Protectionism and international trade: A long-run view

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A R T I C L E I N F O

JEL classification:
F13
F14
F41
F69

Keywords:
Trade
Protectionism
Long-run elasticities
Panel distributed lags

A B S T R A C T

This paper investigates the long-run relationship between international trade and protectionism, which is measured by a sub-component of the KOF globalization index using a standard import model with a heterogeneous balanced panel of 34 countries from 1970 to 2017. The model is tested using GDP and the Import Intensity-Adjusted Demand (IAD) as an activity variable for a performance comparison. Both specifications are estimated using recent advances in the panel autoregressive distributed lag model literature with cross-sectional dependence. The cross-sectional autoregressive distributed lag (CS-ARDL) and the cross-sectional distributed lag (CS-DL) models provide similar results. Mean group estimates show a proportional impact of IAD on international trade whilst the GDP effect is larger. The long-run protectionism elasticity is always negative and significant but less than half of the import price elasticity.

1. Introduction

Since the 1950s, international trade has seen impressive growth, particularly in Western countries. One of the things that made this growth possible was the lowering of trade barriers. This process started with the signing of the General Agreement on Tariffs and Trade (GATT) in October 1947. Successive rounds of trade liberalization were achieved under the Dillon (1960–1961), the Kennedy (1964–1967), and the Tokyo (1973–1979) Rounds. However, the general trend toward trade liberalization was partially reversed after the oil crisis in 1973 and the resulting worldwide recession. This gave rise to what has come to be known as new protectionism which is characterized by the imposition of many non-tariff barriers (Salvatore, 1993). In the second half of the 1970s world trade reduced its growth rate to 5% per year and then to 3% in the first half of the 1980s; the average during the previous two and a half decades was about 8%. Protectionism and sluggish economic growth in advanced economies had clearly squeezed trade flows. This trend was reversed by the Uruguay Round (1986–1994) that eventually established the World Trade Organization (WTO) in January of 1995. The creation of the WTO marked the biggest reform of international trade since the end of the Second World War. While the GATT mainly dealt with trade in goods, the WTO and its agreements also cover trade in services and intellectual property.

Despite its long and troubled progress, the Uruguay Round produced some early results. In December 1988, participants at the Montreal meeting agreed on a package of cuts in import duties on tropical products. They also revised the rules for settling disputes and established the Trade Policy Review Mechanism (TPRM) which provided for the first comprehensive, systematic, and regular reviews of the national trade policies and practices of GATT members. Such a setting made trade regimes more transparent around the world.

The multilateral trading systems that emerged made the business environment more stable and predictable, benefitting both consumers and producers. Consumers started enjoying a greater variety of products and lower prices, especially those goods and services that account for a large share of lower-income households' consumption (IMF, 2019), while stability and predictability created business opportunities which encouraged producers to invest and create new jobs (IMF et al., 2017). Tariffs fell sharply in the 1980s, first in

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Accepted 1 November 2020

advanced economies and then in emerging and developing economies. The latter cut their average tariffs from 31% in 1980 to 9% in 2015; the former cut theirs from 10% to 4%. World trade grew at an annual rate of about 7% from the second half of the 1980s to the Global Financial Crisis (GFC) in 2008. Unfortunately, the GFC also triggered the Great Trade Collapse (GTC); between the third quarter of 2008 and the second quarter of 2009 international trade recorded a sudden, severe, and synchronised downturn (Baldwin, 2009). It was the sharpest fall in recorded history and the deepest since World War II. The trade downturn was not only as large as in the Great Depression, but much steeper. During the Great Depression it took 24 months for world trade to fall as far as it fell in the nine months after November 2008. International trade bounced back after the GTC, but at a very modest pace of 3% or less. This "trade slowdown" caught the attention of scholars around the world who tried to provide plausible explanations for such a phenomenon, known as the "new normal" (Hoekman, 2015). Cyclical and structural factors have been advocated to explain such a worrying decrease.[1] Cyclical factors refer to weak global demand, changes in its composition, and a shift towards economies with lower trade intensity and less trade-intensive components. The structural factors point to waning global supply chains, declining diffusion of technologies, a lower marginal impact of financial deepening, government support for domestic industries, and protectionism (ECB, 2016; Constantinescu et al., 2016; 2020). The increase in protectionism has been observed in the data by The Global Trade Alert database, which shows that many countries, after the GFC, put tariffs, bailouts, subsidies, localization requirements, and dubious trade finance initiatives in place and discriminated against foreign commercial interests (Evenett, 2019). Advanced economies primarily focused on policies aimed at hampering international trade. Evenett and Fritz (2015) find that G20 countries imposed 443 out of the 539 discriminatory effects counted in 2015. However, these authors claim that there is no available data to conclusively demonstrate that trade distortions and associated interventions 'caused' the trade slowdown. Kee et al. (2013) claim that the rise in tariffs and antidumping duties may explain less than 2% of the collapse in world trade during the crisis period. Ghodsi et al. (2017) show that, although non-tariff measures have increased, mostly in richer countries, they have a relatively modest effect on developing economies and on the total volume of international trade flow. However, it would be unwary to claim that protectionism is unimportant since a large amount of literature, using both micro and macro approaches (for a review see Hillberry and Hummels, 2013), has shown that a change in tariffs greatly affects production and welfare.[2]

This paper sheds new light on the long-run relationship between world trade and protectionism. Our empirical approach is based on an extension of a standard import demand function (Kohli, 1991). We account for differences in competitiveness, due to changes in relative prices and protectionism, activity level, measured by GDP and its composition, using the Import Intensity-Adjusted Demand measure advocated by Bussière et al. (2013). IAD explicitly takes into account the different impact of the final demand components and seems to be the most accurate way to describe both worldwide and country-specific import behavior (Gregori and Giansoldati, 2020). To the best of our knowledge, we are the first to estimate the long-run relationship between international trade and protectionism while taking stock of the most recent advances in the nonstationary panel literature. We allow for heterogeneity across countries, pay adequate attention to dynamics, and also assume cross-sectional dependencies due to global factors, such as changes in commodity prices or the GTC, which affect countries at different extents. To estimate the long-run relationship, we use the cross-sectional autoregressive distributed lag model (CS-ARDL) and the cross-sectional distributed lag (CS-DL) approaches proposed by Chudik and Pesaran (2015) and Chudik et al. (2016).

The paper is organized as follows. In the next section we discuss the empirical strategy and the data used in the analysis. Section 3 addresses the time series properties of our dataset. Section 4 presents the estimates for different specifications and the last section summarizes and gives some conclusive remarks.

2. Data and empirical methodology

We estimate a standard import demand model (Kohli, 1991), that links import volume growth to growth in demand or the activity level while controlling for changes in relative import prices and protectionism. Most studies use the GDP of a country as a proxy for demand (Harb, 2005). Here, we also follow the innovation of Bussière et al. (2013), who differentiate the first order terms in a translog import function to get a new measure of economic activity, called Import Intensity-Adjusted Demand (in short IAD), that is a weighted average of the expenditure components of GDP:

$$\ln\mathrm{IAD}_t = \omega_{C,t} \ln C_t + \omega_{G,t} \ln G_t + \omega_{I,t} \ln I_t + \omega_{E,t} \ln E_t \tag{1}$$

where C, G, I, and E are private consumption, government consumption, investment, and exports, while the corresponding weight represents the import intensity of each component:

$$\omega_k = \frac{\boldsymbol{i}_N \mathbf{F}_k^{\mathrm{M}} + \boldsymbol{i}_N \mathbf{A}^{\mathbf{M}} \left(\mathbf{I} - \mathbf{A}^{\mathbf{D}}\right)^{-1} \mathbf{F}_k^{\mathrm{D}}}{\boldsymbol{i}_N \mathbf{F}_k^{\mathrm{M}} + \boldsymbol{i}_N \mathbf{F}_k^{\mathrm{D}}} \quad k = C, I, G \tag{2}$$

where $\mathbf{A}^{\mathbf{D}}$ is the domestic input/output matrix, which represents the technology of national intra-industry relationships, whilst $\mathbf{A}^{\mathbf{M}}$ refers

[1] According to Haugh et al. (2016) the slowdown in world trade growth, if sustained, will have serious consequences for the medium-term growth of productivity and living standards.

[2] For instance, IMF (2018) estimates that the global economy will be 0.5% smaller by 2020 if the various tariffs threatened by the US, China, Europe, Mexico, Japan, and Canada were to be implemented. However, IMF (2018) does not provide any forecast for world trade volume.

to imported flows and $\boldsymbol{i}_N$ is a summation vector. $\mathbf{F}_k^{\mathrm{D}}$ is the vector of goods and services of a component in final demand (i.e. C,I,G,E) provided by domestic firms while $\mathbf{F}_k^{\mathrm{M}}$ refers to imported goods and services.[3] The weights in (2) may be time-variant as they are computed from input-output tables but normalized in each period so that their sum is always equal to one. This approach allows to account for differences in the import content of the various final demand components as investments and exports have particularly rich import content due to the emergence of the global supply chains. Since investments and exports are the most volatile components of GDP, IAD is a measure of demand which is somewhat more volatile than GDP.

The source of the annual data for imports, GDP, exports, and the other final demand components in current and constant US$, as well as the series of import prices and GDP deflators, is the United Nations database. We study the long-run effects on international trade by using a balanced sample of 34 leading, developed, and emerging countries from 1970 to 2017. The 34 countries in our investigation are: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, China, Cyprus, Denmark, Finland, France, Germany, Greece, Great Britain, Hungary, India, Indonesia, Ireland, Italy, Japan, Luxemburg, Malta, Mexico, the Netherlands, Norway, Poland, Portugal, Romania, South Korea, Spain, Sweden, Switzerland, Turkey, and the USA. These are the most important countries in international trade: imports from our sample countries cover about 85% of the world trade in 2015 (81% in 1970). We compute the relative import price by taking the ratio of the import price of goods and services by the GDP deflator for each country as is commonly done in the literature.

To calculate IAD we explored input-output tables, which are available with gaps yet. For instance, Bussière et al. (2013) use OECD input-output tables for the years 1995, 2000, and 2005 and then interpolate the available points linearly to construct weights for other years. Since they estimate an import demand model of the period from 1984:I-2011:IV, Bussière et al. (2013) use the weights of 2005 for the period after 2005 and the weights of 1995 for the period up to 1995. IMF (2016) and Aslam et al. (2018) adopt a different approach as they applied the very same import contents in (1) as (2) are computed as an average from 1990 to 2011 using Eora Multi-Region Input-Output (MRIO) country-specific tables.[4] Our study makes use of the annual world input-output tables released by the WIOD which cover the period from 1995 to 2014 (Timmer et al., 2015). As does Martinez-Martin (2016), we have inferred equal values from 2014 onwards, and similarly from 1995 backwards, applying the corresponding caution in the results.

Measuring protectionism at the country level is far from easy. The measurement of trade policies is challenging, especially in cases of non-tariff barriers, and aggregating trade restrictions, which usually come at a highly disaggregate level, is a daunting task (Goldberg and Pavcnik, 2016). The Trade Restrictiveness Index (TRI), for instance, is the uniform tariff that would maintain welfare at its current level given the existing tariff structure (Anderson and Neary, 1994, 1996). The TRI collapses within-country, cross-sector variations into a single measure that can be compared across nations. Kee et al. (2009) adopt Feenstra's (1995) simplification to derive the TRI for an unbalanced panel of countries for the period 1988–2001, which is too short for a long-run analysis. The same problem is shared by the Global Trade Alert (GTA) initiative coordinated by the Centre for Economic Policy Research (CEPR). The GTA has the most comprehensive coverage of trade-discriminatory and trade-liberalizing measures, but its geographical coverage is rather limited and data is collected only from 2008 onward (Evenett and Fritz, 2015). The World Bank dataset on Temporary Trade Barriers (TTB) covers a longer period (from 1980) but it focuses on specific policies such as antidumping, countervailing duties, and safeguard measures (Bown, 2016). The Fraser Institute also calculates a measure of trade policy openness called the Freedom to Trade Internationally (FTI) index for a large set of countries. The FTI index is made up of four components: tariff barriers, regulatory trade barriers, black-market exchange rates, and controls of the movement of capital and people (Gwartney et al., 2019). Some of these components are also made of sub-components. For instance, the tariff index is derived from the revenue from trade taxes, the mean tariff rate, and the standard deviation of tariff rates. The FTI index was first published by the Fraser Institute in 1996 and featured data in five-year increments from 1975 to 1995 (Gwartney et al., 1992). Subsequent editions of this index have also included some data for the 1970s but annually only since 2000 (Gwartney et al., 2019). Therefore, the FTI index is also of limited use for long-run analyses.

In the present study, we take advantage of the recently revised version of the KOF Globalisation Index, a composite index measuring globalization for every country in the world utilizing economic, social, and political dimensions (Gygli et al., 2019). The original index was introduced by Dreher (2006) and updated revisions distinguish between *de facto* and *de jure* measures.[5] In this paper, we focus on the *de jure* trade globalization sub-dimension, which builds on the economic restriction sub-index that was initially developed by Dreher et al. (2008). This subcomponent refers to policies that facilitate and promote trade between countries and its most recent edition is derived from measures regarding trade regulation, trade taxes, tariff rates, and free trade agreements. Trade regulation is based on the prevalence of non-tariff trade barriers and the compliance costs of exporting. Trade taxes measure tax income on international trade as a share of the total income of a country, while tariff rates refer to the unweighted mean of tariff rates. The *de jure* trade globalization index takes values from 0 to 100 such that higher values relate to higher levels of trade liberalization. Therefore, we can take the complement to 100 as a measure of protectionism. This is the Trade Protectionism Index (TPI). Fig. 1 displays worldwide TPI calculated as an average across all the countries. Its pattern is quite consistent with both historical developments and previous findings. We know tariff barriers decreased slightly during the 1970s and this pattern is partially reflected in the TPI, as shown in Fig. 1. TPI increases at the beginning of the 1980s due to the upsurge of the new protectionism wave. This profile partially matches with the Global Trade Liberalization (GTL) index provided by Haugh et al. (2016). These authors aggregate country specific indexes constructed with data from the Fraser Institute

[3] We neglect imports in the export weight ($\mathbf{F}_E^{\mathrm{M}} = 0$) since we do not allow for reimported exports (Gregori and Giansoldati, 2020).

[4] IMF (2016) observe that if import intensities were perfectly measured in each period and the import intensity weights were allowed to vary over time, the model would be able to fully account for the level of imports but not their growth rates.

[5] *De facto* trade globalization focuses on actual international flow and refers to the exchange of goods and services such as the trade openness ratio and trade partner diversity. Conversely, *de jure* trade globalization measures policies and conditions that, in principle, enable, facilitate, and foster international trade.

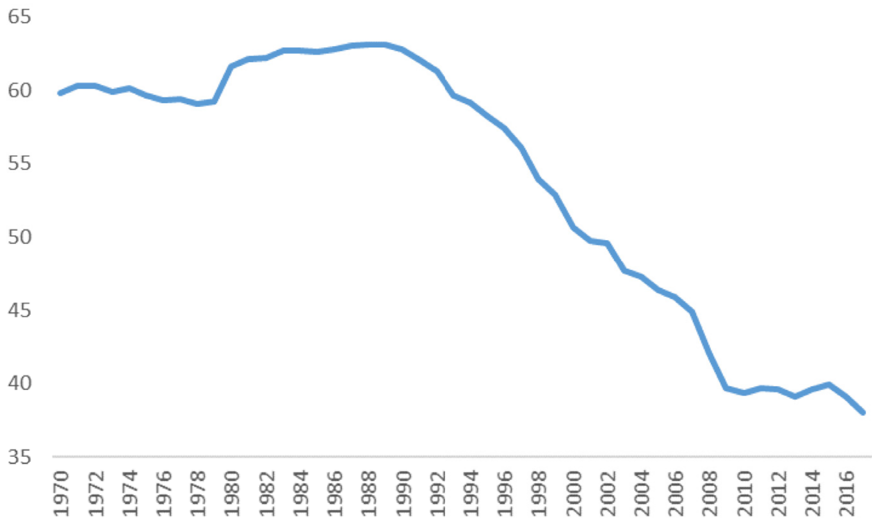

Fig. 1. World average of the Trade Protectionism Index.

and show that trade liberalization improved until the beginning of the new millennium. Both the TPI and GTL indicate the active period of lowering tariff and non-tariff barriers during the 1990s. The TPI also decreases in the new century up until the global financial crisis and eventually flattens due to the last wave of neo-protectionism.[6]

Summary statistics regarding the variables used in the empirical analysis (in logs) are shown in Table 1. All quantities, including imports, GDP, and IAD, are in constant US$ while the relative import price is the ratio of the import price of goods and services to the GDP deflator.

This empirical study adopts the following panel ARDL specification:

$$m_{i,t} = \alpha_i + \sum_{l=1}^{P} \gamma_{il} m_{i,t-l} + \sum_{k=1}^{3} \sum_{l=0}^{Q_k} \beta_{il}^k x_{i,t-l}^k + u_{i,t} \tag{3}$$

$$u_{i,t} = \sum_{m=1}^{M} \gamma_{im} f_{m,t} + \varepsilon_{i,t} \tag{4}$$

where $m_{i,t}$ is (the log of) imports in country i at time t while the set of explanatory variables are (in logs): the activity variable (*gdp* or *iad*), the relative import price (*pm*), and the protectionism index (*tpi*). The error $u_{i,t}$ contains the unobserved common factors $f_{m,t}$, which can also affect covariates. This approach allows for time trends, fixed effects, and heterogeneity since the parameters in (3)-(4) are not restricted to be the same across countries.

There are two approaches to assessing the long-run coefficients. The ARDL approach first estimates (3) and then calculates long-run coefficients:

$$\theta_i^k = \frac{\sum_{j=1}^{Q_k} \beta_{ij}^k}{1 - \sum_{j=1}^{P} \gamma_{ij}} \tag{5}$$

where the short-run coefficients are replaced with their estimates. The other approach addresses the long-run coefficients directly without estimating the short-run ones since (3) can be also written as:

$$m_{i,t} = \delta_i + \sum_{k=1}^{3} \theta_i^k x_{i,t}^k + \sum_{k=1}^{3} \sum_{l=0}^{Q_k} \eta_{il}^k \Delta x_{i,t}^k + \tilde{u}_{i,t} \tag{6}$$

Chudik et al. (2016) show that a consistent estimate of θ_i^k can be obtained directly based on the least-squares regressions of (6) where the truncation lag order is chosen according to the sample size. This distributed lag (DL) representation does not include lags of the dependent variable but it requires the absence of feedback effects from the latter onto the regressors. Moreover, consistent estimates of

[6] Curiously, the GTL index turns back in 2001 when China joined the WTO.

Table 1
Descriptive statistics.

Variable	Obs	Mean	S. D.	Min	Max
m	1632	12.604	2.653	7.129	21.661
gdp	1632	14.059	2.920	6.864	23.266
iad	1632	12.787	2.836	6.209	21.999
pm	1632	0.210	0.345	−1.667	1.272
tpi	1632	−1.481	0.779	−3.819	−0.142

All variables are in logs.

average long-run effects can be easily obtained from the average of the individual long-run estimates in both approaches (Chudik et al., 2016).

If unobserved common factors in (4) are serially uncorrelated and also uncorrelated with the regressors then the long-run coefficients can be consistently estimated from OLS estimates of short-run coefficients irrespective of whether the variables are I(0) or I(1) and covariates are strictly exogenous or jointly determined with imports. When unobserved common factors are correlated, OLS estimation is no longer consistent and cross-sectional dependence (CSD) must be acknowledged. Several methods have been put forward to allow for CSD (Söderbom et al., 2015). We follow the approach that is based on cross-sectional averages and adopt the dynamic common correlated effects mean group (CCEMG) estimator. It must be stressed that this estimator is valid if the number of cross-sectional averages based on regressors and additional covariates is at least as large as the number of common factors minus one (Chudik and Pesaran, 2015). Stock and Watson (2005) suggest that this number is likely to be relatively small in most macroeconomic applications. Hence, we include the cross means of all our regressors, including their lags, up to the integer part of $\sqrt[3]{T}$ as stated by Chudik and Pesaran (2015). We also follow their suggestion to test for the weak CSD of residuals.[7]

The CCEMG estimator can be applied to stationary panels and suffers from small T bias. Correction techniques, such as the jackknife or the recursive mean adjustment, help to mitigate the time series bias but are still quite demanding in terms of the T dimension and cannot fully deal with the size distortion unless T is sufficiently large (Chudik and Pesaran, 2015). It is also essential to specify the appropriate lag orders of the CS-ARDL model as underestimating them leads to inconsistent estimates, while overestimating the lag order could result in low power and loss of efficiency. The CS-DL approach has several advantages over the CS-ARDL (Chudik et al., 2016). Firstly, it performs better with small samples as the CS-ARDL approach often requires large time dimensions for satisfactory performance. This shortcoming is due to the inclusion of the lagged-dependent variable and is particularly severe when the sum of the AR coefficients in the ARDL specification is close to one. Conversely, the CS-DL approach is based on a distributed lag representation that does not include lags of the dependent variable. Monte Carlo simulations show that the CS-DL approach is often superior to the alternative CS-ARDL approach, particularly when the time dimension is not very large and lies between 30 and 50, as in our case (Chudik et al., 2016). Secondly, it is robust to the possibility of unit roots in regressors and/or factors. Thirdly, it does not require knowledge of the number of unobserved common factors (under certain conditions) and it continues to be valid under weak CSD. Finally, it is robust to possible breaks in idiosyncratic errors and does not require specificity regarding the lag order of Q_i. The main drawback of CS-DL is that there must be no feedback effects from lagged values of dependent variable on the regressors. These feedback effects introduce correlation between errors and covariates and a bias which results in inconsistent estimates even if T and N are sufficiently large. The second drawback is that the performance of the CS-DL approach deteriorates when the speed of convergence towards the long-run equilibrium is too slow. All in all, we prefer to see them as complementary and compare results as a robustness check since both approaches have some relative advantages.

3. Empirical results

3.1. Cross-sectional dependence

Cross-sectional units in our panel are likely interdependent as common shocks can affect imports, GDP, IAD, import prices, and protectionism to a different degree. We address weak versus strong dependence by making use of the cross-sectional (CD) test and the estimated confidence bands of α, the exponent of CSD (Pesaran, 2015; Bailey et al., 2016). The null hypothesis of the CD test states that the variable is weakly cross-sectional dependent and, under this null, the CD test is standard normal distributed. This is an appealing feature since only strong cross-sectional dependence makes estimates inconsistent (Chudik et al., 2011). The exponent of CSD supplements the analysis by showing the degree of cross-sectional dependence. The exponent α is a measure of the strength of the factors and can take any value in the range [0,1] (Bailey et al., 2016). Values of α correspond to different degrees of cross-sectional dependence. Pesaran (2015) shows that the null of the CD test is a function of the degree to which T expands relative to N. When T is fixed and N diverges, the null for the CD test is given by $0 \leq \alpha < 1/2$; when both T and N diverge at the same rate the null for the CD test is given by $0 \leq \alpha < 1/4$. Therefore, the value of α in the range of [0.5,1] depicts different degrees of strong CSD while a range of [0, 0.5], depicts different degrees of weak CSD. Results in Table 2 reveal strong sectional dependence in both levels and first differences. The CD statistic always rejects the null hypothesis, suggesting that the exponent of CSD lies in the upper range. We can determine the degree of

[7] For residual testing see also Bailey et al. (2016).

Table 2
Tests of cross-sectional dependence.

	CD test	p-value	$\widehat{\alpha}$ and 90% confidence bands		
			$\widehat{\alpha}_{0.05}$	$\widehat{\alpha}$	$\widehat{\alpha}_{0.95}$
m	163.9	0.00	0.175	1.002	1.832
d.m	82.4	0.00	0.917	1.002	1.088
iad	90.8	0.00	−3.917	1.003	5.923
d.iad	85.6	0.00	0.908	1.002	1.095
gdp	163.0	0.00	0.368	1.003	1.638
d.gdp	103.1	0.00	0.909	1.002	1.095
pm	82.4	0.00	0.591	0.984	1.110
d.pm	43.7	0.00	0.902	0.941	0.981
tpi	156.1	0.00	0.929	0.994	1.060
d.tpi	44.4	0.00	0.727	0.837	0.946

Under the null of no CSD the CD test is standard normal distributed. $\widehat{\alpha}$ is the exponent of CSD; values of $\widehat{\alpha}$ in the range of [0.5,1] depict different degrees of strong CSD.

cross-sectional dependence by checking the bias corrected estimates of α and the 90% confidence bands around it. These results are also presented in Table 2. Exponents of CSD are very close to unity for all variables and the 90% confidence bands are well above 0.5 and include unity exception made for the first differences of the import price and the protectionism index. This confirms our preliminary finding and suggests the presence of strong CSD in all the variables under scrutiny.

3.2. Second generation panel unit root tests

The presence of CSD requires second generation panel unit root tests (Söderbom et al., 2015). These tests explicitly consider a multifactor error structure in which the heterogeneous factor loadings allow for a greater flexibility in modelling the patterns of dependence. To identify the order of integration of the variables, we first apply the Pesaran's (2007) cross-sectional augmented Ims-Pesaran-Shin (CIPS) unit root test, that supplements the standard augmented Dickey-Fueller (ADF) regressions (Dickey and Fuller, 1979; Im et al., 2003) with the cross-sectional averages of the lagged level and the first differences of the individual series. The test statistic is constructed as an average of the normalized *t*-ratios for all the countries so that the averaged '*Z*t-bar' statistic is distributed standard normal (Pesaran, 2007). The null hypothesis of the CIPS test, and all the following second-generation panel unit root tests, is non-stationarity in all country series, whilst the alternative is stationarity in at least some country series (Söderbom et al., 2015). Results in Table 3 concern the *Z*t-bar statistics and the probabilities associated to the null hypothesis. Table 3 shows that the statistics of all the variables in first differences are always larger (in absolute value) than the critical value at 1% significance level. Hence, we can reject the null hypothesis of non-stationarity for the first difference and safely assume that no variable is I(2). Conversely, when we add a trend all the statistics regarding *gdp* are always smaller than the critical value even at the 10% significance level. Since *gdp* is a trending variable, we can claim that *gdp* contains a unit root, as suggested by Aslanidis and Fountas (2014), among others. The protectionism index appears to contain a unit root as well while imports, *iad*, and the import price appear to be stationary but only when we do not include a time trend.

The standard CIPS test allows for a single factor while its extension, defined as CIPSM, assumes (4) for the error process with $M > 1$. The CIPSM is still based on the average of *t*-ratios from ADF regressions augmented by the cross-section averages (CA) of the dependent variable as well as *M* additional regressors with similar common factor features (Pesaran et al., 2013).[8]

Conversely, the PANICCA approach by Reese and Westerlund (2016) combines the cross-sectional averages method of Pesaran (2007) and the PANIC method proposed by Bai and Ng (2004). This approach tests for unit roots (the null is always of non-stationarity) in the unobserved global factors and, separately, in the idiosyncratic component. These authors state that the data generating process (DGP) is given by a deterministic component $d_{i,t}$ (either a constant or a constant with a trend), unobserved common factors $f_{m,t}$, with individual factor loadings, and idiosyncratic error terms $\varepsilon_{i,t}$:

$$z_{i,t} = d_{i,t} + \sum_{m=1}^{M} \gamma_{im} f_{m,t} + \varepsilon_{i,t} \tag{7}$$

Bai and Ng (2004) assume $(1 - \rho_i L)\varepsilon_{i,t} = \mathbf{B}_i(L)v_{i,t}$, $(\mathbf{I} - L)\mathbf{f}_t = \mathbf{C}(L)e_t$ where $\mathbf{B}_i(L)$, $\mathbf{C}(L)$ are polynomials in the lag operator and $\mathbf{f}_t$ is the vector of the unobserved common factors. In this setting we can test $\rho_i = 1$, the non-stationarity of the idiosyncratic components, without assuming that the factors are stationary, and vice versa. Bai and Ng (2010) suggest pooling individual ADF statistics obtained on defactored residuals to check for the non-stationarity of the idiosyncratic components with the Pa, the Pb, and the Panel Modified Sargan–Bhargava (PMSB) tests (Reese and Westerlund, 2016). These test statistics converge to a standard normal under the unit root null hypothesis of $\rho_i = 1$. Provided that the alternative is formulated as $|\rho_i| < 1$ for some i, all three statistics are left-tailed, and the appropriate 5% critical value is therefore given by 1.645. Results for the Pa, the Pb, and the PMSB tests are provided in Tables 4–6.

[8] Results are available upon request.

Table 3
Panel unit root CIPS tests.

Variable	Levels					Differences				
	Lags	without trend		with trend		Lags	without trend		with trend	
		Zt-bar	p-value	*Zt*-bar	p-value		*Zt*-bar	p-value	*Zt*-bar	p-value
m	0	−2.57	0.01	0.83	0.80	0	−23.07	0.00	−21.60	0.00
	1	−4.69	0.00	−1.53	0.06	1	−16.86	0.00	−14.64	0.00
	2	−4.00	0.00	−0.53	0.30	2	−12.30	0.00	−9.58	0.00
	3	−3.52	0.00	−0.04	0.48	3	−9.37	0.00	−6.90	0.00
iad	0	−0.99	0.16	2.25	0.99	0	−20.73	0.00	−19.35	0.00
	1	−3.72	0.00	−0.22	0.41	1	−14.68	0.00	−12.46	0.00
	2	−2.88	0.00	0.80	0.79	2	−9.51	0.00	−6.90	0.00
	3	−3.52	0.00	0.52	0.70	3	−7.55	0.00	−4.94	0.00
gdp	0	1.12	0.87	3.04	1.00	0	−17.32	0.00	−15.83	0.00
	1	−1.90	0.03	−0.33	0.37	1	−12.27	0.00	−10.28	0.00
	2	−1.27	0.10	0.21	0.58	2	−8.44	0.00	−5.81	0.00
	3	−2.33	0.01	−1.11	0.13	3	−8.12	0.00	−5.83	0.00
pm	0	−1.69	0.05	1.23	0.89	0	−23.84	0.00	−22.37	0.00
	1	−2.87	0.00	−0.04	0.49	1	−16.76	0.00	−15.11	0.00
	2	−3.49	0.00	−0.49	0.31	2	−11.96	0.00	−9.85	0.00
	3	−2.58	0.00	0.25	0.60	3	−9.79	0.00	−7.15	0.00
tpi	0	−0.37	0.36	3.68	1.00	0	−25.76	0.00	−25.07	0.00
	1	0.66	0.75	5.28	1.00	1	−16.84	0.00	−15.60	0.00
	2	0.24	0.60	5.31	1.00	2	−8.64	0.00	−6.96	0.00
	3	−1.36	0.09	4.21	1.00	3	−6.69	0.00	−6.02	0.00

The CIPS test has a null hypothesis of a unit root in all country series. The CIPS test reports the *Zt*-bar statistic, distributed N(0,1), and the associated p-value. 'Lags' refers to the lagged differences included in the ADF regression to account for serial correlation.

Table 4
PANICCA unit root test with a constant or a constant and a trend.

	AV	ADF	MQ_c	MQ_f	Pa	Pb	PMSB
				m			
constant	0	−6.93***			−1.32*	−1.05	−0.79
	gdp		−19.98*	−8.59	−2.97***	−2.03**	−1.19
constant & trend	0	−2.02**			−0.51	−0.47	−0.42
	gdp		−12.35	−4.59	0.21	0.22	0.22
				iad			
constant	0	−6.93***			−0.19	−0.18	−0.25
	gdp		−24.91**	−2.71	−4.82***	−2.82***	−1.77**
constant & trend	0	−2.28**			0.07	0.07	0.07
	gdp		−15.17	−9.19	−0.33	−0.32	−0.30
				gdp			
constant	0	−6.93***			−2.39***	−1.70**	−1.56*
	iad		−24.91**	−2.71	−4.00***	−2.59***	−1.81**
constant & trend	0	−6.93***			0.94	1.05	1.15
	iad		−15.17	−9.20	0.45	0.47	0.47
				pm			
constant	0	−0.11			−0.23	−0.23	0.19
	gdp		−17.67	−6.32	−5.87***	−3.38***	−1.78**
constant & trend	0	−2.72***			−0.66	−0.61	−0.52
	gdp		−12.12	−4.91	−0.73	−0.67	−0.57
				tpi			
constant	0	−2.54***			−0.35	−0.25	−1.59*
	gdp		−9.71	−4.42	−6.65***	−4.18***	−2.12**
constant & trend	0	−1.61*			0.20	0.21	0.27
	gdp		−13.19	−4.59	0.57	0.61	0.69

***, **, * indicate statistical significance at the 1%, 5%, and 10% respectively. AV: additional variable (0 means none). Without additional variables other than the variable of interest, the ADF-type test is used to test stationarity in the common factor. Otherwise we adopt the modified "filtered" MQ_f and the "corrected" MQ_c tests whose critical values are reported in Bai and Ng (2004). Three test statistics namely Pa, Pb, and PMSB are used for the idiosyncratic errors regardless of whether additional variables are included or not in the test equation for the variable of interest. In all the cases the null is of non-stationarity.

Table 5
PANIC unit root test with a constant and up to 3 common factors.

CF	ADF	MQ_c	MQ_f	Pa	Pb	PMSB
			m			
1	−6.93***			−0.39	−0.35	−0.43
2		−7.56	−5.01	−0.35	−0.29	−0.98
3		−16.87	−16.25	−1.25	−1.01	−1.16
			iad			
1	−6.93***			−0.52	−0.46	−0.45
2		−7.33	−5.34	−1.11	−0.91	−1.11
3		−7.93	−16.51	−1.58*	−1.27	−1.11
			gdp			
1	−6.93***			−4.30***	−2.82***	−1.87**
2		−11.74	−6.21	−3.69***	−2.51***	−1.95**
3		−15.59	−13.89	−5.88***	−4.15***	−1.89**
			pm			
1	−6.93***			−0.34	−0.33	−0.15
2		−16.85	−2.28	−0.30	−0.27	−0.63
3		−19.87	−7.18	−0.02	−0.02	−0.33
			tpi			
1	−1.69*			1.15	0.94	−0.90
2		−12.31	−7.22	1.06	0.90	−0.87
3		−28.17	−7.11	2.05	1.92	−0.26

***, **, * indicate statistical significance at the 1%, 5%, and 10% respectively. AV: additional variable (0 means none). Without additional variables other than the variable of interest, the ADF-type test is used to test stationarity in the common factor. Otherwise we adopt the modified "filtered" MQ_f and the "corrected" MQ_c tests whose critical values are reported in Bai and Ng (2004). Three test statistics namely Pa, Pb, and PMSB are used for the idiosyncratic errors regardless of whether additional variables are included or not in the test equation for the variable of interest. In all the cases the null is of non-stationarity.

Table 6
PANIC unit root test with a constant and a trend up to 3 common factors.

CF	ADF	MQ_c	MQ_f	Pa	Pb	PMSB
			m			
1	−2.63***			−0.85	−0.77	−0.67
2		−14.59	−10.34	−1.39*	−1.25	−1.05
3		−14.50	−10.96	−1.00	−0.91	−0.77
			iad			
1	−0.14			0.92	1.02	1.12
2		−12.37	−7.83	0.52	0.56	0.58
3		−15.75	−15.36	1.20	1.37	1.55
			gdp			
1	−6.93***			1.00	1.20	1.26
2		−11.95	−5.89	1.45	1.73	2.02
3		−11.24	−12.72	1.85	2.33	2.90
			pm			
1	−2.20**			−0.58	−0.54	−0.47
2		−16.96	−6.89	−0.81	−0.75	−0.64
3		−20.68	−16.63	−3.04***	−2.42***	−1.80**
			tpi			
1	−1.72*			−0.42	−0.40	−0.30
2		−12.31	−7.22	−0.19	−0.19	−0.12
3		−31.06*	−16.79	−0.69	−0.66	−0.53

***, **, * indicate statistical significance at the 1%, 5%, and 10% respectively. CF is the number of common factors. With one common factor, the ADF-type test is used. Otherwise we adopt the modified "filtered" MQ_f and the "corrected" MQ_c tests whose critical values are reported in Bai and Ng (2004). Three test statistics namely Pa, Pb, and PMSB are used for the idiosyncratic errors regardless of whether additional variables are included or not in the test equation for the variable of interest. In all cases the null is of non-stationarity.

To test the non-stationarity of the common factors, the PANIC approach first transforms $z_{i,t}$ by taking first differences and then applying the method of principal components (PC) to estimate the first-differenced common and idiosyncratic components, which can be cumulated up to levels. With a single factor, a simple ADF-type test for the non-stationarity of this factor can be used.[9] With more than one unobserved common factors the sequential procedure of Bai and Ng (2004) must be utilized to derive the modified "filtered" MQ_f and the "corrected" MQ_c tests.[10] The main advantage of the PANIC approach is that the components are estimated from a regression in first differences and the spurious regression problem is avoided. However, the use of PC can render PANIC small-sample distorted when *N* is not large (Pesaran et al., 2013; Westerlund and Urbain, 2015). To avoid these shortcomings, Reese and Westerlund (2016) introduce PANICCA, which combines the PANIC approach with cross-sectional averages. PANICCA leads to the same asymptotic theory as PANIC and the use of CA rather than PC leads to a much improved small-sample performance, especially in small to medium *N* panels. It is also possible to further improve this test by employing additional variables, that may share the common factors of the variable of interest, as suggested by the CIPSM approach.

Table 4 presents results for the PANICCA test with an additional variable, that is *gdp* or *iad*. In Table 4 we address only variable in levels as results from first differences, available upon request, are overwhelmingly against the null of non-stationarity. When we introduce a trend, the non-stationarity is unquestionably attributable to the idiosyncratic components as we can never reject the null of non-stationarity for all the variables in levels. This means that the influences of specific country components generate permanent shocks. Conversely, the evidence regarding the common factor component is mixed. On one side, without additional variables the common factor brings the variables back to their means. On the other side, when we introduce *gdp* or *iad* as an additional variable and allow for more than one factor both the modified "filtered" MQ_f and the "corrected" MQ_c tests cannot reject the null of non-stationarity. Hence, stationarity in the common factor component depends on how many factors we assume.

The picture is different when we only consider a constant. Since *gdp*, *iad*, and imports are trendy variables here we discuss only the relative import price and the protectionism index. Without an additional variable, non-stationarity for the import price is due to both the common factor and the idiosyncratic errors. With *gdp* as an additional variable we can reject the null of non-stationary idiosyncratic errors, while the common factors contain a unit root. The same conclusions apply to *tpi* when *gdp* is added. Conversely, without output we can reject the null of non-stationary in the common factor according to the ADF test results.

The role of common factors can be shown by the PANIC approach as well. In Tables 5 and 6 we present results that assume up to three unobserved common factors. As above, we focus on Table 6 for the trendy variables, that is *gdp*, *iad*, and imports, whereas we consider the test without a trend for the relative import price and *tpi*. Results in Table 6 are clear-cut. Non-stationarity is pervasive for the idiosyncratic errors in all the trendy variables and *tpi*. Conversely, when we consider a single common factor the ADF statistic allows us to reject the null of non-stationarity for all variables but *iad*. However, when we increase the number of the factors such a property disappears. The same finding is confirmed in Table 5. Therefore, assuming a single factor, as in the CIPS test, might be misleading. Finally, without a trend, Table 5 shows that *tpi* and the import price seem to contain a unit root in the idiosyncratic errors too.

All in all, taking into account that either the idiosyncratic errors or the common factors or both are non-stationary we can safely assume that all the variables under scrutiny are I(1) and address their changes.

3.3. *Estimates of the long-run effects*

According to the results of the previous tests, our time series has the typical features of a macro panel: heterogeneity, CSD, non-stationarity, and likely cointegration. In order to address these issues, we implement the ARDL approach using both the CS-ARDL and CS-DL models (Ditzen, 2018). Given that we are working with moderately persistent growth rates, we choose a small lag order, ARDL(1,0,2,1) for the model with IAD and ARDL(1,0,0,1) for the model with GDP, which is enough to account for short- and long-run dynamics. Yet, the focus of this study is on the long-run elasticities whose estimates are provided in Table 7. In the same table we also present the results for the CS-DL model which has lags of (0,1,1) for both activity variables. Findings are in line with Bussière et al. (2013) as well as Gregori and Giansoldati (2020).[11] These authors find an IAD elasticity close to unity while the GDP elasticity is much larger. Our results show that an increase in the IAD variable brings about a similar increase in international trade in both the CS-ARDL and CS-DL models, while an identical expansion in GDP has a more than proportional effect. These findings have interesting implications for the long-standing puzzle of abnormally high estimated elasticities of imports to domestic demand (Marquez, 2002). High elasticities with respect to GDP are mostly driven by recessions while IAD elasticities are lower in magnitude and more stable over the cycle since IAD accounts for the import intensity of demand components (Bussière et al., 2013).

Gregori and Giansoldati (2020) do not find a significant negative relationship with the relative import price while Bussière et al. (2013) and this study both do. Bussière et al. (2013) get an elasticity close to −0.19 in the IAD specification and this figure is smaller when GDP is embraced (−0.16). Our results show slightly larger long-run elasticities in absolute value. When we opt for IAD, both the CS-ARDL and CS-DL models display an almost identical coefficient of −0.26. With GDP, the figure is close for the CS-ARDL (−0.24) but smaller for the CS-DL (−0.18).

More importantly, the coefficients of the protectionism index are always negative and significant. This result should be expected according to the consensus on trade elasticities (Hillberry and Hummels, 2013) but is novel in the recent macro panel literature that

[9] Critical values for this unit-root non-similar test are based on Fuller (1996), while MacKinnon (1994) shows how to approximate the *p*-values.

[10] Appropriate 1%, 5%, and 10% critical values for these non-standard unit-root tests can be found in Bai and Ng (2004).

[11] Bussière et al. (2013) investigate 18 OECD countries from 1985:q1-2011q4 while Gregori and Giansoldati (2020) study 34 countries from 1985:q1-2018:q3. Both analyses exclude China, which accounts for a large share of world trade in the last decade.

Table 7
Mean Group long-run estimates (full sample).

	CS-ARDL		CS-DL	
	IAD	GDP	IAD	GDP
d.activity	0.953***	1.355***	1.033***	1.449***
d.pm	−0.260***	−0.265***	−0.244***	−0.175**
d.tpi	−0.092**	−0.107**	−0.069**	−0.106**
ecm	−1.091***	−1.256***		
observations	1496	1496	1496	1496
RMSE	0.051	0.061	0.050	0.059
CD test	−0.622	−0.398	0.116	0.021
CD prob	0.534	0.691	0.907	0.983
$\hat{\alpha}$	0.438	0.498	0.479	0.511
BB - HR	0.745	0.871	0.409	0.993
AB-1	0.539	0.550	0.261	0.874
AB-2	0.976	0.448	0.123	0.933
AB-3	0.271	0.155	0.791	0.148
BB - LM(1)	0.759	0.904	0.382	0.495
BB - LM(2)	0.596	0.145	0.450	0.659
BB - LM(3)	0.328	0.030	0.630	0.224
Stationarity	I(0)	I(0)	I(0)	I(0)

***, **, * indicate statistical significance at the 1%, 5%, and 10% respectively. RMSE is the root mean squared error. Residual Diagnostics: CD test, H0: no CSD. $\hat{\alpha}$ is the exponent of CSD; values below 0.5 indicate weak CSD. BB-HR is the heteroskedasticity-robust test for first order serial correlation due to Born and Breitung (2016). AB is the robust Arellano and Bond (1991) test for serial correlation up to the third order. BB – LM is the Born and Breitung (2016) Lagrange Multiplier test for serial correlation up to the third order. Values are probabilities associated to the null (for all these tests) of no serial correlation. Maddala-Wu and CIPS test results: I(0), stationary; I(1), non-stationary.

relies on cross-country time-series variations (Goldberg and Pavcnik, 2016). Constantinescu et al. (2016), for example, include World Bank data on TTBs in an ECM model but find that the estimate of the long-run elasticity of world trade with respect to protectionism is not significant. TTB data is also used by Martinez-Martin (2016) who obtains a positive but negligible coefficient in a pooled or a dynamic fixed effects model, where the mean-group estimate turns out to be insignificant. Measures of protectionism do not come up significantly and meaningfully in IMF (2016) and ECB (2016). Auboin and Borino (2017) introduce several measures of protectionism such as FTI, TTB, and the tariffs contained in the World Development Indicators Database. None of these measures of protectionism are statistically significant in a standard model with world real import growth as a dependent variable. Conversely, our results show that an increase in the KOF indicator is always associated with a reduction in international trade. However, protectionism elasticities are less than half of import price elasticities. In the long-run, an upsurge in tariff and non-tariff barriers negatively impacts international trade but to a lesser extent than an identical increase in the relative import price does.

Another interesting finding concerns the size of the speed of adjustment in the CS-ARDL specification determined by the *ecm* coefficient in Table 7. A value larger than unity (in absolute value) implies that, following a shock, the correction overshoots the long-run equilibrium. This finding might explain the recent slow-downs in global trade following the Lehman bankruptcy and the recent Covid-19 pandemic. However, Chudik and Pesaran (2015) caution that the magnitude of the speed of adjustment under the CS-ARDL should only be taken as indicative.

In the lower part of Table 7 we display diagnostics. All the estimated models reject nonstationary residuals according to the Maddala-Wu and CIPS tests. The latter is not actually needed as the CD test strongly supports the null hypothesis of weakly cross sectional dependent residuals. Additionally, the estimated value of α is in the range of [0,1/2] confirming the presence of weak CSD. Errors do not seem to be correlated as Table 7 displays the probability of accepting the null of non-serial correlations up to the third order according to robust Arellano and Bond (1991) as well as the Born and Breitung (2016) Lagrange Multiplier. The only partial exception concerns the CS-ARDL model with GDP. First order serial correlation is also rejected by the heteroskedasticity-robust test statistic introduced by Born and Breitung (2016).

We can wonder whether the global financial crisis and the following trade collapse and trade slowdown affect our estimates.[12] We re-estimate model (3) and (6) with a smaller time span (1970–2006) to address this. Results are shown in Table 8. When GDP is used as an activity variable the protectionism elasticity is insignificant, while the output and the import prices elasticities are as significant as in the full sample. It is therefore confirmed than an increase in GDP has a more than proportional impact on imports while a larger import price has a negative effect on international trade. We find similar results with respect to the import price and the activity variable when we opt for IAD. Conversely, the TPI elasticity is not significant when we include GDP in both models. On the contrary, estimates of protectionism elasticities are puzzling with IAD. On one side, the CS-ARDL model provides a quite large negative elasticity that is significant only at the 10% level. On the other side, the CS-DL is the only model which generates a result which is close to the one obtained with the

[12] I thank a referee for raising this issue.

Table 8
Mean Group long-run estimates (1970–2006).

	CS-ARDL		CS-DL	
	IAD	GDP	IAD	GDP
d.activity	0.796***	1.341***	1.063***	1.605***
d.pm	−0.294***	−0.318***	−0.294**	−0.309**
d.tpi	−0.221*	−0.000	−0.169**	−0.008
ecm	−1.138***	−1.583***		
observations	1122	1122	1122	1122
RMSE	0.058	0.061	0.052	0.060
CD test	1.413	0.800	0.648	0.330
CD prob	0.158	0.424	0.517	0.742
$\hat{\alpha}$	0.584	0.811	0.514	0.580
BB - HR	0.559	0.063	0.246	0.099
AB-1	0.446	0.005	0.051	0.001
AB-2	0.779	0.939	0.879	0.936
AB-3	0.368	0.968	0.335	0.089
BB - LM(1)	0.672	0.039	0.241	0.058
BB - LM(2)	0.778	0.366	0.541	0.423
BB - LM(3)	0.613	0.495	0.571	0.075
I(0)	yes	yes	Yes	yes

***, **, * indicate statistical significance at the 1%, 5%, and 10% respectively. RMSE is the root mean squared error. Residual Diagnostics: CD test, H0: no CSD. $\hat{\alpha}$ is the exponent of CSD; values below 0.5 indicate weak CSD. BB-HR is the heteroskedasticity-robust test for first order serial correlation due to Born and Breitung (2016). AB is the robust Arellano and Bond (1991) test for serial correlation up to the third order. BB – LM is the Born and Breitung (2016) Lagrange Multiplier test for serial correlation up to the third order. Values are probabilities associated to the null (for all these tests) of no serial correlation. Maddala-Wu and CIPS test results: I(0), stationary; I(1), non-stationary.

complete sample.[13] All in all, we can conclude that, apart from the CS-DL model when IAD is utilized, the trade elasticity of protectionism for the pre-crisis era appears to be different from the post-crisis era and protectionism plays a role only when we consider the period of time following the GFC.

4. Discussion and conclusions

From the 1960s up to the eve of the recent global financial crisis, global trade in goods and services grew at an average real rate of about six percent a year, which was twice that of the real GDP growth during the same period. This prolonged expansion was supported by important reductions in shipping, logistics, and information costs as well as in protectionism policies. It is natural to question to what extent the growth of world trade might be attributed to trade liberalization. The international financial meltdown in 2008/09, the contemporaneous world recession, and the following trade slowdown sharply reduced the pace of trade opening. Such a change has led to a renewed attention amongst scholars and policymakers regarding the impact of tariff and non-tariff measures on international trade in an increasingly integrated world economy. Goldberg and Pavcnik (2016) observe that estimates of trade elasticity based on actual trade policy changes are scarce and the few that exist are all over the place (Hillberry and Hummels, 2013). Additionally, some facts are hard to reconcile with the view that tariff reductions were instrumental in the growth of world trade. For instance, Yi (2003) points out that tariff rates declined by only 11% after the mid-1960s when trade grew more rapidly than before. This author argues one would have to appeal to very large trade elasticities that are at odds with the tariff reductions before the mid-1980s when the trade growth was much smaller. Yi (2003) suggests that these patterns can be explained by the interaction of trade policies with vertical specialization, but standard trade models have a hard time generating such nonlinearities in trade elasticities (Goldberg and Pavcnik, 2016).

We make several contributions to the existing literature that relies on cross-country, time-series variation to assess the long-run impact of protectionism on world trade in an appropriate econometric setting. First, we pioneer the use of the *de jure* trade globalization sub-dimension devised by KOF, which also includes non-tariff trade barriers and trade agreements. This index is, on average, quite stable in the 1970s and declines steadily in the 1990s and the first half of the following decade when trade grew more rapidly, pinpointing the role of non-tariff barriers neglected by Yi (2003). Secondly, we make use of IAD, which explicitly weighs final demand components (via input-output tables) to mirror changes in vertical specialization. Thirdly, we pay adequate attention to dynamics and embrace recently developed estimation and inferential methods to explicitly account for parameter heterogeneity and common factors.

We opt for the CS-ARDL and the CS-DL approaches since we find evidence of strong CSD in the panel. We follow Chudik et al. (2016), who state that these methodologies should be complementary since the CS-DL approach exhibits better small sample performance but does not allow for feedback effects from the dependent variable onto the regressors. By contrast, the CS-ARDL model can only be applied to stationary variables. Second order generations tests confirm the variables under scrutiny are I(1) due to non-stationary idiosyncratic components or common factors. Therefore, we estimate the impact of a change in protectionism, demand, and import price on the

[13] We must apply caution when we read these results as the degrees of freedom per group with cross-sectional averages are not very large (11 for the CS-DL model and 7 for the CS-ARDL).

change in world trade.

According to the recent literature, protectionism is not instrumental in explaining the recent reduction in trade (Hoekman, 2015), although many scholars recognize that hampering free trade may be a factor at the margin. On the contrary, we find that protectionism elasticities are always negative and significant. This result suggests that protectionist trade policies are still playing a role in explaining the recent declining responsiveness of world trade to GDP. However, our econometric results also show that, in the long-run, the impact of protectionism cannot be overstated since an increase in the KOF indicator is associated with a reduction of world trade that is less than half of an identical increase in the relative import price.

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