY

Sample	Exports (x)		Imports (m)	
	Price (rpx)	Income (yf)	Price (rpm)	Income (yd)
Food, beverages and tobacco	−0.739	1.430	−0.532	1.240
	(0.078)	(0.111)	(0.059)	(0.060)
Textiles, leather and footwear	−0.668	1.292	−0.475	1.313
	(0.152)	(0.178)	(0.109)	(0.097)
Wood and wood products	−0.869	1.015	−0.448	1.444
	(0.107)	(0.173)	(0.078)	(0.102)
Paper, printing and publishing	−0.737	0.858	−0.168	0.985
	(0.078)	(0.082)	(0.063)	(0.062)
Chemical products	−0.751	2.081	−0.066	1.941
	(0.062)	(0.077)	(0.099)	(0.088)
Rubber and plastics	−0.978	1.598	−0.425	1.685
	(0.106)	(0.131)	(0.101)	(0.086)
Non-metallic minerals	−0.849	1.011	−0.500	1.293
	(0.097)	(0.108)	(0.105)	(0.096)
Basic metal products	−0.706	0.811	−0.048	1.181
	(0.066)	(0.082)	(0.090)	(0.072)
Machinery and equipment	−0.842	2.446	−0.771	2.856
	(0.096)	(0.141)	(0.144)	(0.188)
Other machinery and equipment	−0.877	1.487	−0.503	1.311
	(0.088)	(0.092)	(0.098)	(0.101)
Electrical and optical equipment	−0.941	2.911	−1.234	2.660
	(0.103)	(0.222)	(0.112)	(0.261)
Transport	−0.559	1.557	−0.591	1.805
	(0.073)	(0.079)	(0.114)	(0.115)
Other Manufacturing	−0.723	1.861	−0.521	1.823
	(0.079)	(0.111)	(0.076)	(0.083)
Unweighted Average	−0.788	1.566	−0.483	1.657
(standard deviation)	(0.113)	(0.602)	(0.295)	(0.544)
Median	−0.751	1.487	−0.500	1.444

NOTES: Estimation period is 1988-2002 using annual data. Estimates obtained via the Breitung two-step estimator in (11), with long-run coefficients normalised on exports (x) or imports (m) as appropriate. Figures in $(\cdot)$ denote standard errors. For the industry-specific estimates, separate regressions have been run for each sector, using data pooled across all $N = 11$ countries, across $T = 15$ time periods. *GAUSS code:* `pan2step.src` (kindly provided by Joerg Breitung); *Ox code:* `DataOverview.ox`.

economic theory. Furthermore, they raise several questions to explore in future research.

3.3. **Short-run elasticities.** How do the long-run estimates enter into short-run estimation? The foregoing discussion provided a rationale for allowing for heterogeneity across industries in the long run, so the equilibrium-correction term in all short-run models is given by $\widehat{\boldsymbol{\beta}}_s'\mathbf{z}_t$, which uses the industry-specific long-run elasticities.[29] Looking at the estimates of short-run elasticities in Tables 6 to 9, it is worth starting with three points about general trends.

First, the short-run price elasticities are broadly significant, and correctly signed, and suggest that much of the short-run effect of price on trade comes through the *contemporaneous* relative price, rather than lagged prices.

Secondly, the impact of income on trade is more complex, as many of the estimated coefficients are insignificant, and whilst contemporaneous income growth typically has a positive coefficient, lagged income enters negatively. Within this picture, though, it is possible to draw out two observations. Where the sum of current and lagged coefficients on imports and exports is significant, it is also positive, which supports economic theory. Further, in such cases, the import income elasticity sum is greater than that of exports.

Finally, the feedback coefficient on the equilibrium-correction term is significant in all but one case, and has an appropriate (negative sign) in all. The picture of heterogeneity in long-run elasticities is echoed by the short-run results, which suggest that the estimates from group-wise, and completely heterogeneous regressions, are more robust than those from the completely pooled scenario. There is evidence of serial serial correlation in the residuals from completely pooled regressions, which is consistent with the effect of ignoring, incorrectly, genuine cross-section heterogeneity in parameters, as Pesaran and Smith (1995) predicted.[30] In contrast, the alternative approaches allowing for more heterogeneity do not suffer from the same mis-specification problems.

Besides this general issue, there are specific comments to make about the results from the four separate homogeneity scenarios reported in the Tables.

Addressing the complete pooling case, the main point to note is the effect of allowing for individual-specific fixed effects in estimation. Columns (1) and (2) in Tables 6 and 7 show the estimates obtained first, in an OLS regression of stacked individuals, and secondly, in the same OLS regression but including a set of individual-specific dummy variables.[31] The main impact of this difference manifests in the feedback coefficient, which jumps from −0.001 to −0.185 after allowing for fixed effects. This is consistent with each country-sector pair having a specific intercept, with the possibility that it lies in the cointegrating space. Since the Breitung procedure for the long-run relationships also allows for intercepts varying across individuals, the fixed effects estimator used here is a consistent short-run

[29] In the tables, the equilibrium-correction term is written as $\widehat{\mathsf{ECM}}$. For example, in the case of Chemical product exports (using the abbreviation s to denote the sector) this yields:

$$\widehat{\mathsf{ECM}}_{s,t} = \widehat{\boldsymbol{\beta}}_{s,\mathsf{x}}'\mathbf{z}_{\mathsf{x},t} = \mathsf{x}_{s,t} + 0.751\mathsf{rpx}_{s,t} - 2.081\mathsf{yf}_{s,t}.$$

[30] This is shown in the results of LM tests for first- and second-order serial correlation in the residuals from each regression, reported in the lower panel of Tables 6 to 9.

[31] These regressions also include cross-section means of all variables, following the Pesaran CCE approach. Results of regressions without the CCE estimator are available on request from the author.

Table 6: SHORT-RUN ELASTICITIES ACROSS THE COMPLETE SAMPLE WITH COMMON CORRELATED EFFECTS: IMPORTS

Dependent variable is $\Delta \mathsf{m}_t$	(1) POLS	(2) FE	(3) 2SLS-FE	(4) MGOLS		(5) MG2SLS	
				Mean	Median	Mean	Median
$\Delta \mathsf{m}_{t-1}$	0.075	0.063	0.070	−0.081	−0.120	−0.362	−0.080
	(0.027)	(0.027)	(0.023)	(0.047)	(−)	(0.377)	(−)
$\Delta \mathsf{rpm}_t$	−0.449	−0.424	−0.605	−0.285	−0.410	−0.344	−0.560
	(0.029)	(0.029)	(0.115)	(0.095)	(−)	(0.842)	(−)
$\Delta \mathsf{rpm}_{t-1}$	−0.096	−0.072	−0.049	−0.007	−0.063	0.019	−0.024
	(0.030)	(0.031)	(0.031)	(0.079)	(−)	(0.348)	(−)
$\Delta \mathsf{yd}_t$	2.272	2.428	2.412	2.598	1.894	2.710	2.215
	(0.162)	(0.155)	(0.131)	(0.388)	(−)	(2.213)	(−)
$\Delta \mathsf{yd}_{t-1}$	−1.159	−0.980	−1.113	−0.514	−0.416	1.196	−0.173
	(0.155)	(0.152)	(0.156)	(0.323)	(−)	(2.556)	(−)
$\widehat{\mathsf{ECM}}_{t-1}$	−0.002	−0.165	−0.160	−0.358	−0.254	−0.360	−0.287
	(0.000)	(0.019)	(0.015)	(0.053)	(−)	(0.303)	(−)
Pooled data	Yes	Yes	Yes	No	No	No	No
Fixed effects	No	Yes	Yes	N/A	N/A	N/A	N/A
SC: AR(1)	0.033	0.000	0.000	0.993		0.965	
SC: AR(2)	0.043	0.000	0.000	(−)		(−)	

NOTES: Figures in (·) denote heteroscedasticity-robust standard errors for pooled estimators, and the group average standard error in the case of mean group estimates. The rows marked SC report tests for first- and second-order serial correlation in the errors. For pooled estimates (1) to (3), these are the p-value of incorrectly rejecting the null hypothesis of no serial correlation; for mean group regressions (4) and (5) these are the proportion of all $NS = 143$ tests that rejected the null hypothesis at the 1% significance level. *Ox code:* `TradeEstimation.ox`.

analogue, and so column (2) in both Tables could be seen as the preferred pooled specification, of the two considered so far.

However, the robustness of the fixed effects OLS specification is affected by potential endogeneity bias arising from correlation of the explanatory variables with the error term. Of the variables considered, the contemporaneous changes in income are unlikely to be correlated with country-sector-specific trade shocks, since the size of a particular sector relative to the aggregate scale of both foreign and domestic income is likely to be very small. Similarly, as Carlin, Glyn and van Reenen (2001) note, exchange rates are unlikely to be affected by shocks to an individual sector. Where endogeneity could emerge, though, is through pricing behaviour affecting the price level components of the relative price terms. Thus as a check for robustness, a fixed-effects specification is reported in column (3), in which lagged values of relative price levels (rpm_{t-2} and rpx_{t-2}) are used as instruments for contemporaneous price changes (respectively, $\Delta\mathsf{rpm}_t$ and rpx_t), and the response is estimated via two-stage least squares (2SLS). Neither the import nor export price elasticities change dramatically after doing this, suggesting that endogeneity issues are of second-order concern for the pooled case.

Table 7: SHORT-RUN ELASTICITIES ACROSS THE COMPLETE SAMPLE WITH COMMON CORRELATED EFFECTS: EXPORTS

Dependent variable is Δx_t	(1) POLS	(2) FE	(3) 2SLS-FE	(4) MGOLS		(5) MG2SLS	
				Mean	Median	Mean	Median
Δx_{t-1}	0.060	0.036	0.010	−0.210	−0.124	−0.238	−0.171
	(0.035)	(0.035)	(0.025)	(0.050)	(−)	(0.141)	(−)
Δrpx_t	−0.631	−0.585	−0.302	−0.634	−0.615	−1.558	−0.640
	(0.031)	(0.031)	(0.086)	(0.082)	(−)	(1.077)	(−)
Δrpx_{t-1}	−0.150	−0.117	−0.136	−0.199	−0.115	0.589	−0.111
	(0.029)	(0.030)	(0.026)	(0.048)	(−)	(0.775)	(−)
Δyf_t	2.143	2.011	1.540	−1.008	−0.443	−0.535	−0.011
	(0.373)	(0.395)	(0.376)	(1.174)	(−)	(4.477)	(−)
Δyf_{t-1}	0.055	0.142	0.148	0.577	0.784	1.219	0.154
	(0.266)	(0.248)	(0.226)	(0.343)	(−)	(1.620)	(−)
$\widehat{ECM}_{t-1}$	−0.001	−0.185	−0.195	−0.382	−0.325	−0.519	−0.425
	(0.000)	(0.018)	(0.015)	(0.055)	(−)	(0.209)	(−)
Pooled data	Yes	Yes	Yes	No	No	No	No
Fixed effects	No	Yes	Yes	N/A	N/A	N/A	N/A
SC: AR(1)	0.020	0.000	0.001	0.958		1.000	
SC: AR(2)	0.006	0.000	0.000	(−)		(−)	

NOTES: See notes to Table 6. *Ox code:* `TradeEstimation.ox`.

The fully pooled results, whilst showing signs of mis-specification, are nonetheless useful in providing a guide to the appropriate choice of estimator for the group-wide regressions, since they suggest that where data is pooled, a fixed-effects model should be used, and in the face of potential endogeneity, it should also be ready to correct for it.

Thus the next step in analysis is to compare the fully pooled results to the group-by-group pooled estimates in Tables 8 and 9. These are obtained by running separate regressions in which all the individuals in a group are pooled, and then the average of all group estimates is taken. For example, in the case of country-by-country results in the first block of each table, 11 sets of country-specific pooled coefficients are produced, and the mean and median are reported here.[32] In a sense, these represent pseudo-mean group estimates where the $NS = 143$ individual OLS regressions in the conventional MG approach are replaced by 11, or 13, pooled regressions.

The most important message that emerges from these results is that allowing for heterogeneity across groups leads to a dramatic improvement in diagnostic test statistics. As the lower panels of Tables 8 and 9 show, the fraction of group-wide regressions that pass the serial correlation tests is very high, with the country-by-country results showing less sign of mis-specification than the industry regressions. This lends support to the idea that the sectors in a given country behave in a similar way in the face of shocks in the short run (when shocks are more likely to hit whole

[32]The 2SLS estimator allowing for fixed effects (via group-specific dummies), and cross-section dependence (via the CCE estimator), is used for these regressions. Full country- and industry-specific breakdowns are available for this method, and alternatives, on request from the author.

Table 8: SHORT-RUN ELASTICITIES FROM DISAGGREGATED GROUP REGRESSIONS: IMPORTS

Dependent variable is $\Delta\mathsf{m}_t$	Country groups 2SLS-FE-CCE		Industry groups 2SLS-FE-CCE	
	Mean	Median	Mean	Median
$\Delta\mathsf{m}_{t-1}$	0.068	0.055	0.020	0.005
	(0.080)	(–)	(0.039)	(–)
$\Delta\mathsf{rpm}_t$	−1.933	−0.622	−0.692	−0.349
	(2.740)	(–)	(0.293)	(–)
$\Delta\mathsf{rpm}_{t-1}$	−0.174	−0.050	−0.030	−0.163
	(0.091)	(–)	(0.071)	(–)
$\Delta\mathsf{yd}_t$	0.517	0.044	2.463	2.425
	(0.352)	(–)	(0.194)	(–)
$\Delta\mathsf{yd}_{t-1}$	−0.498	−0.180	−1.079	−0.675
	(0.359)	(–)	(0.456)	(–)
$\widehat{\mathsf{ECM}}_{t-1}$	−0.217	−0.223	−0.190	−0.225
	(0.065)	(–)	(0.030)	(–)
SC: AR(1)	1.000		0.769	
SC: AR(2)	0.909		0.846	

NOTES: The coefficients are the mean and median of separate group-by-group pooled regressions. For example, in the case of Country Groups (columns 2-4), this amounts to running 11 separate 2SLS regressions, including fixed effects and Pesaran CCE effects. The choice of estimator is directed by its robustness to the empirical problems discussed in the text. Estimates from other methods, and a complete breakdown of results by country and industry, are available by request from the author. *Ox code:* `TradeEstimation.ox`.

countries, rather than particular industries), whilst in the long run, behaviour is common to industries *across* countries (when sectors have the ability to adopt new technology from abroad, for example).

Moving beyond the group-wide regressions, the final element of the short-run analysis reports Mean Group results, in blocks (4) and (5) of Tables 6 and 7, and Figures 2 and 3.

Although there are constraints on inference imposed by the fact that the number of time periods available ($T = 13$, once lagged changes are included) is only just higher than the number of regressors (10, including a constant and the CCE cross-section means), there are nonetheless several points to make.

First, the individual models do not suffer from the same serial correlation as their fully pooled counterparts in columns (1) to (3), which supports the hypothesis that the diagnostic failure of the latter is due to parameter heterogeneity.

An immediate question that follows from this is whether the superior diagnostic performance is accompanied by any substantial differences in coefficient estimates. In this regard, the mean and median of individual-specific feedback coefficients on the equilibrium-correction terms are significantly higher across MG estimates than any of the pooled alternatives, and as the top right-hand panel of Figures 2 and 3 show, the majority if estimates lie between 0 and −1.

Figure 2: MEAN GROUP OLS SHORT-RUN IMPORT COEFFICIENT ESTIMATES: COMPLETE HETEROGENEITY

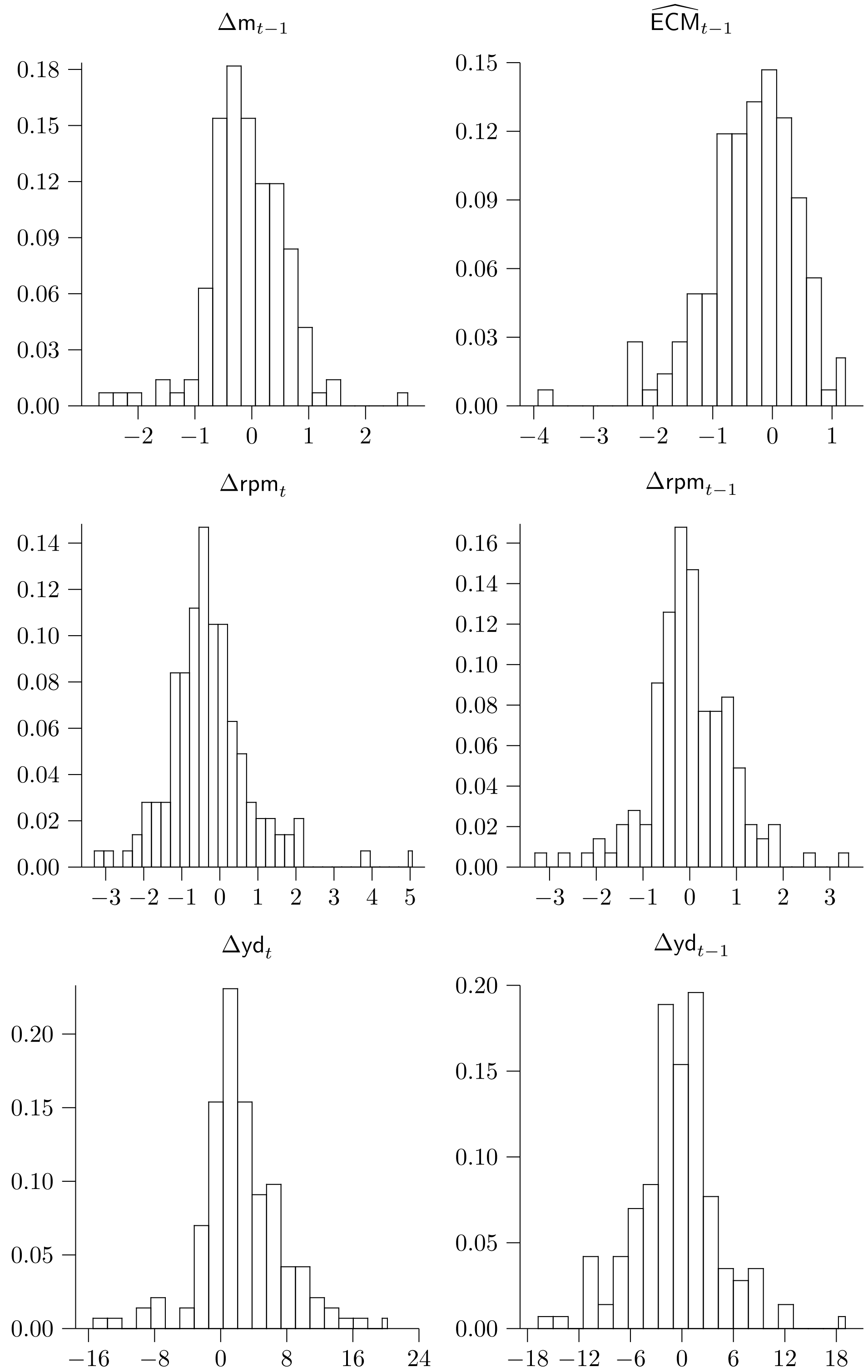

Figure 3: MEAN GROUP OLS SHORT-RUN EXPORT COEFFICIENT ESTIMATES: COMPLETE HETEROGENEITY

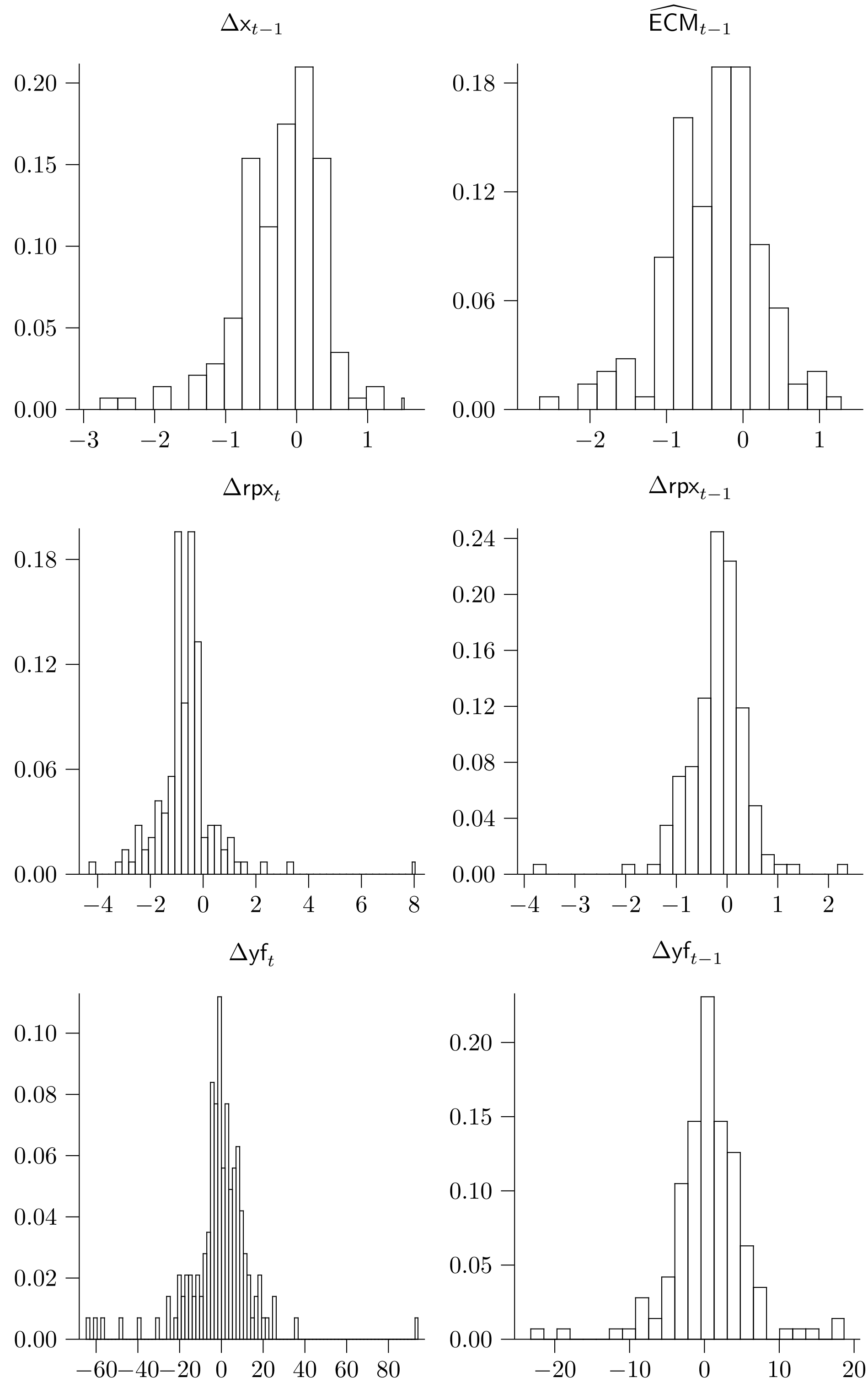

Table 9: SHORT-RUN ELASTICITIES FROM DISAGGREGATED GROUP REGRESSIONS: EXPORTS

Dependent variable is Δx_t	Country groups 2SLS-FE-CCE		Industry groups 2SLS-FE-CCE	
	Mean	Median	Mean	Median
Δx_{t-1}	−0.007	0.025	0.077	0.065
	(0.028)	(−)	(0.024)	(−)
Δrpx_t	−1.249	−1.153	−0.438	−0.312
	(0.502)	(−)	(0.139)	(−)
Δrpx_{t-1}	−0.045	−0.048	−0.047	−0.058
	(0.021)	(−)	(0.029)	(−)
Δyf_t	1.665	0.959	2.356	2.245
	(0.949)	(−)	(0.450)	(−)
Δyf_{t-1}	−0.016	−0.056	−0.978	−0.819
	(0.084)	(−)	(0.373)	(−)
$\widehat{ECM}_{t-1}$	−0.202	−0.195	−0.246	−0.219
	(0.033)	(−)	(0.031)	(−)
SC: AR(1)	0.909		0.846	
SC: AR(2)	0.909		0.769	

NOTES: See notes to Table 8. *Ox code:* `TradeEstimation.ox`.

Thirdly, the robustness check for endogeneity on an individual level via the 2SLS regression reported in block (5) does not point to significant differences in the relevant elasticities, although the standard errors obtained in this case are substantially higher, which affects the precision of any judgment about the impact of endogeneity.

Finally, the distribution of estimates in Figure 2 and 3 provides an idea of how plausible the MG results are, given the small dimension of the sample. In broad terms, the behaviour of the elasticity coefficients corresponds to the general trends seen in pooled estimates. Looking at the middle row of both Figures, the distributions of price elasticities are generally skewed towards negative values, although there is some evidence of positive coefficients for lagged import prices. With regard to income elasticities in the bottom row, the distribution of estimates on contemporaneous income growth is heavily skewed towards positive values, whilst those of lagged growth are more evenly distributed around zero, echoing the pooled coefficient results. Besides some extreme outliers (e.g. an export income elasticity of 90), the overall picture painted by the MG estimates seems to follow that of the group-wise pooled regressions, with the exception that the responsiveness of trade to long-run disequilibrium is higher in the heterogeneous case than in the alternative approaches.

4. Concluding comments

These results augur well for a wider research agenda on disaggregated trade elasticities. First, a disaggregated view was shown to be necessary to understand how imports and exports in a particular country will respond to a change in the exchange rate. To see why, consider an aggregate measure of the exchange rate, such as the effective exchange rate index (ERI), which weights a country's bilateral exchange rates according to each partner's share of total trade. An appreciation in the ERI may come about due to movements in any one of the bilateral rates, and if some industries trade more with a particular partner than others, then the same movement in the ERI can have different effects on industries, depending on which exchange rate is moving.

Secondly, the framework established above can readily be extended to include additional factors such as innovation or research and development (as explored by Driver and Wren-Lewis (2005)), which would allow wider questions about the determinants of trade performance to be analysed.

Finally, extending the time span of the database could open an avenue to examining the long-run impact on trade performance, of short-run shocks. Thus if an exchange rate shock changes the properties of the long-run cointegrating vector (such as its mean, or the income and price elasticities), then analysis of the impact of such breaks over time would offer insight into the response of individual sectors to macroeconomic shocks (as studied, for example, by Kitson and Primost (2005)).

5. Data Appendix

5.A. **STAN.** The Structural Analysis (STAN) Database from the OECD is compiled from member countries' annual national accounts, national surveys and censuses and other sources needed to fill any missing entries. In this paper the latest version of STAN is used, containing data running up to 2003 (see OECD (2005, 2006))[33] and data comes from two parts of the database:

- Real and Nominal Value Added, and Nominal Imports and Exports, all in national currencies, are taken from the main STAN Database;[34]
- Bilateral trade data, which measures Nominal Imports and Exports broken down by trading partner, for each country-industry unit, are taken from the STAN Bilateral Trade Database (BTD).[35]

Drawing on the approach of Carlin *et al.* (2001), the industry coverage of the empirical work in this paper is set out in Table 10, which indicates the highest level of disaggregation available in STAN, and the level actually used in this work.

5.B. **Industry, time and country coverage of STAN.** The criteria for selecting variables are as follows:

- The variables of interest are nominal imports and exports, and nominal and real value added. Using the latter pair, deflators can be constructed for both value added, and imports and exports. In order to construct trade-weighted variables where relevant, *bilateral* trade data, which decomposes trade for a particular country's sector into partner countries of origin (for imports) or of destination (for exports), are taken from the STAN Bilateral Trade Database (BTD).[36]
- Although the main STAN database covers all areas of activity, there are practical constraints on the number of sectors that can be used. First, the BTD data, which are essential in calculating trade weights, only cover manufacturing sectors at present. This is clearly a limitation that future versions of BTD could resolve, but for now, the effect is that the empirical work in this paper focuses on manufacturing industries. Within these,

[33]Although the empirical work here uses data up to 2002, due to partial country-sector coverage of the data for 2003.
[34]OECD (2005): see http://www.oecd.org/sti/stan/.
[35]OECD (2006): see http://www.oecd.org/sti/btd/.
[36]The Bilateral Trade Database is available from http://www.oecd.org/sti/btd.

Table 10: STAN INDUSTRY COVERAGE

Overall Group	ISIC	Group breakdown
Food, beverages and tobacco	*15-16*	Food and beverages*; tobacco*
Textiles, leather and footwear	*17-19*	Textiles*; Leather and footwear*
Wood and wood products	*20*	Wood and wood products
Paper, printing and publishing	*21-22*	Pulp and paper*; Printing and Publishing*
Chemical products	*23-25*	Coke, refined petroleum and nuclear fuel*; Chemical products* (non-pharmaceutical chemicals*; pharmaceuticals*); rubber and plastics
Non-metallic minerals	*26*	Non-metallic mineral products
Basic metal products	*27-28*	Basic metals* (iron and steel*; other metals*); Fabricated metal products excluding machinery and equipment*
Machinery and equipment	*29-33*	Electrical and optical equipment (office and computing*; radio, television and communication*; medical equipment*; other equipment*); other machinery and equipment
Transport	*34-35*	Motor vehicles*; Other transport* (ships and boats*; aircraft*; railroad equipment*)
Other manufacturing	*36+37*	Furniture*; other manufacturing*; recycling*

NOTES: Source: OECD (2005). The ISIC codes refer to the two-digit classification under ISIC Revision 3. An * indicates that the particular group breakdown was not used due to lack of data across all countries in the sample.

activity is disaggregated into groups according to the International Standard of Industrial Classification of Economic Activities (ISIC), revision 3. This has the advantage of providing a consistent definition of each sector, making comparison across countries more meaningful, although as Carlin *et al.* (2001) note, "... because of the way in which the data set was constructed, the extent of measurement error increases the more disaggregated the data" (p. 131). For this reason, in combination with data availability, the sectoral data used here is disaggregated to the ISIC two-digit level. In total, this leaves nine broad industry groups and a residual manufacturing sector, of which some of these are split into subgroups (still at the two-digit level), so that the S (industry) dimension of the panel comprises 13 'individuals.'[37]

- Although STAN covers 29 countries, there are two concerns about including all in the panel dataset. First, echoing Carlin *et al.* (2001), some countries, such as Mexico and Korea, were at relatively low levels of development in the early period of the sample, and so their experiences would partly reflect an adjustment process not shared with the others. Secondly, data availability affects a number of countries, leaving 11 to include in the dataset.
- The time dimension of the panel, once the countries and sectors have been selected, covers fifteen years, from 1988 to 2002. Since the data has annual frequency, it is immediately clear that conventional time-series approaches

[37]The full list of industries is presented in Table 10.

will have very low power in such a small sample. Thus the empirical work below, makes use of the panel dimension in a number of ways.

5.C. **Variable definitions.** The variables used in the empirical modeling are as follows:[38]

- Imports, denoted m_{ist} measure the real value of all imports of goods in sector s into country i, in year t. This has been deflated by the GVA deflator in each partner country, with weights to account for the share of each partner in total s imports into country i.
- Exports, denoted x_{ist} measure the real value of all exports from sector s in country i. The nominal value of exports is deflated using the GVA deflator for that particular sector's output, since an explicit export price measure is not available in the STAN database; under the assumption that the overall GVA deflator for a particular sector provides an appropriate measure of the price of exported goods for that sector, this derived index is a suitable one to use.
- Relative import prices, rpm_{ist}, measure the price of imported goods from sector s, adjusted by the exchange rate, relative to the price of *domestic output* from sector s. This definition is closest to the most accurate theoretical measure of the robust relative price series that was identified in Section 1. The trade-weighted exchange rate measure is constructed using bilateral exchange rates between each country and its trading partners, weighted by the share of each partner in the imports for each sector. This provides sector-specific exchange rate indicies.
- Relative export prices, rpx_{ist}, are similarly adjusted for the exchange rate, and measure the price of exports in sector s relative to the price of the same sector's output in each trading partner, weighted according to the share of exports of s that go to the partner country. The trade-weighted exchange rate is constructed in the same way as the relative import price above, except that bilateral export data is used to construct the country weights.
- Domestic Income, yd_{ist}, measures the whole-economy GVA for country i. This is a more suitable choice of income measure than sector-only income, since the demand for imports of a particular sector (say, k) is not confined solely to demand from the *domestic* k sector.[39] As a result, the yd_{ist} terms are common to all S sectors in each country: $\mathsf{yd}_{ist} = \mathsf{yd}_{it}$ for all $s = 1, \ldots, P$. This does not pose any problem for empirical modeling, although the CCE estimator in country-by-country analysis does not include the mean of domestic income terms, since they do not vary across individual sectors.
- Foreign Income, yf_{ist}, measures the weighted whole-economy GVA for each partner country, where countries are weighted by the share of sector s's exports they demand.

6. Additional results

6.A. **Unit root and cointegration test statistics.** The test statistics from unit root tests on the level of all six variables of interest are presented in Table 11, whilst cointegration test statistics are reported in Table 12.

[38]All variables are denoted in logged form.

[39]For example, whilst the domestic Electrical Equipment sector might import goods from foreign Electrical Equipment sectors, the import measure for that category includes demand for Electrical Equipment imports from other sectors, such as Wood Products.

Table 11: PANEL UNIT ROOT TESTS

Variable	Lag Order	CADF$^\diamond$	BD	IPS$^\diamond$
	1	-1.936^{**}	0.458^{**}	-2.150^{**}
Exports‡	2	-1.330^{**}	0.270^{**}	-1.761^{**}
	3		-0.761^{**}	
	1	-2.568^{**}	-0.500^{**}	-2.708
Imports‡	2	-1.845^{**}	-0.407^{**}	-2.735
	3		-0.467^{**}	
	1	-1.810^{**}	-1.047^{**}	-1.561^{**}
Relative Export Price†	2	-1.882^{**}	0.538^{**}	-1.197^{**}
	3		0.080^{**}	
	1	-1.137^{**}	0.151^{**}	-1.167^{**}
Relative Import Price†	2	-0.721^{**}	0.530^{**}	-0.965^{**}
	3		0.342^{**}	
	1	-3.887	-0.072^{**}	-2.803
Foreign Income‡	2	-2.261^{**}	-0.289^{**}	-2.535
	3		-0.129^{**}	
	1	-2.560^{**}	-0.145^{**}	-3.445
Domestic Income‡	2	-1.283^{**}	-0.153^{**}	-2.711
	3		-0.266^{**}	

NOTES: Tests, performed on the full sample of $NS = 143$ individuals over $T = 15$ time periods, are as follows: CADF is the cross-section augmented DF test of Pesaran (2007); BD is the cross-section robust test of Breitung and Das (2005); IPS is the earlier test of Im *et al.* (2003), which assumes cross-section independence. Symbols are as follows: $\diamond$ indicates that truncated test statistics have been used, where appropriate, to account for the small T property of the sample; † indicates that tests were performed assuming the presence of a constant alone; ‡ indicates both a constant and linear time trend were included. ** denotes a failure to reject the null hypothesis (of a unit root) at the 1% significance level, for which critical values are: CADF: †: -2.29; ‡: -2.93; BD (asymptotic): † and ‡: -1.945; IPS: †: -1.75, ‡: -2.42. *GAUSS code:* `ub_robust.src` (BD); `CIPSmarch06.prc` (CADF); `IPSmarch06.prc` (IPS). BD code was kindly provided by Joerg Breitung, and CADF and IPS code by M. Hashem Pesaran.

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Table 12: PANEL COINTEGRATION TESTS

		Imports	Exports
H_{NOHET}	Pooled sample	−4.888	−2.733
H_C: Country by Country tests	Belgium	−1.428**	−1.884**
	Canada	−0.206**	−1.798**
	Denmark	−2.305	−1.751**
	Finland	−3.230	−1.578**
	Germany	−1.088**	−2.853
	Italy	−3.202	0.441**
	Japan	1.504**	−2.141
	Netherlands	−1.537**	−1.583**
	Norway	1.210**	1.745**
	UK	−2.364	1.188**
	US	−1.231**	0.404**
H_I: Industry by Industry tests	Food, beverages and tobacco	−1.940**	−1.227**
	Textiles, leather and footwear	−1.918**	−0.606**
	Wood and wood products	−1.525**	0.479**
	Paper, printing and publishing	−0.390**	−0.337**
	Chemical products	−1.855**	−1.614**
	Rubber and plastics	−2.535	−0.912**
	Non-metallic minerals	−1.963	0.704**
	Basic metal products	−0.813**	−1.094**
	Machinery and equipment	−1.126**	−1.446**
	Other machinery and equipment	−1.410**	−0.979**
	Electrical and optical equipment	−0.747**	−1.254**
	Transport	−1.594**	−0.749**
	Other Manufacturing	−1.502**	−1.113**

NOTES: Figures are test statistics from a test for one cointegrating vector (against an alternative of none); ** indicates that the null hypothesis is accepted at the 1% significance level (critical value: 1.946). *GAUSS code:* `pan2step-ctest.src`, written by the author and including original code from Joerg Breitung to obtain long-run parameter estimates.

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