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Import demand in heterogeneous panel data with cross-sectional dependence

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ABSTRACT

We investigate the long-run income and price elasticity of import demand functions with a heterogeneous unbalanced panel of 34 countries over the period 1985:q1-2018:q3. To estimate world elasticities the model is tested with the activity variables derived from the theoretical and empirical literature: GDP, GDP minus exports, Private Demand, Aggregate Domestic Demand, National Cash Flow, and Import intensity-Adjusted Demand (IAD). First, we evaluate time series properties using second generation panel unit root and cointegration tests. Second, we rely on the dynamic common correlated effects mean groups (CCEMG) estimator to deal with cross-sectional dependence (CSD). We find that the IAD, whose world elasticity is close to one, is the best performing specification. Our results confirm that the most appropriate activity variable to assess import demand should encompass intermediate goods as suggested by the recent literature on global supply chains. Moreover, we partially solve the puzzle of the recent trade slowdown since, taking stock of the role of intermediates, the time needed to resort to the long run equilibrium in the aftermath of a global turmoil is greater than that predicted by previous studies.

KEYWORDS

World import function; import income elasticity; import price elasticity; IAD; CCEMG

JEL CODES

F14; F41; F69; C33; C52

I. Introduction

The empirical investigation of trade elasticities is still a challenging topic in the research agenda of international economics. Practitioners devoted considerable efforts to assess import demand functions, and there is a large literature that provides estimates on price and income elasticities for both advanced and developing countries (Houthakker and Magee 1969; Caporale and Chui 1999; Hong 1999; Hooper, Johnson, and Marquez 2000; Harb 2005; IMF 2016). These are pivotal for addressing a wide range of important policy issues such as trade liberalization, the stability of the foreign exchange market or a monetary union, and the sustainability of external deficits (Marquez 2002). Perhaps, the most significant contribution amongst the earliest works is due to Houthakker and Magee (1969) who report an overall income elasticity of about 1.62 for 15 leading economies and a value of 1.5 for the United States. A value larger than unity has the puzzling implication that, in the absence of a relative price increase, a country will change from a self-sufficient economy to a nation unable to pay for its imports. Harb (2005) obtains an income elasticity of 2.77 in New Zealand and of 0.58 in South Africa, and similar differences are found between emerging markets and developed economies too (IMF 2016). Such a large heterogeneity calls for an appropriate specification of the import demand function at both the country- and world-level.

The abovementioned debate has received renewed attention after the last global financial crisis that trigged an unprecedented contraction in commercial flows (Baldwin 2009). After a sudden recovery, trade growth has slowed with respect to its previous track. Practitioners and policy makers are questioning whether the actual slowdown is due to cyclical or structural factors since trade is a vital channel to allow for knowledge transfer and an important engine for long-term growth. Demand for traded goods is clearly a function of economic activity and several studies use world's GDP as a proxy for domestic demand (Constantinescu, Mattoo, and Ruta 2015, 2016; Slopek 2015; OECD 2016). Another strand of literature focuses on the components of GDP and their different impact on imports using panel data (Martinez-Martin 2016; Giansoldati and Gregori 2017; Konstantakopoulou 2018). Within this setting, several scholars follow the innovation of Bussière et al. (2013) who use Input-Output data to compute the

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Supplemental data for this article can be accessed here.

Import intensity-Adjusted Demand (Jääskelä and Mathews 2015; Morel 2015; IMF 2016; Martinez-Martin 2016; Aslam et al. 2017).

Our contribution fits into the abovementioned literature as we assess the world elasticity that measures, *ceteris paribus*, the impact of a change in the activity level on international trade.

This paper fills two gaps recorded in the literature. First, we emphasize the role of intermediate imports, extending the contributions which address consumer behaviour only. We focus on the former since international trade nowadays largely concerns part and components produced in several countries which are sequentially assembled along global supply chains. Our review allows us to identify the candidate activity variables to better explain import behaviour. These are Gross Domestic Product (GDP), Aggregate Domestic Demand (ADD), Private Demand (PD), GDP minus exports (GDP-X), National Cash Flow (NCF), and Import intensity-Adjusted Demand (IAD). Second, we estimate price and quantity elasticities hinging on recent panel analysis that takes into account how common factors affect imports as latent variables.

We assess the relative performance of these activity variables in an unbalanced panel of 34 countries from 1985:q1 to 2018:q3.[1] Based on the most recent advances in the nonstationary panel literature, we discuss time series properties and provide estimates of world income and price elasticities for all the abovementioned activity variables. We take into account both parameter heterogeneity and cross-sectional dependence (CSD) since a copious literature shows at least three relevant facts. First, there are large differences in elasticities across developed and emerging economies (IMF 2016). Second, global shocks, such as the great trade collapse and the following slowdown, affect countries to a different extent (Yi 2010; Constantinescu, Mattoo, and Ruta 2016). Third, some supra-national agreements, such as a monetary or a custom union, are in common to some but not all the countries under investigation. To deal with these issues we adopt a common factor approach and employ the Common Correlated Effects Mean Group (CCEMG) estimator recently developed by Chudik and Pesaran (2015). This allows us to account for local or global spillovers and common shocks.

We find that the specification based on the Import intensity-Adjusted Demand (IAD) measure of economic activity is the best performing. Using this variable we estimate both world- and country-specific elasticities. We observe that the IAD worldwide elasticity is close to one. It shows a large variability across countries and has the smallest half-life value. This aspect carries important implications as researchers should rely on this measure, rather than on other more traditional variables, to understand international trade dynamics and compute the time needed to resort to long run equilibrium. IMF (2016) adopts IAD to address the world trade slowdown, but it neglects to provide a precise indication on how long the world economy should have taken to recover after the trade collapse. Our study complements IMF's approach and shows that about 2 years would have been needed to restore the equilibrium.

The paper is organized as follows. In the next section, we discuss the literature underpinning import function specifications within a theoretically rigorous framework. Section 3 addresses time series properties of our dataset. Section 4 presents the estimates of the different specifications, whilst Section 5 summarizes and provides some conclusive remarks.

II. Modelling considerations

This section discusses the theoretical model behind the import demand function. We distinguish between a static approach that focuses on intermediate inputs and an intertemporal model which builds on consumption behaviour by a representative rational agent. These models embrace different activity level variables that are adopted for model comparisons in the empirical analysis.

Intermediate imports

A large part of the import literature is based on the assumption that producers find the mix of foreign

[1]We limit our analysis on these countries since no complete series are available for a larger set of nations. Nevertheless, the countries we selected represent a large share of world GDP, ranging from 80% in 1990 to 68% in 2017 (World Bank 2019). The empirical analysis is based on a suite of panel time series commands the interested reader can find at the following URL: https://sites.google.com/site/medevecon/code.

intermediate and domestic primary inputs that minimizes the cost of attaining a given output (Kohli 1991). Within this setting, we can easily derive a Marshallian demand function that relates total imports to their price, the price of the domestic bundle of primary factors, and the level of output. If the production function exhibits constant returns to scale then the demand for imports is linearly homogeneous in output and its elasticity is unity. This result is extendable to the profit maximization case when aggregate factor endowments are interpreted as national income, because an efficient economy will maximize the net output (GDP) subject to prices and availability of primary factors.

Let's assume GDP to be defined by the profit function:

$$v(P_M, P, K) = \underset{X,M}{Max}[PX - P_M M/f(K, M) \geq X], \tag{1}$$

where K is the vector of primary inputs, X output, M imports, whose prices are, respectively, P and P_M. Hence, $PX - P_M M$ is nominal GDP. According to Hotelling's lemma, optimal demand for imports and output supply are respectively given by:

$$M(P_M, P, K) = -\frac{\partial v(P_M, P, K)}{\partial P_M}, \tag{2}$$

$$X(P_M, P, K) = \frac{\partial v(P_M, P, K)}{\partial P}, \tag{3}$$

Both functions are homogeneous of degree zero in import and domestic prices. $M(P_M, P, K)$ may be approximated by a translog function. When factor endowments are exogenous we get the traditional import function where K is usually given by GDP or National Income. This is the log-linear model analyzed in earlier studies with unitary income elasticity (Marquez 2002).

Equation (3) can be used to derive domestic prices from equilibrium conditions with exogenous demand, i.e. $X(P_M, P, K) = F$, where F is final demand. However, domestic prices are also the solution of the following market clearing problem:

$$v(P_M, F, K) = \min_P[v(P_M, P, K) - PF], \tag{4}$$

where optimal prices are given by:

$$P(P_M, F, K) = \frac{\partial v(P_M, F, K)}{\partial F}, \tag{5}$$

which, in turn, take into account a different value added function:

$$V(P_M, F, K) \equiv v(P_M, F, K) + P(P_M, F, K)F. \tag{6}$$

This yields a new import demand too:

$$M(P_M, F, K) \equiv -\frac{\partial V(P_M, F, K)}{\partial P_M}. \tag{7}$$

Then, the desired import function can be obtained in two ways. Either we directly impose the translog function in (7) or on $v(P_M, F, K)$, as suggested by Kohli (1978). Bussière et al. (2013) explore both routes and allow for time-varying parameters in final demand components. Using the first approach, Bussière et al. (2013) differentiate the first-order terms in the translog import function to get the following specification:

$$\Delta \ln M_t = \beta_D \sum_k \Delta(\omega_{k,t} \ln F_{k,t}) + \Delta\beta_P \ln P_{M,t}, \tag{8}$$

where $F_{k,t}$ is the k-th component of (final) demand and time-varying parameters $\omega_{k,t}$ are given by an Input-Output model with N sectors and K domestic final demand components. Within this setting gross output is given by:

$$x = \left(\mathbf{I} - \mathbf{A^D}\right)^{-1}\left(e + \mathbf{F}^D i_K\right), \tag{9}$$

where $\boldsymbol{x}$ and $\boldsymbol{e}$ are, respectively, the $N\times$ 1 vectors of total output and gross exports, $\mathbf{F}^D$is the $N\times K$ matrix of domestic final demand components, i_K a summation vector, while the input matrix $\mathbf{A}$, which represents the technology of intra-industry relationships, accounts for domestic ($\mathbf{A^D}$) and imported flows ($\mathbf{A^M}$). The latter can premultiply the Leontief inverse to obtain $\mathbf{Q} = \mathbf{A^M}\left(\mathbf{I} - \mathbf{A^D}\right)^{-1}$. This shows, in each column, the bundle of imported intermediate goods and services directly and indirectly activated by a unit of the corresponding final demand item since q_{ij} indicates total imports of commodity i required to obtain one unit of final product of industry j. The column sums of $\mathbf{Q}$ thus provide the total import content in one unit of final product in each sector (Chenery, Robinson, and Syrquin 1986). Hummels, Ishii, and Yi (2001) revive attention for this matrix.

They focus on exports and Vertical Specialization, where the latter is defined as the value of imported inputs embodied in goods that are exported. They consider both intermediate imports directly activated by exports, i.e. $\mathbf{A^M}e$, as well as the total value $\mathbf{A^M}\left(\mathbf{I}-\mathbf{A^D}\right)^{-1}e$, because imported inputs are allowed to circulate through value chains before being exported.

Total imports can be expressed as the sum of direct and indirect imports:

$$\mathbf{M}=\mathbf{M}^{dir}+\mathbf{M}^{indir}=\mathbf{F}^{M}i_K+\mathbf{A^M}\left(\mathbf{I}-\mathbf{A^D}\right)^{-1}\mathbf{F}^{D}i_K, \tag{10}$$

where $\mathbf{F}^M$ is the $N\times\ K$ matrix of imported final demand. Then, we can compute the (relative) total import content of each expenditure components that is given by:

$$\omega_k=\frac{i_N\mathbf{F}_k^M+i_N\mathbf{A^M}\left(\mathbf{I}-\mathbf{A^D}\right)^{-1}\mathbf{F}_k^D}{i_N\mathbf{F}_k^M+i_N\mathbf{F}_k^D}, \tag{11}$$

where k refers to private consumption, government spending and investment. Since we do not allow for reimported exports, the export weight is given by:

$$\omega_e=\frac{i_N\mathbf{A^M}\left(\mathbf{I}-\mathbf{A^D}\right)^{-1}e}{\boldsymbol{i}_N\boldsymbol{e}}, \tag{12}$$

Hence, Bussière et al. (2013) propose a new measure of aggregate demand, the already mentioned IAD, that is computed as a weighted average of all final demand components:

$$\begin{aligned}\ln IAD_t=\omega_{C,t}\ln C_t+\omega_{G,t}\ln G_t+\omega_{I,t}\ln I_t\\+\omega_{E,t}\ln E_t.\end{aligned} \tag{13}$$

Weights are time-variant but normalized in each period so that their sum is always equal to one.[2] According to these authors, IAD is the best performing measure of activity level since final demand components have different degrees of procyclicality and import content. For instance, during the trade collapse of 2008–2009 investment and exports fell much more than private consumption, while government spending was expansionary in several countries.

Final imports

Another strand of literature addresses consumption and imports within an intertemporal setting. Clarida (1994, 1996) considers an infinitely lived representative agent who consumes both a domestic good, H_t, and an imported one, M_t:

$$\underset{H_t,M_t,A_t}{Max}\ \sum_{t=0}^{\infty}(1+\rho)^{-t}U(H_t,M_t) \tag{14}$$

$$s.t.\,H_t+P_t^MM_t+A_t=(1+r)A_{t-1}+Y_t, \tag{15}$$

where P_t^M is the relative price of imports, as the domestic price is the numeraire, Y_t is labour income, A_t represents assets, r is the interest rate, and ρ is the subjective rate of time preference. Assuming an addilog instantaneous utility function with curvature parameters α and η, first-order conditions yield the Euler equation and:

$$A_tH_t^{-\alpha}=\lambda_t, \tag{16}$$

$$B_tM_t^{-\eta}=P_t\lambda_t \tag{17}$$

where A_t and B_t are exponential random shocks to preferences, and λ_t is the Lagrange multiplier on the accumulation constraint (15). Taking logs of the latter:

$$\ln M_t=\frac{1}{\eta}\ln B_t-\frac{1}{\eta}\ln P_t^M-\frac{1}{\eta}\ln\lambda_t \tag{18}$$

We obtain a log-linear import demand model defined on the actual import price and the marginal utility of wealth, which itself depends on the entire future time path of labour income and import prices. This utility index of permanent income is the activity variable that should be included in the intertemporal specification (Clarida 1994). Since data are not available, we can plug (16) and use consumption of domestically produced goods as a noisy proxy. Hence, we obtain the double log specification where the activity variable is GDP minus exports (Senhadji 1998):

$$\ln M_t=\beta_0+\beta_A\ln\left(Y_t-P_t^MM_t\right)+\beta_P\ln P_t^M+\varepsilon_t \tag{19}$$

[2]The IMF (2016) noted that if import intensity could be exactly measured in each period and its weights allowed to change over time, then it could be possible to rely on a model that precisely takes into account the level of imports.

Emran and Shilpi (2010) include liquidity constraints, while Xu (2002) deems a more general model where output is no longer exogenous but it is obtained via a production function that depends on capital, with random productivity shocks. Home production can be either consumed domestically, or invested without depreciation, or exported. The solution of the model provides an import demand equation which includes a trend term that captures any trend-stationary shock to consumption, and an activity variable, labelled National Cash Flow, given by GDP minus investment, government expenditure, and exports. However, in several countries the National Cash Flow can take negative values for very long time spans and may lead to meaningless results in the standard econometric framework (Tang 2003). Nonetheless, Xu (2002) argues his import demand equation is more general and flexible than the previous partial equilibrium settings. These include Reinhart (1995), who takes into account the steady-state budget constraint and uses GDP as a proxy of permanent income, and Amano and Wirjanto (1997), whose activity variable is private consumption plus investment.

Finally, we note that an import demand equation, which relates growth in real imports to changes in aggregate demand and relative prices, can be derived from virtually any international real business cycle model (IMF 2016). However, the practice of first-differencing is useful to deal with variables that follow a I(1) process, but it has the drawback that throws away the long-run level of information which is instead the focus of our analysis.

In order to shed some light on these issues, we decide to look at several specifications with six different activity variables. These are GDP, IAD, Private Demand (PD), GDP minus exports (GDP-X), the National Cash Flow (NCF), and Aggregate Domestic Demand (ADD) or absorption.

III. Data and preliminary analysis

Our objective is to compare the six specifications we have introduced above, making use of an unbalanced panel database, which is skewed towards developed countries, but that nevertheless allows us to take into account a number of non-negligible developing nations. The 34 countries in our investigation are Australia, Austria, Belgium, Brazil, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Great Britain, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxemburg, Mexico, Nederland, Poland, Portugal, Russia, Slovakia, Slovenia, Spain, Sweden, Turkey, USA. The source of the quarterly data for imports, exports, GDP and final demand components, as well as the series of import prices and GDP deflators, covering the period 1985:q1-2018:q3, is the OECD Economic Outlook database. We compute the relative import price (PrM) taking the ratio of the import price of goods and services by the GDP deflator for each country. We calculate IAD using the recent release of WIOD (Timmer et al. 2015) as suggested by Giansoldati and Gregori (2017). Summary statistics are shown in Table 1.[3]

The time dimension of our panel is quite sizeable as it ranges from 90 to 135 quarters. Such a large time span is required for satisfactory small sample performances especially if the speed of convergence towards the long-run relation is quite slow (Chudik et al. 2016). The first step in our empirical analysis is to establish the statistical properties of the data by carrying out unit root-tests.[4] Researchers proposed a variety of panel unit-root tests (Söderbom et al. 2015). First-generation tests do not account for CSD and tend to overreject the null due to considerable size distor-

Table 1. Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
M	4133	4.187	0.570	1.980	5.271
IAD	4133	4.360	0.369	2.652	5.215
GDP	4133	4.412	0.290	2.971	5.153
ADD	4133	4.415	0.283	3.139	5.155
PD	4133	4.415	0.297	3.113	5.150
GDP-X	3855	4.598	0.029	4.148	4.694
NCF	3013	4.612	0.500	−0.370	6.251
PrM	4129	0.102	0.191	−0.366	1.265

Source: our elaboration from OECD and WIOD data

[3]We must discard negative values of GDP-X and NCF as we take logs of all the activity variables. We also get rid of some gaps recorded after the great trade collapse. After this procedure, we are left with 25 and 32 countries for GDP-X and NCF, respectively.

[4]Following Eberhardt and Teal (2013), we first assess stationarity within each nation with standard ADF and KPSS tests. Then, we allow for structural breaks through the Clemente, Montañés, and Reyes (1998) tests. Results are not reported here for the sake of brevity, but available upon request, and show quantities are non-stationary in almost all the countries. When we impose the presence of two structural breaks, we observe that all the series are I(1), but the relative price in Lithuania. These results point to a large heterogeneity on the timing of structural breaks across countries for each activity variable. Thus, we cannot apply the approach proposed by Banerjee and Carrion-i-Silvestre (2015), as it is based common breaks.

Table 2. Cross-sectional dependence test statistics (CD-test) and pairwise correlation.

	Variables in levels				Variables in first differences			
Variables	CD-test	p-value	corr	abs (corr)	CD-test	p-value	corr	abs (corr)
M	236.2	0.00	0.94	0.94	67.2	0.00	0.27	0.27
IAD	232.3	0.00	0.93	0.93	58.2	0.00	0.23	0.24
GDP	233.2	0.00	0.93	0.93	68.1	0.00	0.27	0.28
ADD	224.1	0.00	0.89	0.89	37.7	0.00	0.15	0.17
PD	218.8	0.00	0.87	0.87	40.1	0.00	0.16	0.18
GDP-X	51.8	0.00	0.22	0.65	11.1	0.00	0.05	0.1
NCF	17.7	0.00	0.12	0.6	5.9	0.00	0.04	0.1
PrM	118.8	0.00	0.46	0.55	36.6	0.00	0.14	0.22

tion, while second-generation panel unit-root tests relax this hypothesis. Hence, we must check whether CSD is present. Table 2 presents average absolute correlations for variable series as well as the Pesaran (2004) cross-sectional dependence test statistics (CD-test). The former are the simple average of the pairwise correlation coefficients between all countries series or the average of their absolute values. Correlation is very large for quantities, exception made for GDP-X and NCF. The CD-test is based on the mean pairwise correlation coefficients and is distributed as a standard normal for a sufficiently large number of countries under the null of cross-sectional independence (Pesaran 2004). As we can observe in Table 2, data overwhelmingly reject the null for variables in levels and first differences.

Second generation tests with and without trend are reported in Table 3, which also shows the results for the test on first differences without a trend.[5] The cross-sectional augmented IPS (CIPS) adds current and lagged cross-sectional averages of the dependent variables and their changes to the usual ADF equation. Pesaran (2007) argues the unobservable processes driving CSD may be represented by a single common factor that is modelled by these cross-sectional averages. When we include a trend, the CIPS is very supportive of the null hypothesis the activity variables are I(1), exception made for National Cash Flow but only without lags. Without a trend, the CIPS rejects the null for Aggregate Domestic and Private Demand when we include more than two lags. On the contrary, the relative price is stationary without a trend, or with it only if less than two lags are used. Finally, the behaviour of imports is puzzling, as, at the usual confidence level and without a trend, CIPS is supportive of stationarity, while the opposite holds when we include a trend.

We may allow for more than a single common factor and adopt the test introduced by Pesaran,

Table 3. CIPS test.

	Without trend		With trend		First differences		Without trend		With trend		First differences	
	Wt-bar	p-val	Wt-bar	p-val	Wt-bar	p-val	Wt-bar	p-val	Wt-bar	p-val	Wt-bar	p-val
				M					PD			
0	−2.38	0.01	1.32	0.91	−28.10	0.00	0.50	0.69	4.07	1.00	−27.99	0.00
1	−1.79	0.04	2.00	0.98	−26.86	0.00	−0.13	0.45	3.69	1.00	−24.18	0.00
2	−2.06	0.02	1.85	0.97	−23.61	0.00	−1.25	0.11	2.91	1.00	−18.18	0.00
3	−2.56	0.01	1.33	0.91	−20.80	0.00	−2.50	0.01	1.75	0.96	−15.61	0.00
4	−2.36	0.01	1.87	0.97	−16.72	0.00	−1.92	0.03	2.35	0.99	−12.74	0.00
				IAD					GDP-X			
0	0.19	0.57	3.22	1.00	−28.10	0.00	4.67	1.00	0.81	0.79	−26.83	0.00
1	0.18	0.57	3.95	1.00	−27.02	0.00	6.84	1.00	1.78	0.96	−25.57	0.00
2	−0.69	0.25	3.26	1.00	−21.87	0.00	6.94	1.00	1.74	0.96	−21.00	0.00
3	−1.65	0.05	2.73	1.00	−18.22	0.00	7.07	1.00	1.97	0.98	−17.65	0.00
4	−1.67	0.05	2.82	1.00	−14.62	0.00	6.85	1.00	2.13	0.98	−13.90	0.00
				GDP					NCF			
0	3.71	1.00	6.51	1.00	−28.08	0.00	2.20	0.99	−2.22	0.01	−21.83	0.00
1	2.77	1.00	6.41	1.00	−25.66	0.00	4.33	1.00	1.09	0.86	−21.83	0.00
2	1.24	0.89	5.48	1.00	−19.38	0.00	5.62	1.00	3.55	1.00	−21.11	0.00
3	0.52	0.70	4.61	1.00	−16.09	0.00	6.51	1.00	4.26	1.00	−18.19	0.00
4	0.47	0.68	4.73	1.00	−12.29	0.00	6.36	1.00	4.24	1.00	−15.37	0.00
				ADD					PrM			
0	0.57	0.72	4.22	1.00	−28.01	0.00	−5.31	0.00	−2.36	0.01	−28.10	0.00
1	−0.05	0.48	4.04	1.00	−24.11	0.00	−4.72	0.00	−2.08	0.02	−27.72	0.00
2	−1.21	0.11	3.09	1.00	−18.04	0.00	−3.26	0.00	−0.37	0.36	−25.34	0.00
3	−2.64	0.00	1.92	0.97	−15.88	0.00	−3.08	0.00	−0.13	0.45	−21.01	0.00
4	−2.21	0.01	2.56	1.00	−12.39	0.00	−2.51	0.01	0.36	0.64	−17.24	0.00

[5]We do not provide results for the first differences with a trend as results are similar to those with a trend.

Smith, and Yamagata (2013), which adds cross-sectional averages of other variables to the ADF equation, called CIPSM (Söderbom et al. 2015). The intuition is that there exists a number of macro-variables that are simultaneously affected by the same set of multiple unobserved common factors. The test is based on the null of non-stationarity in all country series, while the alternative is stationarity in at least one country series. We perform this test for imports only, using in turn each one of all the (other) variables under investigation, exception made for NCF. Results are shown in Table 4. We cannot reject the null of non-stationarity in all the cases even at the 10% confidence level. Since in a cointegrated framework long-run relationships only exist between I(1) variables, we can safely address import models with multiple unobserved common factors.

Long-run relationships between variables in a panel setting have been investigated with different approaches, since there is no formal way to pre-test them. These relationships can be addressed either by analyzing the stationarity of residuals or by checking the significance of the error-correction term. It is also possible to allow for cross-sectional dependence.

Westerlund (2007) and Gengenbach, Palm, and Urbain (2010) fit in the second generation category tests. They are both based on structural rather than residual dynamics. They test the null hypothesis of no-cointegration by checking whether the error-correction term is equal to zero against the alternative of at least one country with a negative term (group test) or, either, all the other countries with the same negative term (panel test). Persyn and Westerlund (2008) also suggest to detect cross-sectional independence in the residuals of a panel error-correction model with the very same lags and leads for all the countries. If results indicate CSD, they recommend to use a bootstrap approach, which allows to perform inference even under very general forms of CSD (Westerlund 2007). This is indeed the case of all our specifications. Hence, we estimate the error correction model relying on the Akaike Information Criterion (AIC) to choose optimal lag and lead lengths for each country series, while the Bartlett kernel window is set to $4(T/100)^{2/9}$ following Newey and West (1987).[6]

Results are provided in Table 5 for both mean group and panel tests. Asymptotic tests are often supportive of a long-run relationship, but probabilities obtained from the bootstrapped distribution dramatically change this picture, exception made for GDP. Since the homogenous alternative hypothesis considered for this particular test may be overly restrictive we do not wish to overemphasize the relevance of such probabilities. In addition, this approach suffers from at least two drawbacks. First, the bootstrap technique is based on residual rather than structural analysis and tests may have potentially low power. Second, the testing procedure is undertaken in steps with no clear-cut indication of the final outcome (Westerlund and Larsson 2009). Therefore, we prefer to focus on a different approach with a very general data generating process where the common factors are allowed to enter both the short-run dynamics and the cointegrating relationship in line with Gengenbach, Urbain, and Westerlund (2016).

Table 4. CIPSM test.

	Additional regressors without trend						Critical values		
lags	IAD	GDP	ADD	PD	GDP-X	PrM	1%	5%	10%
0	−2.095	−2.126	−2.166	−2.291	−1.755	−2.199	−2.56	−2.41	−2.33
1	−1.867	−1.959	−1.943	−2.085	−1.596	−1.942	−2.54	−2.40	−2.32
2	−1.829	−1.980	−1.909	−2.042	−1.643	−1.777	−2.51	−2.37	−2.28
3	−1.884	−2.074	−1.982	−2.113	−1.646	−1.720	−2.50	−2.35	−2.26
4	−1.915	−2.110	−2.054	−2.184	−1.650	−1.652	−2.48	−2.31	−2.23
	Additional regressors with trend						Critical values		
lags	IAD	GDP	ADD	PD	GDP-X	PrM	1%	5%	10%
0	−2.077	−2.273	−2.157	−2.194	−2.042	2.171	−3.00	−2.86	−2.79
1	−1.787	−2.100	−1.873	−1.917	−2.064	−1.888	−2.99	−2.85	−2.77
2	−1.753	−2.068	−1.826	−1.892	−2.180	−1.717	−2.96	−2.81	−2.72
3	−1.815	−2.173	−1.904	−1.995	−2.240	−1.651	−2.94	−2.79	−2.71
4	−1.789	−2.146	−1.941	−2.043	−2.367	−1.531	−2.91	−2.75	−2.66

[6]The average lag length is often close to one, while the lead length is much often close to zero.

Table 5. Westerlund (2007) and Gengenbach, Palm, and Urbain (2010) group and panel tests of cointegration.

	Without trend						With trend					
	IAD			GDP			IAD			GDP		
Statistic	*Z value*	*P value*	*P* value*	*Z value*	*P value*	*P* value*	*Z value*	*P value*	*P* value*	*Z value*	*P value*	*P* value*
Group τ	−2.22	0.01	0.10	−3.77	0.00	0.00	−6.67	0.00	0.00	−6.90	0.00	0.00
Group α	−1.87	0.03	0.17	−3.04	0.00	0.00	−2.35	0.01	0.27	−2.13	0.02	0.00
Panel τ	−4.34	0.00	0.49	−5.46	0.00	0.00	−11.46	0.00	0.05	−6.63	0.00	0.00
Panel α	−7.40	0.00	0.09	−8.24	0.00	0.00	−9.26	0.00	0.15	−4.37	0.00	0.00
	ADD			PD			ADD			PD		
Group τ	0.22	0.59	0.65	1.20	0.89	0.91	−4.68	0.00	0.00	−4.72	0.00	0.00
Group α	0.19	0.58	0.55	1.21	0.89	0.88	−0.55	0.29	0.34	−1.28	0.10	0.17
Panel τ	−1.55	0.06	0.69	−0.95	0.17	0.82	−5.07	0.00	0.33	−5.39	0.00	0.27
Panel α	−3.11	0.00	0.29	−2.14	0.02	0.53	−2.69	0.00	0.57	−3.25	0.00	0.47
	GDP-X			NCF			GDP-X			NCF		
Group τ	3.27	1.00	1.00	−2.88	0.00	0.12	−0.09	0.46	0.62	−0.88	0.19	0.39
Group α	2.83	1.00	0.99	0.13	0.55	0.50	1.12	0.87	0.72	1.20	0.89	0.78
Panel τ	2.16	0.99	0.96	−3.20	0.00	0.31	−0.91	0.18	0.85	0.16	0.56	0.67
Panel α	1.95	0.97	0.95	−2.65	0.00	0.26	−0.57	0.29	0.66	1.12	0.87	0.87

P values* are obtained from the bootstrap approach (1,000 replications).

Table 6. Gengenbach, Urbain, and Westerlund (2016) panel error correction test.

lags	IAD	GDP	ADD	PD	GDP-X	NCF
No Trend						
0	−4.022***	−3.904***	−3.739***	−3.806***	−3.906***	−2.846
1	−3.946***	−3.908***	−3.715***	−3.811***	−3.943***	−2.817
2	−3.859***	−3.790***	−3.638***	−3.752***	−3.788***	−2.713
3	−3.918***	−3.831***	−3.744***	−3.836***	−3.811***	−2.779
4	−3.817***	−3.767***	−3.588***	−3.701***	−3.801***	−2.740
With Trend						
0	−4.436***	−4.086***	−3.991***	−4.049***	−3.290*	−3.062
1	−4.364***	−4.132***	−3.987***	−4.072***	−3.381**	−3.041
2	−4.319***	−4.041***	−3.989***	−4.074***	−3.357**	−3.000
3	−4.388***	−4.148***	−4.131***	−4.186***	−3.371**	−3.058
4	−4.264***	−4.119***	−4.014***	−4.051***	−3.293*	−3.071

Critical values for the test: without trend 1%: −3.120; 5%: −2.981; 10%: −2.909; with trend 1%: −3.460; 5%: −3.337; 10%: −3.269. *** significant at 1%; ** significant at 5%; * significant at 10%

These authors develop a new test based on the significance of the error correction term in a model with non-stationary common factors. Under the null of no error correction they show the asymptotic distributions of the test statistics are not affected by nuisance parameters. This result holds whether the factors are treated as known or if they are estimated using the cross-sectional averages of the observed data (Gengenbach, Urbain, and Westerlund 2016).[7] Ideally, each country equation should be estimated with unit-specific optimal lag-length according to a selection criterion. These could be either the more traditional Schwartz Bayesian Criterion (BIC) or the AIC, or emerge from careful judgment whether some lags are needed or not according to the t-ratios, following the indications of Eberhardt (2012). All in all, the results of the test suggested by Gengenbach, Urbain, and Westerlund (2016) reported in Table 6 indicate that imports appear to be cointegrated with the activity variables, exception made for the National Cash Flow.[8]

IV. Panel estimation results

The previous section showed all activity variables follow a I(1) process, while relative prices are stationary. Since higher series dominate, the linear combination on the right side of our specifications is always I(1), while imports are very likely to follow the same process in the presence of one or more common factors. If some conditions are met, an autoregressive distributed dynamic panel specification, ARDL(P, Q_1,Q_2), provides a suitable framework to estimate long-run elasticities when the underlying variables are I(0) or I(1) (Pesaran and Smith 1995; Pesaran and Shin 1999). This model is given by:

$$m_{c,t} = \alpha_c + \sum_{j=1}^{P} \gamma_{c,j} m_{c,t-j} + \sum_{j=0}^{Q_1} \beta^Y_{c,j} y_{c,t-j} + \sum_{j=0}^{Q_2} \beta^M_{c,j} p_{c,t-j} + u_{c,t} \quad (20)$$

where $m_{c,t}$ is the log of real imports of country c at time t, $y_{c,t}$ is the log of the activity variable, and $p_{c,t}$ is the log of its relative import price, while $u_{c,t}$ contains unobservables and the error terms $\epsilon_{c,t}$. Time trends and other fixed covariates may be included in larger specifications. This approach allows for heterogeneity since the parameters in (20) are not restricted to be the same across countries. It also allows to address the short- and long-run effects of activity and prices on imports, reparametrizing (20) into the well-known error correction model:

$$\Delta m_{c,t} = \delta_c + \varphi_c\left(m_{c,t-1} - \theta_{c,y} y_{c,t} - \theta_{c,p} p_{c,t}\right) + \sum_{j=1}^{P-1} \lambda_{m,j} \Delta m_{c,t-j} + + \sum_{j=0}^{Q_1-1} \mu_{c,j} \Delta y_{c,t-j} + \sum_{j=0}^{Q_2-1} \rho_{c,j} \Delta p_{c,t-j} + u_{c,t} \quad (21)$$

$\varphi_c = -\left(1 - \sum_{j=1}^{P} \gamma_{c,j}\right)$ is the error-correcting speed of adjustment term, $\theta_{c,y} = -\sum_{j=1}^{Q_1} \beta^Y_{c,j}/\varphi_c$, $\theta_{c,p} = -\sum_{j=1}^{Q_2} \beta^M_{c,j}/\varphi_c$, $\lambda_{m,j} = -\sum_{l=j+1}^{P} \gamma_{c,l}$ for $j = 1,2,\dots,P-1$, $\mu_{c,j} = \sum_{l=j+1}^{Q_1} \beta^Y_{c,l}$ for $j = 1,2,\dots,Q_1-1$, $\rho_{c,j} = \sum_{l=j+1}^{Q_2} \beta^M_{c,l}$ for $j = 1,2,\dots,Q_2-1$. Parameters of particular interest are $-\varphi_c\theta_{c,y}$ and $-\varphi_c\theta_{c,p}$, i.e. long-run elasticities.

The standard ARDL approach assumes the errors in (20) to be cross-sectionally independent. This is hardly true when global shocks hit all economies. A typical multifactor error structure takes the following form:

[7]Gengenbach, Urbain, and Westerlund (2016) simulate the error correction tests of Westerlund (2007), but they omit to publish the results as their performance (in terms of size accuracy and power) is much lower than that of the tests we provide in Table 6.

[8]Tang (2004) finds a cointegrated relationship between NCF, imports, and import prices for two out of five ASEAN countries.

$$u_{c,t} = \alpha_{1c} + \lambda_c f_t + \epsilon_{c,t} \quad (22)$$

where unobservables may contain country fixed effects and unobserved common factors f_t with heterogeneous factor loadings λ_c that capture CSD and time-variant heterogeneity.[9] Unfortunately, quite often these unobserved factors cannot be modelled by a simple linear trend that can be added in (21) solving the CSD problem (Coakley, Fuertes, and Smith 2006; Eberhardt and Teal 2011).

A different approach estimates the factors by principal component analysis (Bai and Ng 2002), a path we do not follow since it relies on routines that are cumbersome in unbalanced panels. In addition, it is very challenging to identify the appropriate number of factors or distinguish between strong and weak ones (Söderbom et al. 2015). Pesaran (2006) solves this problem for static models by approximating the unknown common factors with cross-sectional means of the dependent and independent variables. The so-called common correlated effect (CCE) estimator is consistent under a variety of further assumptions on the idiosyncratic term with exogenous regressors (Chudik, Pesaran, and Tosetti 2011; Kapetanios, Pesaran, and Yamagata 2011), and can be applied to non-dynamic panels (Chudik and Pesaran 2015; Everaert and De Groote 2015).

The standard CCE estimator is consistent only in static models and does not cover the case when the panel includes a lagged dependent variable and/or weakly exogenous variables as regressors. To solve this issue Chudik and Pesaran (2015) propose the CCEMG estimator that is the CCE augmented with a sufficient number of lags of cross-sectional averages. A necessary condition for the CCEMG estimator to be valid in the case of panel ARDL data models is that the number of cross-sectional averages based on regressors must be at least as large as the number of unobserved common factors minus one. These are unlikely to be numerous in a macroeconomic setting (Stock and Watson 2002, 2005). Whatever the number, we can easily check its appropriateness by testing for weak CSD residuals (Pesaran 2004; Bailey, Kapetanios, and Pesaran 2015). Then, if the matrix of cross product of cross-sectional averages is full rank, Chudik and Pesaran (2015) prove the CCEMG estimator to be consistent and asymptotically normal even at the country level. If the rank condition does not hold, but factors are serially uncorrelated, then unit-specific estimates are inconsistent due to the correlation between regressors and factors. Nevertheless, the mean group average parameters are consistent and asymptotically normal, and the world trade elasticities can still be estimated.

Given these premises, we estimate and ARDL with a homogeneous lag structure, by making use of the command developed by Ditzen (2018). We adopt the same lag orders for imports and regressors because it is desirable to start with a balanced lag structure to avoid potential problems arising from persistent covariates (Chudik and Pesaran 2015). Moreover, employing the same lag order across all variables and countries should limit the potential side effects associated with the data mining that inevitably arise when country- and variable specific-lag orders are chosen on the basis of either AIC or BIC (Chudik et al. 2016). A further justification to the choice of a homogeneous lag structure is that our research objective is estimating world long-run estimates rather than country-specific dynamics. Long-run elasticities and error correction term estimates are provided in Table 7, where we address models with different lags to investigate the sensitivity of the results[10] It is worth reminding here that sufficiently long lags are necessary for the consistency of the ARDL estimates, but specifying longer lags than necessary can lead to estimates with poor small sample properties (Chudik et al. 2016). We also test for the presence of linear country-specific trends and keep them since the estimated mean is almost always statistically significant. Yet, their effects are negligible.

Our analysis shows a key finding, which is clearly visible to the reader who, for the sake of clarity, is advised to concentrate only on the coefficients that are statistically significant and reported between the third and the sixth row of Table 7. Only the coefficient of the IAD elasticity is always close to one and significant at the 1% level across all specifications. Conversely, all other activity variables show long-run coefficients that differ markedly across specifications (and, thus, lags), and may be quite misleading.

[9]It is worth noting that covariates can also be affected by f_t.

[10]Long-run elasticities are derived from short-run ones as shown above. When significant, all the short-run activity coefficients are positive, whereas the few significant price coefficients are always negative. Results on short-run elasticities are available from the authors upon request..

Table 7. Long run results of the common correlated effects mean group estimator (CCEMG).

	ARDL(4,4,4)						ARDL(3,3,3)					
LR	IAD	GDP	ADD	PD	GDP-X	NCF	IAD	GDP	ADD	PD	GDP-X	NCF
Activity	0.957***	0.079	0.954	2.026	20.523	-44.606	0.791***	0.646	3.127	0.016	-8.874	-1.407
	(0.155)	(1.283)	(1.025)	(2.142)	(19.843)	-42.522	(0.273)	(0.625)	(2.662)	(0.614)	(9.387)	-0.938
Price	-0.316	-0.557	-0.265	-0.791	-1.959	0.806	-0.461	-0.302	-0.088	-0.323	-9.241	-1.040*
	(0.212)	(0.415)	(0.411)	(0.563)	(1.663)	-3.013	(0.291)	(0.214)	(0.353)	(0.506)	(9.265)	-0.631
ECM	-0.193***	-0.200***	-0.146***	-0.133***	-0.106***	-0.093***	-0.196***	-0.204***	-0.156***	-0.152***	-0.105***	-0.098***
	(0.027)	(0.032)	(0.023)	(0.021)	(0.021)	-0.022	(0.026)	(0.029)	(0.023)	(0.022)	(0.016)	-0.018
Trend	0.001	0.001***	0.002***	0.001***	0.002***	0.001***	0.001*	0.001***	0.001***	0.001***	0.002***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0
N	3823	3823	3823	3823	3477	2331	3857	3857	3857	3857	3508	2351
rmse	0.02351	0.02687	0.02597	0.02585	0.02808	0.02953	0.02385	0.02709	0.02612	0.02606	0.02844	0.02969
CD	-0.229	0.703	0.497	0.900	1.992	0.82	-0.408	0.635	0.422	0.870	2.082	0.532
CDP	0.819	0.482	0.619	0.368	0.046	0.412	0.683	0.525	0.673	0.384	0.037	0.595
half-life	3.23	3.10	4.39	4.84	6.17	7.09	3.18	3.03	4.08	4.19	6.23	6.69
AB-1	0.697	0.675	0.784	0.820	0.684	0.59	0.690	0.747	0.755	0.657	0.596	0.722
AB-2	0.242	0.880	0.932	0.734	0.553	0.714	0.624	0.342	0.669	0.940	0.528	0.467
AB-3	0.695	0.533	0.842	0.816	0.845	0.807	0.414	0.405	0.373	0.325	0.415	0.77
AB-4	0.412	0.328	0.296	0.340	0.961	0.758	0.035	0.023	0.038	0.026	0.274	0.39
BB-0	0.672	0.786	0.791	0.960	0.633	0.886	0.677	0.786	0.750	0.970	0.622	0.323
BB-1	0.502	0.375	0.516	0.561	0.530	0.66	0.447	0.496	0.512	0.475	0.397	0.826
BB-2	0.028	0.762	0.530	0.376	0.153	0.34	0.782	0.222	0.895	0.646	0.670	0.484
BB-3	0.864	0.716	0.785	0.818	0.861	0.395	0.513	0.416	0.492	0.448	0.481	0.982
BB-4	0.445	0.456	0.282	0.306	0.601	0.972	0.011	0.003	0.011	0.009	0.455	0.405
	ARDL(2,2,2)						ARDL(1,1,1)					
LR	IAD	GDP	ADD	PD	GDP-X	NCF	IAD	GDP	ADD	PD	GDP-X	NCF
Activity	0.986***	1.428**	5.823	0.352	0.185	-1.947*	1.121***	2.718**	-0.149	0.618**	9.676	-3.640
	(0.128)	(0.633)	(5.316)	(0.337)	-6.568	(1.141)	(0.096)	(1.641)	(0.930)	(0.246)	-16.482	(3.255)
Price	-0.227	0.043	-0.240	-0.076	0.369	-1.660	-0.102	0.625	-0.100	0.183	0.155	-0.799***
	(0.152)	(0.357)	(0.261)	(0.349)	-0.709	(1.013)	(0.107)	(0.682)	(0.366)	(0.270)	-0.412	(0.257)
ECM	-0.185***	-0.185***	-0.146***	-0.144***	-0.098***	-0.098***	-0.199***	-0.184***	-0.155***	-0.152***	-0.101***	-0.108***
	(0.023)	(0.025)	(0.020)	(0.019)	-0.016	(0.021)	(0.025)	(0.025)	(0.021)	(0.020)	-0.016	(0.022)
Trend	0.001**	0.001***	0.001***	0.001***	0.001***	0.001**	0.000	0.001***	0.001***	0.001***	0.001***	0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	0	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	0	(0.001)
N	3891	3891	3891	3891	3539	2371	3925	3925	3925	3925	3570	2391
rmse	0.02435	0.02767	0.02675	0.02669	0.02879	0.03023	0.02489	0.02816	0.02748	0.02736	0.02923	0.03076
CD	-0.598	0.208	0.268	0.648	1.828	-0.144	-1.352	-0.243	-0.341	-0.045	1.043	-0.421
CDP	0.550	0.836	0.788	0.517	0.068	0.886	0.176	0.808	0.733	0.964	0.297	0.674
half-life	3.38	3.38	4.39	4.45	6.73	6.72	3.12	3.41	4.11	4.22	6.52	6.08
AB-1	0.324	0.511	0.396	0.549	0.915	0.442	0.321	0.741	0.550	0.486	0.992	0.549
AB-2	0.739	0.206	0.991	0.764	0.634	0.844	0.003	0.035	0.000	0.000	0.074	0.506
AB-3	0.688	0.147	0.987	0.973	0.039	0.531	0.024	0.003	0.057	0.063	0.002	0.131
AB-4	0.322	0.003	0.285	0.226	0.197	0.689	0.620	0.060	0.508	0.548	0.415	0.548
BB-0	0.052	0.999	0.078	0.052	0.511	0.374	0.198	0.909	0.721	0.814	0.966	0.245
BB-1	0.455	0.611	0.543	0.708	0.748	0.460	0.297	0.965	0.584	0.494	0.683	0.367
BB-2	0.951	0.088	0.583	0.379	0.84	0.911	0.006	0.128	0.033	0.016	0.192	0.753
BB-3	0.940	0.005	0.688	0.651	0.003	0.088	0.026	0.002	0.028	0.018	0.008	0.012
BB-4	0.289	0.001	0.511	0.421	0.44	0.898	0.894	0.024	0.812	0.845	0.727	0.769

Notes: ECM indicates the error correction term, CD refers to the cross-sectional dependence test statistic, CDP indicates the p-value of the cross-sectional dependence test statistic. AB-1, AB-2, AB-3, AB-4 indicate the Arellano and Bond (1991) test p-values at 1, 2, 3, 4 lags, respectively. BB-0, BB-1, BB-2, BB-3, BB-4 indicate the Born and Breitung (2016) test p-values at 0, 1, 2, 3, 4 lags, respectively. *** significant at 1%; ** significant at 5%; * significant at 10%.

For instance, GDP minus exports, whose elasticity spans from 0.18 to 20.52, is never statistically different from nihil. Similarly, the NCF specification always yields (one significant) negative elasticity figures. This is in line with the findings of Tang (2003) for China, but a negative income elasticity for import demand may be registered only if an increase in domestic income leads to an increase in the production of import substitutes (Bahmani-Oskooee and Niroomand 1998). This result might be appropriate for an emerging economy, but it is incorrect for world trade. The GDP coefficient plummets and is no longer significant with more than two lags, while the ARDL(2,2,2) model shows that a 10% rise in GDP generates, *ceteris paribus*, a 14.2% increase in imports, which grows to 27.2% when only one lag is employed. The use of Aggregate Domestic Demand leads to an even worse shortcoming as no elasticity is significant. Quite surprisingly, simple dynamics offer a more precise estimate for the main component of GDP, i.e. Private Demand, whose elasticity is significant but small (0.618) only in the ARDL(1,1,1) specification. All significant long-run activity elasticities are in the range between 0.62 and 2.72. This interval is even smaller if we take into account the import content of final demand as a 1% increase in IAD leads approximatively to a 1% increase in imports.

As far as the relative price is concerned, the estimated coefficients are mostly negative but only twice statistically significant. Both refer to the NCF specifications, whereas all other price elasticities display quite large standard errors. Nonetheless, the IAD specifications always yield negative point estimates.

Turning to the diagnostics, all the estimated models reject nonstationary residuals according to IPS, Maddala-Wu, Fisher and CIPS tests. In addition, the error correction term is always negative and significant at 1% confidence level, despite its value is often small, indicating a slow convergence towards a long-run equilibrium. Half-lives range from three to more than seven quarters. Cross-sectional independence is never rejected, with the exception of GDP minus exports. Robust Arellano and Bond (1991) as well as Born and Breitung (2016) Lagrange tests suggest the absence of residual serial correlation up to the fourth order, exception made for a few models.

Since we wish to differentiate our empirical models through the abovementioned testing procedure, the conclusion is to discard GDP-X that should not be employed to pursue further investigation as residuals are affected by CSD, exception made for the ARDL (1,1,1) that displays serially correlated residuals yet. Actually, the last shortcoming is shared by all but NCF activity variables in a model with only one lag that is too parsimonious to capture import dynamics. Furthermore, NCF provides meaningless long-run elasticity estimates and it does not appear to be cointegrated with imports and import prices according to the Gengenbach, Urbain, and Westerlund (2016) panel error correction test. Hence, this activity variable should be put aside and the other ones must deem more than a lag. Actually, Chudik et al. (2016) show that sufficiently long lags are necessary for the consistency of the ARDL estimates, but specifying higher lags than necessary can lead to estimates with poor small sample properties. We are left with specifications with at least two lags which yield quite imprecise world trade elasticities exception made for GDP in ARDL(2,2,2) and IAD whose elasticity is always significant and close to one. Finally, the measure of fit indicates that all the models have similar residual standard deviations but IAD, which always displays the smallest root mean square error for the same lag order.

Taking into account both results and diagnostics, IAD is the best specification that can also be used to analyze elasticities at the country-level given that the rank condition on matrix of cross product of cross-sectional averages is satisfied. Hence, both mean group and country-specific estimates are consistent (Chudik and Pesaran 2015, Theorem 2). The latter are reported in Table 8 for both the ARDL(4,4,4) and ARDL(3,3,3). We observe that income and price elasticities have the incorrect sign in some countries whilst, as far as the activity elasticity is concerned, negative coefficients are never significant. On the contrary, long-run price elasticities are sometimes positive and significantly different from zero, as in the cases of Finland, Greece, Indonesia, and Luxemburg.

Setting aside negative values, IAD elasticities range between 0.18 in Sweden (although not different from zero) to 2.33 in Denmark, whilst the smallest significant digit is recorded in Russia (0.63). This variability is not novel. Harb (2005), for example, shows a 0.40–2.77 range, while Senhadji (1998) reports significant values between 0.34 and 5.48. Most of our estimates

Table 8. Long-run income and price country-level elasticities.

	IAD	elasticity	Price	elasticity
	ARDL(4,4,4)	ARDL(3,3,3)	ARDL(4,4,4)	ARDL(3,3,3)
World	0.957***	0.791***	−0.316	−0.461
Countries				
AUS	1.578*	1.532*	−0.439	−0.433
AUT	1.495	1.548	0.433	0.351
BEL	1.095*	1.157**	−0.158	−0.104
BRA	0.678	0.372	−0.711	−0.766
CAN	−1.25	−7.22	−2.68	−8.489
CZE	−0.178	−0.35	−1.686	−1.252
DEU	−0.780	−0.257	−4.22	−3.123
DNK	2.328	1.94	2.246	2
ESP	1.214	1.285	−0.543	−0.554
EST	1.464	1.408**	1.346	0.998
FIN	1.176***	1.168***	0.506***	0.464***
FRA	1.579	1.46	0.145	0.024
GBR	−1.113	0.674	−2.642	−1.211
GRC	1.092***	1.06***	0.663***	0.234
HUN	1.248	1.29	0.652	0.6
IDN	1.435***	1.096***	−0.064	−0.409
IND	2.160***	2.204***	0.882***	0.87***
IRL	1.478***	1.381***	0.225	0.173
ITA	1.468**	1.433***	−0.215	−0.17
JPN	0.677	0.252	−0.089	−0.131
KOR	1.963***	2.163**	0.017	−0.108
LTU	1.167***	1.19***	0.161	0.219
LUX	0.685	0.717*	0.685	0.725
LVA	0.988***	0.988***	0.838**	0.95***
MEX	2.192**	2.227***	−0.01	−0.179
NLD	1.140	1.03	0.125	0.039
POL	1.044**	1.094**	−0.955	−0.727
PRT	1.079***	1.057***	−0.154	−0.21
RUS	0.756***	0.631**	−0.71	−0.789
SVK	−0.131	0.383	−2.023	−1.66
SVN	1.231*	1.219*	0.032	0.108
SWE	0.176	−0.826	−1.341	−1.838
TUR	−0.488	−0.276	−0.66	−0.835
USA	1.888	1.872	−0.401	−0.435

*** significant at 1%; ** significant at 5%; * significant at 10%

are close to one as only Indonesia and Turkey out of about 30 positive activity elasticities are statistically different from one in both specifications.

Our point estimates of the import price elasticity are negative for 20 countries in the ARDL(3,3,3) and 19 in the ARDL(4,4,4). Nonetheless, they are never statistically different from zero even at 10% significant level, and they extend on a very large span, i.e. from −8.5 in Canada to 2.2 in Denmark. Large differences have also been reported by Senhadji (1998), whose bounds are −0.01 and −6.66, and by Harb (2005), whose price elasticities range between −0.02 and −2.08. Our results are in any case more robust than theirs because of the quite long spanned data available for each country and because we control for the presence of CSD.

One final remark is worth adding. We cannot split the sample into the two categories of developed and developing countries since most of the panel falls into the first group. The only developing countries are Brazil, Indonesia, India, Mexico, Russia, and Turkey. Nonetheless, we do not neither find that elasticities in developing countries are higher than those recorded in developed countries as claimed by Harb (2005), nor the opposite, as suggested by Houthakker and Magee (1969) and confirmed by Senhadji (1998), IMF (2016) and Borin et al. (2017).

Table 8 also shows that in some emerging markets, such as Russia and Turkey, both income and price elasticities are very small or not statistically different from zero, while the opposite holds in Mexico and India. Similarly, in some advanced countries (Australia, Korea, and Italy) IAD elasticities are large, while in others are sometimes close to zero (Sweden and Japan) or even negative (Canada and Germany), but statistically insignificant. As expected, cross-country differences matter.

V. Conclusions

The 2008–2009 financial crisis, the related great trade collapse and the subsequent trade slowdown have determined a renewed attention amongst scholars and policy makers on the appropriate measurement of levels, variations and interplay between activity variables, prices and imports. Amongst others, practitioners emphasized the importance to properly study import functions in an increasingly integrated world economy.

Within this setting, we assess long-run income and price import elasticities using a panel ARDL up to four lags. Our dynamic specifications are estimated via the CCEMG technique proposed by Chudik and Pesaran (2015) that provides robust results with country heterogeneity and CSD. Equipped with this tool we compare the behaviour of six activity variables in a panel of 34 countries over the period 1985:q1-2018:q3. We find IAD is the best performing. Long-run IAD elasticity takes a world average close to one, whereas country-specific estimates exhibit large variability. On the contrary, there is no significant mean group long-run price elasticity.

IAD explicitly takes into account diverse weights for different demand components and seems to be the most accurate variable to describe worldwide and country-specific import behaviours.

This finding has research and policy implications.

First, our estimates do not suffer from the Houthakker and Magee puzzle. Actually, several country studies report an estimate for the income elasticity larger than unity so that, in the absence of price increases, the GDP share of imports will eventually exceed one (Houthakker and Magee 1969; Bahmani-Oskooee, Harvey, and Hegerty 2013; Buzaushina 2015). These large income elasticities point at an over-proportional demand for foreign goods in case of increasing real domestic demand. This finding is puzzling even if several countries, such as Singapore, Malaysia, and Hong Kong, nowadays record import penetration rates larger than one. This situation is not tenable at the world level making standard global trade estimates questionable. However, we find that when we take into account the different import content of final demand components, a 10% increase in IAD generates an equal increase in imports.

Second, scholars should take stock of the outcome recorded by the IAD as a clear indication that product differentiation and Global Value Chains are key features of trade relations at the macro level too. We claim that making use of IAD to understand import demand behaviour on the basis of the role played by intermediates is more appropriate than traditional measures that merely considered final goods and services. The international fragmentation of production processes that has been featuring the world economy in a pervasive fashion since the early '90s, is a stylized fact that strongly supports the adoption of comprehensive measures of import demand such as the IAD. In this respect, previous studies that failed to account for the role of intermediates are thus flawed and caution must be used to draw conclusions from usual activity variables such as GDP or domestic demand.

Third, policy makers should put more emphasis on this measure of aggregate activity as it helps to properly define the timings of policy actions. IMF (2016) adopts IAD in an effort to describe the world trade slowdown and shows that estimating the import demand model separately for each country has a superior explanatory power than pooling panels. However, it neglects to provide a precise indication on how long the world economy should have taken to recover after the trade collapse. Our study complements IMF's approach and shows that about 2 years would have been needed to restore the equilibrium. Yet, the elasticity of trade may also be affected by business cycle fluctuations as suggested by Borin et al. (2017). This issue is beyond the scope of the present investigation but is in the agenda of future research.

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No potential conflict of interest was reported by the authors.

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