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Export dynamics since the Great Trade Collapse: a cross-country analysis

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Abstract

Using a panel model of goods exports for 16 OECD economies, we quantify advanced economies' export performance since the 'Great Trade Collapse' (GTC). We go beyond the traditional determinants of trade to include a variable measuring shifts in the sectoral composition of world trade and split the real exchange rate into its constituent parts to allow for a differential response to unit labour costs and the nominal exchange rate. We find that, a pre-crisis model based on average coefficients explains the recovery in aggregate exports since the GTC well. But at the country level, we do find substantial cross-country variation in export performance.

Key words: International trade, forecasting, cross-country panel.

JEL classification: C23, F14, F17.

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1 Introduction

In the immediate aftermath of the financial crisis, the sharp falls in output across developed economies were accompanied by even stronger falls in international trade. This so-called "The Great Trade Collapse" (GTC) was by far the largest drop in global trade in history, as global trade plunged by 15% year-on-year in late 2008 and early 2009. In addition, the GTC was characterized by an extremely high level of synchronization with falls in exports across all advanced economies and nearly all industries (Baldwin, 2009; IMF, 2013).

This rekindled the debate on the relationship between trade and the macroeconomy. Whilst the sharp GDP fall undoubtedly had a role to play, the consensus is that this alone cannot explain the size of the fall in trade. Some authors have argued this reflected short-term factors, such as impaired trade finance (Chor and Manova, 2012; JaeBin, Amiti and Weinstein, 2011) or heightened uncertainty (Novy and Taylor, 2014). But others have argued that the GTC heralded a fundmental shift to an era of lower world trade relative to GDP -either because aspects of globalization such as offshoring may have run their course (Krugman, 2013) or because of a rise in hidden protectionism (Davies, 2013). The goal of this paper is to provide an empirical exploration of these two competing explanations, by looking at the behaviour of exports in the wake of the GTC. We find clear evidence that the recovery in advanced economy exports after the trough is very much line with the predictions of a pre-crisis model, suggesting that the GTC is better characterized as a temporary shock, rather than a structural break in the relationship between output and world trade

We estimate a panel error correction model (ECM) of goods exports for 16 advanced economies, extending the imperfect substitutes model of Goldstein and Kahn (1985). Our model is estimated using a panel error correction model (ECM) framework for 16 advanced economies. Whereas recent empirical work using ECMs to model exports estimated either a system of country-specific equations or focused on aggregate exports[1], we instead adopt a panel approach using the Common Correlated Effects (CCE) estimator of Pesaran (2006) to control for the possible existence of unobserved common factors. We extend the traditional model in several ways.

First, we develop a novel measure of sectoral shifts in world trade and include it alongside the more traditional relative price and foreign income determinants of exports. Elsewhere compositional effects have been found to be important for trade in the long run (Mayer, 2010) and in the short run (Levchenko, Lewis and Tesar, 2010). This is distinct from a decomposition of aggregate demand into its expenditure components according to their trade intensity as employed in Bussière and others (2013), because it divides the data up along sectoral lines.[2] We find this variable to have only a significant lagged impact on export in the short run.

Second, we split up the real exchange rate (our preferred measure of relative prices) into its two constituent parts, the nominal exchange rate and relative unit labor costs to allow for possibly differential responses of exports and find that the source of the real exchange rate shock matters for exports. Specifically, the coefficients for both components of the real exchange rate differ significantly in the short run -where the response to relative unit labor costs is around six times as large as to an equivalent sized move in the nominal exchange rate.

We then use this model estimated over a pre-crisis sample period to undertake two forecast exercises to examine the dynamics of trade since the GTC. At the aggregate level[3], in keeping with emerging consensus in the literature, we find that the fall in trade during

[1] Ca'Zorzi and Schnatz (2007) estimate an ECM for aggregate euro area exports, with a focus on assessing the best measure of competitiveness from a forecasting perspective. di Mauro, Rüffer and Bunda (2008) estimate country specific export demand equations for France, Germany and Italy, as well as a pooled version for the three. Breuer and Klose (2013) estimate individual export demand equations for 9 euro area countries using the SURE methodology.

[2] to the import content weighted measure in Bussière and others (2013) is also unfeasible to construct given the lack of export content data.

[3] The forecasts are conditional on both the country-specific variables and the cross section averages of all variables in the model (which account for the unobserved common factors in the residual of the model).

the GTC was significantly larger than can explained by GDP alone; but once common correlated effects are included, the model can explain around 95% of the fall in exports between 2008Q2 and 2009Q2. But the subsequent recovery in advanced economy exports was very much in line with the predictions of pre-crisis models, providing evidence in favor of the short term shock explanation for the GTC. We then also examine the forecasts for each individual country to gauge each country's performance against its peers. This exercise reveals significant variation across countries- with the UK and Nordic economies amongst the worst performers; and the Netherlands, Germany and Austria amongst the best.

The remainder of the paper is organized as follows: section 2 reviews the relevant literature on the traditional export determinants, section 3 describes the specification of our model and outlines our data and estimation approach, section 4 presents the empirical results, section 5 the conditional forecasts and section 6 concludes.

2 The changing nature of international trade

The literature on estimating trade elasticities dates back to the seminal work of Houthakker and Magee (1969) and the standard imperfect-substitutes model of international trade by Goldstein and Khan (1985).

However this standard model has been challenged by several related developments in the global economy. First, as economies have become more opened to international trade by reducing trade barrier, tariffs and transport costs, the overall volume of world trade has increased. Alongside traditional Ricardian channels, this evolution has increased the attractiveness of offshoring certain stages of the supply chain, often to lower cost producers (Strauß, 2002; Kleinert and Zorell, 2012; Yi, 2013). Offshoring (sometimes referred to as vertical specialization or outsourcing) results in an enlarged trade in intermediate goods between the offshoring firm and the foreign intermediate good producer and further boosts the volume of world trade (Kleinert and Zorell, 2012; Yi, 2013). As such globalization is likely to have increased the trade intensity of GDP. And since trade is measured in gross terms rather than net, the coefficient on foreign GDP can have a coefficient of greater than unity, because an extra dollar of GDP can create create more than one extra dollar of gross trade. This difference in measurement terms in turn means, that the coefficient on GDP cannot be directly interpreted as a tradtional income elasticity. [4]

Second, globalization is associated with increased international competition. As it is commonly assumed that the sensitivity of exports to cost changes depends on the degree of competition in the market (Carlin, Glyn and Van Reenen, 2001), higher competition may have increased the elasticity of exports with respect to their relative price. On the other hand, an enlarged import content of exports due to offshoring may have reduced the responsiveness to exchange rate changes (di Mauro and others, 2008) because the competitiveness gain associated with a nominal exchange rate depreciation is partially undone by a rise in the cost of imported inputs.

Third, there may be an important role for compositional effects in international trade due to structural shifts in global demand (Mayer, 2010). Countries that specialize in the sectors in which world demand growth is concentrated or that are better able to respond to changes in the structure of international demand by adjusting their production accordingly, are likely to gain export market share . So shifts that do not necessarily result in significant effects at the aggregate level may be important for individual countries' exports.

In this paper, we address each issue in turn by refraining from imposing a unit coefficient on the income elasticity coefficient, by controlling for unobserved common factors[5] and by introducing a proxy for the changing composition of trade for a given level of international trade.

[4]Recently, the OECD and WTO (2012) have published a dataset of bilateral trade flows in gross value added (GVA). However, since this is only available for a single year (2009), it is unsuitable for the kind of dynamic panel analysis undertaken here.

[5]The CCE estimators allow to account for the influence of unobserved common factors by including the cross-sectional averages of the dependent and independent variables (see page 14).

3 Empirical methodology

3.1 Imperfect substitutes model

Our starting point is the standard export equation based on the imperfect substitutes model of international trade (Goldstein and Kahn, 1985).

$$X_{i,t} = f\left(Y^*_{i,t}, E_{i,t}\right) \tag{1}$$

where X is real exports in domestic currency, Y^* is a country-specific trade-weighted external demand measure, and E is real effective exchange rates. Exports are expected to increase when overseas output rises or the real exchange rate depreciates.

We extend this basic setup along two different dimensions. First, we allow for changes in the sectoral composition of world trade to also play an important role in determining exports, and to do so in a way that may differ across countries. For example, lower cost emerging market economies (EMEs) may have displaced more established advanced economy producers in certain product types such as clothing and footwear. The effect of this will vary across countries according to whether they specialize in the sectors most affected.[6] On the other hand, sectoral shifts may also be beneficial for certain countries. For example, whereas the group of rich developed countries' demand tends to center on manufactured consumer goods, rapidly industrializing emerging economies' demand is more focused on industrial raw materials, energy and food products (Mayer, 2010). Countries specializing in these products may benefit more from the growth in emerging economies than those who do not. Compositional effects however do not only relate to medium or long term structural changes, they can be important in the short run as well (Levchenko and others, 2010). Given the potential importance of compositional shifts in

[6] For example, Giovanetti, Sanfilippo and Velucchi (2012) find evidence that Italy has been much more adversely affected by the rise of Chinese exports than Germany because Italy's exports are in sectors with greater competition from China.

international trade, we add a variable (C^{*}) to the benchmark model to explore the effect of sectoral preferences for advanced economies' exports, which we spell out in more detail in the next section.

Second, alongside the more standard approach of including the real exchange rate , we also explore the consequences of decomposing this into separate nominal exchange rate and domestic costs terms, denoted by S and U respectively, following Carlin and others (2001), Allard and others (2005), Breuer and Klose (2013) and Chen, Milesi-Ferretti and Tressel (2013). There are several reasons why the response of exports to a given real exchange rate shock may depend on which of these components is driving the change. If production of exported goods requires the use of imported inputs, then a given nominal depreciation may be partially offset by a rise in non-labor production costs. But this offset would not occur if the real depreciation stemmed from an improvement in unit labor costs. Also the presence of nontraded local costs reduces the response of prices to nominal exchange rates (Goldberg and Hellerstein, 2008) and implies pricing-to-market (i.e. exchange rate changes are associated with markup variation). Alternatively, Obstfeld and Rogoff's (2001) "exchange rate disconnect puzzle" highlights the fact that nominal exchange rates are far more volatile than fundamentals and that in the short run, the correlations between exports and nominal exchange rate appear low. Given the larger persistence of relative costs compared to nominal exchange rates, exporters may react more swiftly to cost changes than to movements in nominal exchange rates.

Equation (1) is thus extended as follows:

$$X_{i,t} = f\left(Y^{*}_{i,t}, S_{i,t}, U_{i,t}, C^{*}_{i,t}\right) \tag{2}$$

where S refers to nominal exchange rates, U captures relative domestic costs and C^{*} is a measure of sectoral shocks.

3.2 Data

We estimate our equation over an unbalanced panel at the quarterly frequency, comprising 16 advanced economies[7] between 1984Q1 and 2008Q2. A panel approach provides us with estimates of average elasticities over a comparable group of countries which can be used to examine individual countries' export performances relative to their peers.

Our dependent variable, X, is real export volumes in domestic currency for the goods sector. Our preferred measure of international price competitiveness, E, is the IMF's unit labor cost (ULC) based real effective exchange rate (REER) index. This captures relative unit labor costs versus competitors, using double weights to capture import and export competition in third markets.[8] Export prices are also commonly used as a measure of international price competitiveness but they suffer from the drawback of being determined endogenously with export quantities. In addition, they may be influenced by pricing-to-market effects or other pricing behavior, which are conceptually distinct from true cost competitiveness.

We prefer the ULC based REER to a consumer price index (CPI) based index because unit labor costs are likely to better reflect underlying cost shocks to producer prices. The CPI basket includes non-traded goods, regulated prices and services which may be a misleading indicator of traded goods prices. In addition, for many countries the CPI basket includes a substantial imported component, which makes it more difficult to separate out the index into exchange rate and domestic price terms. By contrast, ULCs for the manufacturing sector[9] give a broad indication of international price competitiveness as the manufacturing sector is representative for traded goods and labor costs represent a major component of total costs per unit of output. Moreover, by focusing on costs rather

[7]The 16 countries are: Australia, Austria, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Portugal, Sweden, Switzerland, UK and the US.

[8]For more details on the methodology, see Bayoumi, Lee and Jayanthi (2006).

[9]We prefer ULCs for the manufacturing sector because they correspond more closely to goods exports than total economy ULCs which also include services and the government sector.

than prices, the competitiveness indicator is less subject to direct exchange rate effects on pricing behavior. A ULC based REER is nevertheless by no means perfect as it also abstracts from indirect taxes and non-labor costs such as costs of raw materials or capital costs.

To measure the role of external demand conditions, we calculate trade-weighted world output growth (ΔY^*), given by:

$$\Delta Y^*_{i,t} = \sum_{p=1}^{P} \omega_{ipt} \Delta Y_{p,t} \tag{3}$$

where ω_{ipt} is the weight of country i's exports at time t going to partner p, where the weights are given by a three-year moving average of the export shares calculated for 76 trading partners using bilateral trade flows.[10] $\Delta Y_{p,t}$ is real GDP growth in each trading partner. The growth rate of trade-weighted world output growth is subsequently used to construct the indexed level variable Y^* (2009Q1=100).

We prefer this over an index of partners' import growth for a couple of reasons. Over the sample period, part of the rise in advanced economy imports reflects the supply-side shock of greater exports from emerging markets, rather than any intrinsic rise in demand for imported goods. This supply shock will either be orthogonal to demand for advanced economies -and hence a source of unwelcome noise- or even negatively correlated if they compete away advanced economies' market share. In addition, because our left hand side variable covers advanced economies accounting for the bulk of world trade, trade-weighted world import growth is likely to be closely related to some weighted sum of LHS variables and so may create simultaneity problems.

To capture the effect of changes in the sectoral composition of trade, we construct an

[10] The weights are calculated as the mean shares over the 12 previous quarters to avoid endogeneity problems.

index of sectoral shifts.[11]

$$\Delta C^*_{i,t} = \sum_{k=1}^{K} \phi_{ikt} \Delta S^*_{ikt} \tag{4}$$

where ϕ_{ikt} is the weight of sector k at time t for country i, which is determined by a three-year moving average of the share of sector k in total exports. To avoid simultaneity issues, shares of each good in "rest of world trade" are calculated over all other countries (i.e. excluding the country concerned). Thus S^*_{ikt} is given as:

$$S^*_{ikt} = \frac{\sum_{j=1, j \neq i}^{I} X_{jkt}}{\sum_{j=1, j \neq i}^{I} \sum_{k=1}^{K} X_{jkt}} \tag{5}$$

Constructed this way, the level variable C^* measures the general evolution in the relative importance of sectors in the export flows of advanced economies, weighted by the country-specific export shares of the particular sectors. A rise in C^* indicates that sectoral demand shifts create an increase in the demand for a country's exports. We opt for a group of 34 OECD countries (j) as the benchmark group for our sample of reporting countries (i), as we wish to analyze how the composition of world demand affects advanced economies' exports.[12]

In practice, the sectoral shift variable does exhibit significant variation across countries, and in a way which appears orthogonal to trade-weighted GDP growth. By

[11] An example may help here. Suppose there are two goods in the world, gin and tonic. Initially these are combined in the ratio 1:4 to form the composite drink "G&T". Suppose that the total number of servings of G&T (i.e. world output) is unchanged, but that due to a preference shock consumers now prefer the drink to be mixed with a ratio of 1:3. The share of gin in world trade thus rises by 5 percentage points (from 20% to 25%), the share of tonic in world trade falls by the same amount (from 80% to 75%). Globally, the demand for gin would be 25% higher than before. This benefits countries specialized in the export of gin, at the expense of those specializing in tonic. For a country which only exported gin, the change in demand arising from this shock will be 25 %.

[12] The 16 reporting countries are a subsample of the reference group of 34 OECD countries.

way of illustration, the left panel of figure 1 shows trade-weighted GDP growth for a selection of countries. Australia and Japan who are more exposed to China and other emerging Asian economies have experienced stronger external demand growth than Europe or the US. But the right hand panel shows that changes in the sectoral composition of trade have affected these two countries very differently. Australia, where commodities, fuel and minerals account for over 60% of exports (more than double any other country in our sample) has benefited from a shift in trade composition towards these items. By contrast Japan, where exports have been geared towards the machinery sectors, has seen a modest decline in C^* over the sample period. Further details of the coverage and data definitions are given in the appendix.

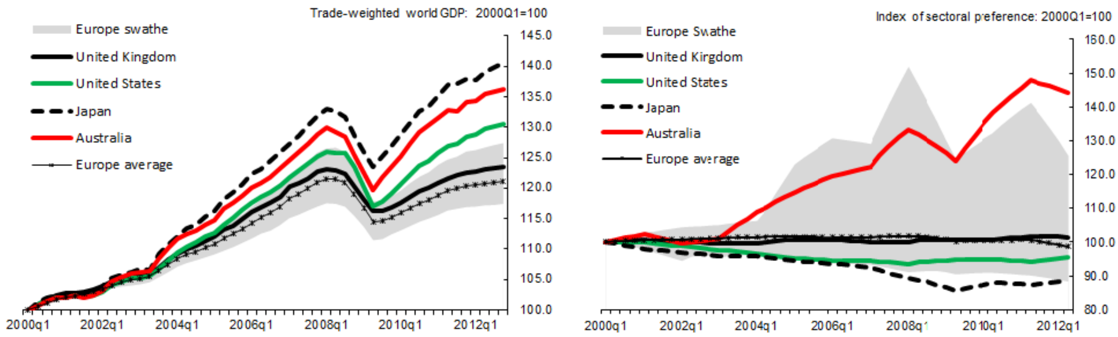


Figure 1 External growth and sectoral shocks: 2000-2011

3.3 Econometric model specification

The econometric analysis is based on a single equation error correction model (ECM) specification, in line with e.g. Ca'Zorzi and Schnatz (2007), di Mauro and others (2008) and Breuer and Klose (2013). Our variables are expressed in natural logarithms and are within-country demeaned to bring them to the same scale and hence allow us to focus on the time variation within countries. Denoting these transformed variables with lower case letters, our baseline specification is:

$$\Delta x_{i,t} = \alpha(x_{i,t-1} - [\gamma^l y^*_{i,t-1} + \beta^l e_{i,t-1} + \delta^l c^*_{i,t-1}]) + \sum_{j=1}^{L_d} \lambda_j \Delta x_{i,t-j}$$
$$+ \sum_{j=0}^{L_e} (\gamma^s_j \Delta y^*_{i,t-j} + \beta^s_j \Delta e_{i,t-j} + \delta^s_j \Delta c^*_{i,t-j}) + con_i + \nu_{i,t} \quad (6)$$

The ECM framework permits us to separate out the influence of short-run versus long-run factors on trade. Since volumes may adjust only slowly to changes in relative prices and demand, there are good grounds to believe that the longer-run reaction of exports to a given shock may differ from that which happens in the same quarter. In addition, the property that exports tend to revert back to a long-run equilibrium level following a shock may be important in capturing the bounce-back effects of exports witnessed since the financial crisis. The choice of an ECM is furthermore appropriate for the non-stationary level variables given the finding of significant error correcting properties in the model from diagnostic tests (see appendix B for details). The first (round) brackets in equation (6) represent the long-run relationship and the second term captures the short-run dynamics.[13] The average speed of adjustment to the long-run equilibrium is governed by α, the error correction coefficient.

Two econometric characteristics of macro panel data sets need to be considered for the choice of the appropriate panel estimator- cross-sectional dependence of the error terms and slope heterogeneity across panel units, both of which can lead to biased coefficient estimates. Cross-sectional dependence in the errors can arise from common factors across countries which are not explicitly accounted for in the model specification. Failure to account for cross section dependence results in inappropriate standard errors and even in biased coefficient estimates if the common factor in the residuals is correlated with the regressors (Pesaran, 2006). Imposing slope homogeneity, can also result in biased

[13] The long-run coefficients are indicated with the superscript l, the short-run coefficients with the superscript s.

coefficients in dynamic panel models when slope heterogeneity is in fact present (Pesaran and Smith, 1995).

To ensure consistent and unbiased estimates, we use diagnostic tests to adjudicate between three candidate estimators: Fixed Effects (FE), Mean Group (MG) and pooled Mean Group (PMG) estimators. The FE estimator assumes all slopes to be homogeneous, the MG assumes that all are heterogenous, and the PMG assumes only the short-run coefficients differ. The Akaike Information Criterion (AIC) is employed to select the lag length in equation (6). The maximum number of lags is restricted to 3 based on the rule $4*(T/100)^{2/9}$ suggested by Gengenbach, Urbain and Westerlund (2008) with T=53, i.e. the minimum time dimension of the individual country series when no additional lags are included, to preserve a sufficient number of degrees of freedom. The AIC suggests a lag order choice of one for the FE estimator and three for the MG and PMG estimators, so $L^d = L^e = 1$ and $L^d = L^e = 3$.

The estimation results are shown in table 1 for a lag length of one.[14] The Bewley (1979) transformation is used to obtain the long-run coefficients and their standard errors. This is a two-step procedure in which the dependent variable ($\Delta x_{i,t}$) is first regressed on its lagged level, the contemporaneous levels of the exogenous regressors and the differenced terms. In a second step, $x_{i,t}$ is regressed on the first stage fitted value, the contemporaneous levels of the exogenous regressors and the differenced terms. The estimates on the level variables of this second regression provide the long-run coefficients. In case of the MG estimator, the estimated individual long-run coefficients are averaged to obtain the long-run MG coefficients. As the table makes plain, the estimated results are sensitive to the estimator chosen, therefore careful consideration of the validity of their underlying assumptions is

[14] The empirical analysis was carried out in Stata 13, and we employed the user-written Stata routines xtcd and xtmg written by Markus Eberhardt (Eberhardt, 2012) and xtpmg written by Edward Blackburne and Mark Frank (Blackburne and Frank, 2007). The MG results are based on outlier-robust means (by employing the robust option of the xtmg command). To enhance the readability of the table, the estimates for the lagged first difference terms are not shown. The estimation results are quantitatively and qualitatively very similar for $L^d = L^e = 3$ and are shown in appendix C.

$$\Delta x_{it} = \alpha(x_{i,t-1} - [\gamma^l y^*_{i,t-1} + \beta^l e_{i,t-1} + \delta^l c^*_{i,t-1}] + \sum_{j=1}^{L_d} \lambda_j \Delta x_{i,t-j} + \sum_{j=0}^{L_e} (\gamma^s_j \Delta y^*_{i,t-j} + \beta^s_j \Delta e_{i,t-j} + \delta^s_j \Delta c^*_{i,t-j}) + con_i + \nu_{it}$$

		FE	**PMG**	**MG**	**CCEP**	**CCEPMG**	**CCEMG**
				Short-run coefficients			
World output	y^*	1.626***	1.455***	1.833***	0.838***	0.326	0.330
		(0.206) *0.000*	(0.304) *0.000*	(0.241) *0.000*	(0.317) *0.008*	(0.473) *0.491*	(0.406) *0.416*
Real exchange rate	e	-0.123***	-0.149***	-0.148***	-0.173***	-0.150***	-0.069**
		(0.028) *0.000*	(0.043) *0.001*	(0.056) *0.008*	(0.030) *0.000*	(0.038) *0.000*	(0.032) *0.030*
Sectoral composition	c^*	-0.096	0.175	-0.106	-0.315	-0.298	-0.050
		(0.272) *0.724*	(0.364) *0.631*	(0.476) *0.824*	(0.281) *0.263*	(0.279) *0.286*	(0.362) *0.890*
Error correction		-0.047***	-0.103***	-0.266***	-0.300	-0.349	-0.540
		(0.010) *0.000*	(0.022) *0.000*	(0.039) *0.000*	(0.023)	(0.051)	(0.060)
				Long-run coefficients			
World output	y^*	2.020***	1.848***	2.124***	0.884***	0.700***	1.415***
		(0.005) *0.000*	(0.045) *0.000*	(0.205) *0.000*	(0.063) *0.000*	(0.189) *0.000*	(0.537) *0.008*
Real exchange rate	e	-0.865***	-0.521***	-0.501***	-0.611***	-0.637***	-0.328***
		(0.008) *0.000*	(0.055) *0.000*	(0.127) *0.000*	(0.015) *0.000*	(0.034) *0.000*	(0.112) *0.003*
Sectoral composition	c^*	0.545***	-0.092	-0.193	-0.191***	0.011	0.293
		(0.021) *0.000*	(0.152) *0.545*	(0.599) *0.747*	(0.046) *0.000*	(0.122) *0.928*	(0.435) *0.501*
CD statistic:		12.09***	9.43***	8.54***	-5.55***	-4.48***	-4.29***
average correlation:		0.134	0.105	0.096	-0.060	-0.048	-0.047

Number of observations (for $L^d = L^e = 1$): Total=1260, N=16, min T=52, max T=96, average T=79; for CCE estimators: Total=1248, N=16, min T=52, max T=94, average T=78. Note:*, ** ,*** denote significance at 10, 5, and 1% levels respectively. Standard errors are in brackets, p-values in italics.

Table 1 Estimation results - standard and CCE estimators

important.

We first apply the cross section dependence test (CD test) of Pesaran (2004) to the residuals of equation (6) to analyze the extent of correlation between the cross section errors. The CD tests indicate the presence of a substantial amount of cross-sectional correlation in the residuals in both cases (see bottom lines of table 1). This outcome is of course not surprising given our discussion in section 2.[15] The inclusion of country-weighted measures of global external demand (y*) and changes in the sectoral composition of advanced economies' exports (c*) is thus insufficient to account for all common behavior of exports.

We therefore opt to use Common Correlated Effects (CCE) estimators as these estimators allow us to take account of the influence of unobserved common factors on the coefficient estimates by augmenting the model with the cross section averages (CSAs) of both the dependent and independent variables. More specifically, the residual term is

[15] In the particular case of our export model, common factors can be linked to the globalization of the world economy, increased international competition, general trends in the importance of country blocks in the world economy and common cost shocks to the model.

specified as follows:

$$\nu_{i,t} = \lambda_i^{'} f_t + \varepsilon_{i,t} \tag{7}$$

where f_t captures an unspecified number of unobserved common factors. Together with the country-specific factor loadings, λ_i, the term $\lambda_i^{'} f_t$ allows to control for cross section dependence and time-variant heterogeneity.

The right part of table 1 depicts the estimates for the different CCE estimators and shows that the error terms are substantially less correlated across countries in these cases. The CD-test statistics remain significant but the statistics and average pairwise correlations are considerably smaller. This leads us to conclude that the possible bias of the coefficient estimates due to cross-sectional correlated residuals is considerably reduced in light of weak cross section correlation. Note that the p-values for the error correction term are not listed for the CCE estimators because the t-statistic is not standard normally distributed due to the approximation of unobserved common factor by the CSAs. The significance levels for the CCEMG estimator can instead be based on the simulated critical values provided by Gengenbach et al, (2008). See appendix B for details.

A second consideration concerns the possible heterogeneity of the coefficients across countries.[16] Looking at the coefficient estimates again suggests that the estimates of the error correction term and the long-run coefficients vary substantially between the estimators. Formal Wald tests can be applied to examine the homogeneity restrictions imposed by the pooled and (pooled) mean group estimators. Table 2 displays the F-test statistics and the corresponding p-values for the homogeneity restrictions underlying the different estimators. Wald tests on the homogeneity assumption of the CCEP versus the CCEMG, the CCEP versus the CCEPMG and the CCEPMG versus the CCEMG

[16] Similar to the standard estimators, the pooled estimator (CCEP) is the most efficient estimator of the CCE estimators but will be inconsistent if the slopes actually differ between the panel units. The same holds for the CCE pooled mean group (CCEPMG) estimator if the long-run slope coefficients actually differ between the panel country units.

	CCEP **versus** CCEPMG	CCEP **versus** CCEMG	CCEPMG **versus** CCEMG
statistic:	1.54	2.29	3.60
p-value:	0.000	0.000	0.000

Table 2 Tests of homogeneity restrictions ($L^d = L^e = 1$)

estimators, suggest a rejection of the restrictions at the 1 per cent level. Based on these tests, the CCEMG estimator would be the preferred estimator.

Phillips and Sul (2003) however show that Wald tests are not reliable in a dynamic panel setup with cross section dependence. Given the finding of a low extent of cross-section dependence under the CCE estimators, the results should be interpreted with care. A Hausman test on the estimated coefficients of the CCEMG and CCEPMG estimators however also reveals that the obtained long-run panel coefficients are significantly different. The test statistic is 18.65 with a p-value of 0.000 and suggests that the consistent estimator, CCEMG, is to be preferred over the efficient estimator, CCEPMG. The finding of cross-country variation in the slope coefficients of the export demand model is furthermore in line with the evidence for cross-country variation in the literature (e.g. Carlin and others, 2001; di Mauro and others, 2008).

Given the results of the cross-section dependence and homogeneity tests, we use the CCEMG estimator for the remainder of our empirical analysis. The CCEMG estimator is shown to be consistent in a dynamic single equation model (Chudik and Pesaran, 2013) under the assumptions that the regressors are weakly exogenous, that the time dimension of the panel is sufficiently long and that the number of CSAs corresponds to the number of unobserved factors. To save degrees of freedom and to avoid over-parameterization, a general-to-specific method was employed on the CCEMG estimates based on the method proposed by Hendry (1993). Starting from 3 lags in the dynamics, any insignificant lags were stepwise excluded. This procedure resulted in a parsimonious specification for the CCEMG estimator which includes the contemporaneous first differences of the exogenous regressors, except for the sectoral variable for which up to two lags of the first differences remain included in the model. This results in the following empirical model specification:

$$\begin{aligned}\Delta x_{i,t} &= \alpha_i(x_{i,t-1} - [\gamma_i^l y_{i,t-1}^* + \beta_i^l e_{i,t-1} + \delta_i^l c_{i,t-1}^* + \widetilde{\lambda}_i^l \widetilde{csa}^l]) + \\ &+ \sum_{j=0}^{2}(\gamma_i^s \Delta y_{i,t}^* + \beta_i^s \Delta e_{i,t} + \delta_{ij}^s \Delta c_{i,t-j}^* + \widetilde{\lambda}_{ij}^s \widetilde{csa}_{t-j}^s) + con_i + \varepsilon_{i,t} \qquad (8)\end{aligned}$$

where $\widetilde{csa}^l$ and $\widetilde{csa}^s$ denote the CSAs for the variables in the long-run and short-run part of ECM.

4 Estimation results

The estimation results of specification (8) are shown in table 3. Regression I shows the baseline specification, with output, real exchange rate and the sectoral composition variable appearing in both the long-run and short-run parts of the ECM. Regression II explores the possibility of differential reactions to the two components of the real exchange rate. Separating these out reveals a clear difference in the short run -the elasticity with respect to the nominal exchange rate is 0.05, but the elasticity with respect to unit labor costs is about six times as large. A formal Wald test rejects (p-value of 0.06) the null that the two coefficients are equal. This finding supports the theoretical reasoning that one could expect a larger impact of relative unit labor costs to export prices due to the co-movement of nominal exchange rates and imported inputs and due to their larger persistence relative to the nominal exchange rate. The point estimates of the two coefficients also show a notable difference in the long run and the corresponding Wald test rejects their equality as well, although the p-value is close to the 10% boundary (p-value of 0.09). The differential effects of the REER components thus continue to hold in the long run.

An expansion in world GDP by 1% leads on average to a 0.89% expansion in a country's exports, while the long-run response is 1.9%. The short-run elasticity of exports with

Estimation sample:		I	II	III
		1984Q1-2008Q2		1984Q1-2012Q1
Short-run coefficients				
World output	y^*	0.519 (0.407) *0.202*	0.886* (0.495) *0.073*	0.852 (0.520) *0.102*
Real exchange rate	e	-0.098** (0.045) *0.029*	-	-
Nominal exchange rate	s	-	-0.051 (0.056) *0.361*	-0.089* (0.046) *0.054*
Unit labor costs	u	-	-0.300** (0.117) *0.011*	-0.288** (0.121) *0.017*
Sectoral composition	c^*	-0.008 (0.416) *0.984*	0.419 (0.563) *0.457*	0.779* (0.409) *0.057*
	c^*_{t-1}	0.669 (0.408) *0.101*	0.475 (0.459) *0.301*	0.179 (0.362) *0.621*
	c^*_{t-2}	0.791*** (0.197) *0.000*	0.665** (0.270) *0.014*	0.512** (0.229) *0.025*
Error correction		-0.571 (0.050)	-0.643 (0.056)	-0.584 (0.067)
Long-run coefficients				
World output	y^*	1.695*** (0.404) *0.000*	1.947*** (0.480) *0.000*	1.892** (0.521) *0.000*
Real exchange rate	e	-0.366*** (0.088) *0.000*	-	-
Nominal exchange rate	s	-	-0.209** (0.088) *0.017*	-0.331** (0.065) *0.000*
Unit labor costs	u	-	-0.415*** (0.081) *0.000*	-0.546** (0.082) *0.000*
Sectoral composition	c^*	0.180 (0.318) *0.571*	0.144 (0.346) *0.677*	0.317 (0.360) *0.378*
CD statistic:		-4.41***	-4.33***	-4.30***
average correlation:		-0.047	-0.046	-0.042

Number of observations for respectively columns I and II and column III: Total=1276, N=16, min T=53, max T=97, average T=80 and Total=1516, N=16, min T=68, max T=112, average T=95. Note: *,**,*** denote significance at 10, 5, and 1% levels respectively. Standard errors are in brackets, p-values in italics. Note that the p-values for the error correction term are not listed, given that the t-statistic is not standard normally distributed due to the approximation of unobserved common factor by the CSAs (see appendix).

Table 3 Estimation results - benchmark model (8) respect to the nominal exchange rate is not significant but has a significant long-run coefficient of -0.21. Similarly, the short-run elasticity of exports with respect to the relative ULCs is 0.30, rising to 0.42 in the long run. The values of these coefficients are in line with earlier work.[17] The contemporaneous sectoral composition variable is not significant although the lagged first differences have a significant positive effect on exports. The error correction term is strongly significant, with a value of -0.64, implying that any disequilibrium is corrected over less than two quarters. The results for the sample including the GTC (1984Q1-2012Q1) are further displayed in column III. Comparing the second and third column, it is clear that the estimates for the pre-GTC and entire period are fairly similar.

Given the results of the Wald tests on the REER components, our preferred specification allows for different effects of the components both in the short run and the long run. The model estimates in column II are thus used to construct the dynamic forecasts in the next section.

5 Conditional forecasts

We use the model to conduct two dynamic forecast exercises in order to better understand export performance since the GTC.[18] We employ the CCEMG estimates of our preferred model to examine whether actual export outturns during and following the GTC were in line with the pre-crisis *average* coefficients of the traditional demand and competitiveness determinants. The sample under analysis is the pre-GTC period (1984Q1 to 2008Q2), with the forecast period beginning at the turning point in global trade (2008Q3).

In the first instance, we use the model to generate out-of-sample forecasts for aggregate exports across all countries in our sample. Aggregate actual and forecast exports are

[17] E.g. Bayoumi, Harmsen and Turunen (2011) and Chen and others (2013)

[18] As with any dynamic forecast, we forecast the change in each quarter and then compute a levels forecast by accumulating these forecasts in changes over time.

measured as the weighted sum of the individual country profiles, where the weights reflect the average nominal US dollar value of each country's exports between 2008Q1 and 2011Q4 relative to the total for all 16 countries. The dashed line in Figure 2 below shows actual aggregate exports in combination with the out-of-sample forecast (depicted by the yellow diamonds). The forecast is in addition decomposed into the contribution of each of the exogenous variables, the unwind of previous error correction dynamics and the influence of the CSA terms.

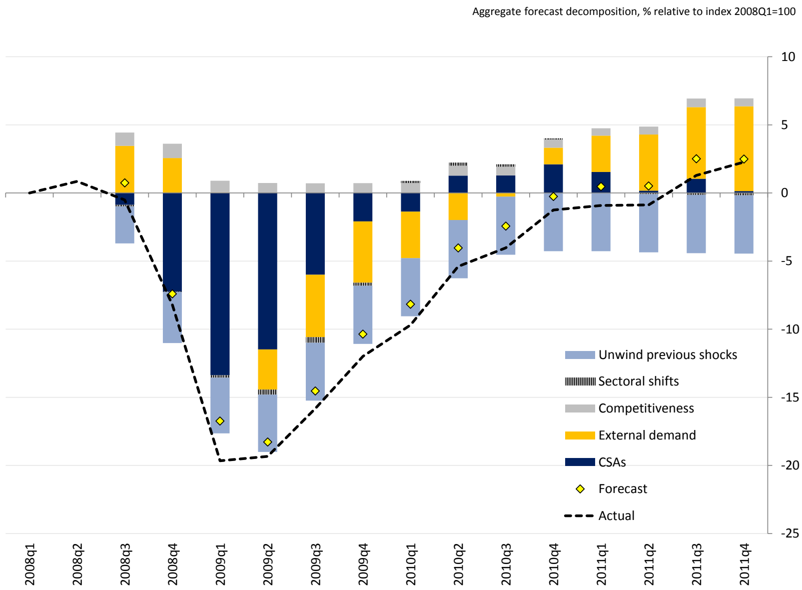


Figure 2 Forecast decomposition (weighted average)

Several facts stand out. Overall, the forecast profile fits the actual data fairly closely. But during the GTC, the biggest contribution comes from the unobserved common correlated effects, shown by the dark blue "CSA" bars, and hence the fall in trade was far larger than would have been expected on the basis of the weakness in external demand. In the subsequent recovery phase however, the influence of the CSA terms wanes considerably, with the CSAs making a close to zero contribution by the end of the forecast period. In other words, these unobserved common factors which might reflect global factors like trade protectionism, credit constraints or uncertainty reduced trade substantially during the GTC according to our model but appear to have unwound by the end of the forecast period. Most important of all, the level to which aggregate exports recover is very close to that implied by the forecast for the advanced-economy exports as a whole using the pre-crisis model. The GTC did hence not appear to herald a permanent structural break in the relationship between the level of exports, world GDP and other traditional determinants.

Of course if one were using the pre-crisis model to forecast exports in real time, one would not be able to include the CSA terms since they are unobserved at the time. To evaluate the contribution of the CSAs, we calculated an alternative forecast variant where the informational content of the CSAs is "switched off" in the forecast period. We achieve this by re-coding the levels of the CSA terms to their values at the jumping-off point, i.e. 2008Q2.[19]

Figure 3 plots this alternative forecast profile alongside the actual data and the forecast including the CSAs. The dashed line represents actual exports, the solid line the aggregate forecast when the influence of the CSAs is not taken into account and the yellow diamonds again depict the aggregate forecast that in addition takes into account the observed values of the CSAs.

At the time of the GTC itself, actual exports fell faster and further than the model would have predicted out of sample when ignoring the influence of the CSAs and explains only about half of the fall in exports between the peak in 2008Q2 and the through in 2009Q2. The forecast conditional on the CSAs in contrast almost fully captures that fall from peak to through. But during the recovery phase, the out-of-sample forecast tracks the actual data very well. This provides corroboration for the previous result that trade recovered to levels very close to those implied by pre-crisis models and hence the GTC was a temporary phenomenon rather than a structural break in the output-trade nexus,

[19] To remove the influence of the CSA terms during the forecast period, the CSAs of the level variables are kept at their value of 2008Q2 and all CSAs of the first differences are set to zero from 2008Q3 onwards.

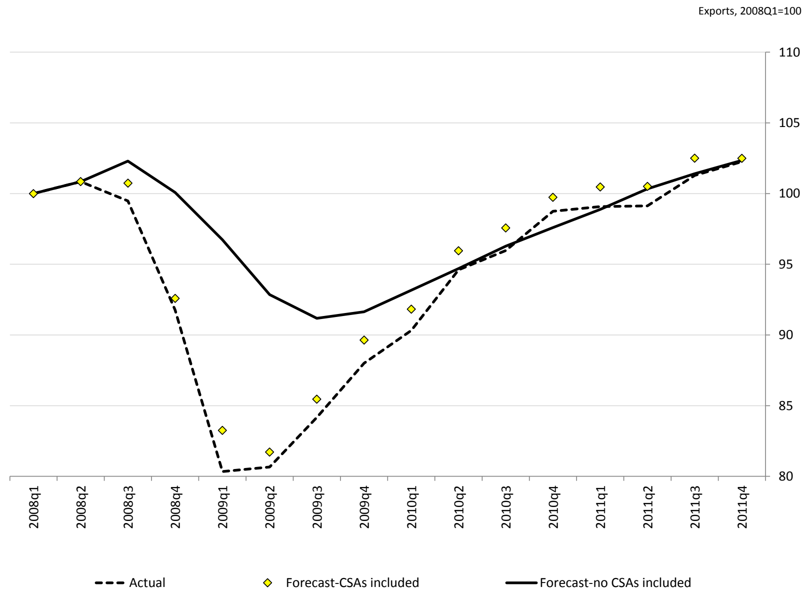


Figure 3 Actual weighted average of exports versus forecast

and shows that this result is robust to the exclusion of the influence of the CSAs in the forecast period.

Next, we use the estimated average coefficients reported in Table 3 to construct a dynamic forecast for each country's exports.[20] These country-specific forecasts represent a benchmark for what country exports "should have been" based on the obtained CCEMG coefficient estimates and given the evolution of the country-specific exogenous variables and the CSAs. By using average coefficient estimates, we obtain a uniform benchmark to compare each country's export performance relative to that of their peers. The forecast profiles for each country conditional on the observed country-specific variables and the CSAs, together with the actual outturn are shown in Figure 4.

This approach allows us to capture the influence of unobserved common components which may have affected export performance and are captured in the cross section average

[20]Given that the aggregate forecast conditional on the observed CSAs captures the evolution of average actual exports since the GTC to a very large extent, we consider the individual-country forecasts based on the CCEMG coefficients to be relevant benchmarks to evaluate individual export performances since the GTC.

Figure 4 Actual exports versus forecasts for individual countries

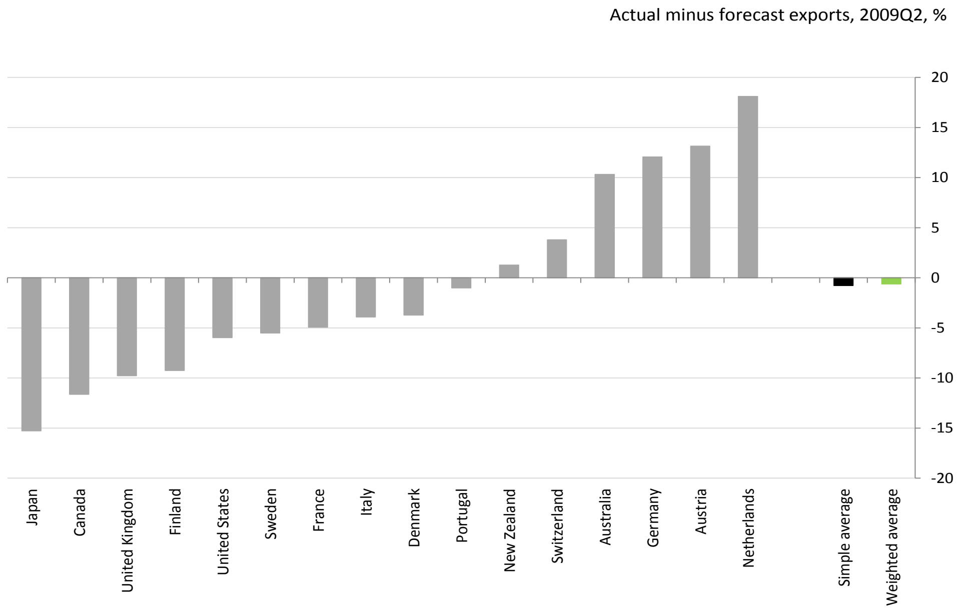
terms. If for example the general export performance across developed economies were influenced by some common factor outside of the exogenous variables included in our ECM, this would show up via the CSA terms. This is potentially important because failure to account for these factors may otherwise yield a misleading benchmark.

To measure performance over the whole forecast period, we compute the gap between actual and forecast exports, expressed as a percentage of forecast exports. A positive value indicates that a country has outperformed the forecast based on the average coefficients, a negative value indicates under-performance. The measure of relative performance is shown below in figures 5 and 6, for respectively 2009Q2 and 2011Q4. [21]

The relative performance varies substantially across the countries in our panel, though

[21] We compare actual versus forecast exports at these two points in time to evaluate the export performance in the immediate aftermath of the GTC in 2009Q2 and next in 2011Q4, to gauge the longer-run effects of the GTC on trade dynamics.

Figure 5 Actual exports versus benchmark, 2009Q2



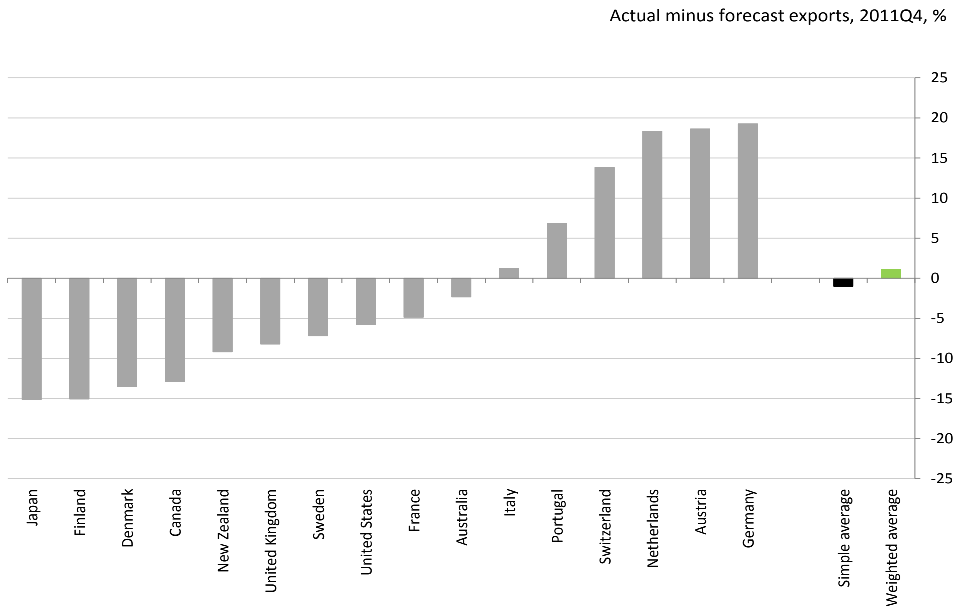


Figure 6 Actual exports versus benchmark, 2011Q4

on average there is no systematic over or under-performance . The best performers are Germany, the Netherlands and Austria. The worst performers are Japan and Finland. The UK has also underperformed relative to the benchmark. Conditional on the average coefficient estimates, UK exports underperformed by around 10% in 2009Q2 and by 8% in 2011Q4. Whilst the UK's cumulative growth in exports from 2008Q1 to 2011Q4 is close to the cross-country median, the large depreciation in sterling (and accompanying fall in the ULC-based real exchange rate) failed to boost exports by as much as the model would have predicted.

6 Conclusions

We estimate a dynamic panel model of goods exports for 16 advanced economies that includes the traditional export determinants, being foreign demand and competitiveness and extend this framework by incorporating a measure of the sectoral composition of trade as an additional determinant of the demand for exports and we allow for a different effect of nominal exchange rates and relative costs on exports. In addition, by using the Common Correlated Effects estimator of Pesaran (2006) we control for unobserved common factors such as common globalization dynamics and evolutions in the degree of international competition. We find that the two components of the real effective exchange rate, the nominal exchange rate and relative unit labor costs, have a significant different effect on exports. The sectoral composition variable has only a small influence on export dynamics which is confined to a lagged effect in the short run.

We use the model to construct a forecast benchmark to evaluate countries' export performance based on the average panel estimates of the model prior to the Great Trade Collapse. First, we consider how the pre-crisis model fared in predicting the overall path of advanced economy exports. We find that the model can only explain around half of the fall in exports during the Great Trade Collapse based on country-specific evolutions in the variables but subsequently approximates actual exports very well. If the common unobserved factors, proxied by the cross section averages of all variables, are taken into account, the model fits the evolutions of actual exports pretty well over the entire forecast period. This finding suggests that common factors played a major role during the Great Trade Collapse although their influence receded afterwards. Thus, we conclude that the Great Trade Collapse did not appear to mark a structural change in the relationship between exports and the traditional macroeconomic determinants.

Given this good average forecast performance, we evaluate individual countries' export performance against their peers by constructing a forecast conditioning on both the path of the country-specific variables and the common unobserved factors. We find substantial variation across countries in terms of their actual exports relative to the forecasts based on the average panel coefficients. The UK and Nordic countries have been amongst the worst performers, with the Netherlands, Germany and Austria amongst the best.

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Appendices

A Data sources and construction of variables

Real Exports: chain volume index (2010=100) of good exports in national currencies, seasonally adjusted (OECD Quarterly National accounts). US export data are instead based on the IMF series on volume of exports (IFS, code USQ72...H), seasonally adjusted via CensusX12 because of a longer time coverage. UK export data are a Bank of England goods export series corrected for MTIC fraud.

Trading partners' GDP: real GDP volume, seasonally adjusted, (Datastream, ??GDP...D code, except for Spain [code ESGDP..VE], Brazil [code BRGDP...G], Poland [code POSMGDPC], Estonia [code EOGDPPIPDF], China [IMF World Economic Outlook data], Malta [Eurostat data],the CensusX12 procedure is applied if the series are not yet seasonally adjusted)

-> sample of countries for construction trade-weighted external demand measure: 76 countries

[UK, Austria, Belgium, Estonia, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Netherlands, Portugal, Slovak Republic, Slovenia, Spain, Cyprus, Malta, United States, Japan, Canada, Australia, New Zealand, Denmark, Norway, Sweden, Switzerland, Singapore, South Korea, Albania, Bulgaria, Croatia, Czech Republic, Hungary, Latvia, Lithuania, Poland, Romania, Serbia, Turkey, Jordan, Belarus, Georgia, Moldova, Russia, Ukraine, Argentina, Brazil, Chile, Colombia, Costa Rica, Ecuador, Mexico, Peru, South Africa, China, India, Indonesia, Malaysia, Philippines, Thailand, Israel, Kenya, Namibia, Uganda, Venezuela, Egypt, Iran, Morocco, Tunisia, Paraguay, Mozambique, Sri Lanka]

Total exports to world and to trading partners: total goods exports, current US dollar (OECD, Monthly Statistics of International Trade (MSIT) database, w.r.t. world and w.r.t. 76 trading partners

Bilateral export flows, for different sectors: goods exports for 63 sectors, current US dollar (OECD International Trade by Commodity Statistics database, Standard International Trade Classification (SITC) Revision 2)

-> sample of countries for advanced economies group: 34 OECD countries

[Australia, Austria, Belgium, Canada, Chile, Czech republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, South Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States]

-> 63 sectors: 69 available sectors - sector 35, 91, 93, 95, 96 and 97 due to data quality (large amount of missing observations)

-> annual data: 1980-2012, interpolated to quarterly data

Effective exchange rates: nominal and real ULC-based effective exchange rate indices, double-weighted to capture import and export competition in third markets (IMF, International Financial Statistics). For more details on the methodology, see Bayoumi, Lee and Jayanthi (2006).

COUNTRY	TIME SPAN		NUMBER	COUNTRY	TIME SPAN		NUMBER
Australia	1989q2	2012q1	92	Japan	1995q2	2012q1	68
Austria	1989q2	2012q1	92	Netherlands	1989q2	2012q1	92
Canada	1984q2	2012q1	112	New Zealand	1990q2	2012q1	88
Denmark	1992q2	2012q1	80	Portugal	1996q2	2012q1	64
Finland	1991q2	2012q1	84	Sweden	1994q2	2012q1	72
France	1984q2	2012q1	112	Switzerland	1984q2	2012q1	112
Germany	1984q2	2012q1	112	UK	1984q2	2012q1	112
Italy	1992q2	2012q1	80	US	1984q2	2012q1	112

Table 4 Overview number of observations per country

B Time series properties

We apply the cross-section dependence test of Pesaran (2004) to the residuals of individual augmented Dickey-Fuller (ADF) tests.[22] The results signify substantial cross section residual correlation between the country-specific series (see table 5), which calls for the use of second generation panel unit root tests which take into account cross-sectional dependence and provide critical values at the panel level which are simulated such that they are valid under dependence of the individual series.

Lag order	x	y^*	e	c^*
0	0.21	0.68	0.09	0.05
1	0.20	0.64	0.10	0.12
2	0.20	0.64	0.09	0.12
3	0.20	0.64	0.09	0.13
4	0.21	0.64	0.09	0.14

Table 5 Average cross-sectional correlation of residuals ADF tests

Given the unbalanced nature of our dataset, we opt for the cross-sectionally augmented IPS (CIPSM) test of Pesaran, Smith and Yamagata (2013).[23] The extent of cross-sectional dependence of the residuals from the individual cross section augmented ADF tests (CADF) based on this approach, is substantially reduced for all variables (table 6, bottom part). The CIPSM tests further indicate that the variables x, y^*, e and c^* can considered to be nonstationary, although the test results on the y^* and e variables depend on the imposed lag order.

To find out whether equation (8) constitutes a meaningful long-run relation, we apply the panel error correction test of Gengenbach, Urbain and Westerlund (2008). This approach tests the significance of the error correction term within a conditional

[22] A constant and trend are included for x, y^*, a constant only for c^* and e, both in the ADF and CIPSM tests

[23] The cross-sectional averages of the other variables in (1) are added as additional common factors for the CIPSM tests on x, y^*, e and c^*.

	CIPSM			
	average test statistics			
Lag order	x	y^*	e	c^*
0	-4.18***	-2.66	-2.25	-0.85
1	-3.63***	-2.41	-2.83*	-2.30
2	-3.25***	-2.45	-2.90**	-2.15
3	-2.97*	-2.31	-3.03***	-2.21
4	-2.63	-2.29	-2.94**	-2.31
	average residual cross section dependence			
0	-0.03	0.02	-0.04	-0.02
1	-0.02	0.02	-0.02	0.04
2	-0.02	0.02	-0.02	0.04
3	-0.02	0.03	-0.02	0.04
4	-0.02	0.03	-0.02	0.04
Note: *, **, *** denote significance at 10, 5, and 1% levels respectively.				

Table 6 Average cross-sectional correlation of residuals CIPSM tests

ECM framework that allows for possible nonstationary common factors. If the error correction term is found to be significant, this implies the existence of a long-run equilibrium relationship. Two panel tests of the null hypothesis of no error correction that the error correction term for every i are provided, given by the (truncated) average of individual t-tests and Wald tests. Based on the results of the unit root tests, we test the following reparametrized conditional ECM-specification:

$$\begin{aligned}\Delta x_{it} \quad = \quad & \alpha_i(x_{i,t-1}-[\beta_{1,i}y^*_{i,t-1}+\beta_{2,i}e_{i,t-1}+\beta_{3,i}c^*_{i,t-1}])+\sum_{j=1}^{L}\beta_{4,ij}\Delta x_{i,t-j}+ \\ & \sum_{j=0}^{L}(\beta_{5,ij}\Delta y^*_{i,t-j}+\beta_{6,ij}\Delta e_{i,t-j}+\beta_{7,ij}\Delta c^*_{i,t-j})+\sum_{j=0}^{L}\tilde{\psi}_{ij}\widetilde{CA_{t-j}}+\rho_{it} \qquad (9)\end{aligned}$$

where $\widetilde{CA}$ stands for the cross section averages which are used as proxies for unobserved common factors. The t-test directly tests whether α_i is significantly different from zero whereas the Wald tests test whether α_i and the coefficients on the lagged levels of the exogenous regressors are jointly equal to zero. The panel tests' null hypotheses are both rejected at the 5% significance level for a lag order choice of 4, respectively with a statistic of -3.88 and 34.96 where the critical values at the 1% significance level and for N=20 are respectively-3.53 and 20.36. Also for a lag order choice of 3, both tests reject the nulll with statistics of respectively -4.12 and 34.62.[24] The individual t-tests and Wald tests cannot reject the null for respectively 9 and 6 of the 16 countries for both lag order choices. The panel test thus displays evidence of error correction, whereas the individual tests cannot reject the null for an important subset of countries. Taking into account that the power of the tests are greatly improved by pooling (Gengenbach and others, 2008), we conclude that including the level information in our variables next to their differences is appropriate.

[24] The lag order L is determined based on the Aikaike Information Criterion, where the maximum number of lags is set equal to $4*(T/100)^{2/9}$ as suggested in Gengenbach and others (2008). This resulted in a maximum of 4 lags and a lag order choice of 4 for average and maximum T and in a maximum of 3 lags and a lag order choice of 3 for the minimum T.

C Additional estimations results for lag order=3

$\Delta x_{it} = \alpha(x_{i,t-1} - [\gamma^l y^*_{i,t-1} + \beta^l e_{i,t-1} + \delta^l c^*_{i,t-1}] + \sum_{j=1}^{L_d} \lambda_j \Delta x_{i,t-j} + \sum_{j=0}^{L_e} (\gamma^s_j \Delta y^*_{i,t-j} + \beta^s_j \Delta e_{i,t-j} + \delta^s_j \Delta c^*_{i,t-j}) + con_i + \nu_{it}$							
		FE	**PMG**	**MG**	**CCEP**	**CCEPMG**	**CCEMG**
Short-run coefficients							
World output	y^*	1.534***	1.236***	1.673***	0.926***	1.449**	0.843*
		(0.207) *0.000*	(0.341) *0.000*	(0.242) *0.000*	(0.326) *0.005*	(0.631) *0.022*	(0.488) *0.084*
Real exchange rate	e	-0.103***	-0.083	-0.086	-0.175***	-0.216***	-0.132***
		(0.028) *0.000*	(0.051) *0.104*	(0.061) *0.162*	(0.033) *0.000*	(0.069) *0.002*	(0.022) *0.000*
Sectoral composition	c^*	-0.264	0.205	0.060	-0.118	-0.208	0.321
		(0.272) *0.331*	(0.375) *0.584*	(0.377) *0.874*	(0.288) *0.681*	(0.436) *0.633*	(0.572) *0.575*
Error correction		-0.044***	-0.102***	-0.272***	-0.252	-0.408	-0.701
		(0.010) *0.000*	(0.031) *0.001*	(0.050) *0.000*	(0.030)	(0.081)	(0.093)
Long-run coefficients							
World output	y^*	2.130***	1.852***	2.135***	0.974***	2.142***	1.810***
		(0.006) *0.000*	(0.040) *0.000*	(0.208) *0.000*	(0.071) *0.000*	(0.112) *0.000*	(0.465) *0.000*
Real exchange rate	e	-0.853***	-0.580***	-0.467**	-0.767***	-0.708***	-0.340***
		(0.008) *0.000*	(0.049) *0.000*	(0.207) *0.024*	(0.019) *0.000*	(0.026) *0.000*	(0.096) *0.000*
Sectoral composition	c^*	0.662***	-0.063	0.184	-0.124**	0.192	0.274
		(0.022) *0.000*	(0.154) *0.681*	(0.615) *0.765*	(0.063) *0.047*	(0.161) *0.233*	(0.499) *0.583*
CD statistic:		12.16***	7.08***	7.05***	-5.27***	-3.05***	-2.33**
average correlation:		0.138	0.081	0.080	-0.058	-0.033	-0.025

Number of observations (for $L^d = L^e = 3$): Total=1228, N=16, min T=50, max T=94, average T=77. Note:*, ** ,*** denote significance at 10, 5, and 1% levels respectively. Standard errors are in brackets, p-values in italics.

Table 7 Estimation results for $L^d = L^e = 3$ - standard and CCE estimators