

Innovation, export performance and trade elasticities across different sectors and countries

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CCEPP WP04-19

DEPARTMENT OF LAND ECONOMY
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SEPTEMBER 2019

Abstract: This paper provides new evidence on the role of technological competitiveness for export performance across different sectors and country groups. Using a sample of 15 countries over the period 1976-2012, the investigation reveals that technological competitiveness, measured as the ratio of domestic to foreign patent stocks, is a relevant determinant of exports. The empirical investigation shows that: (i) excluding technological competitiveness inflates income elasticities due to omitted variable bias; (ii) income elasticities remain significant even when technological competitiveness is introduced; (iii) Krugman's hypothesis that income elasticities are proportional to each country's share in the world's product variety is not confirmed; (iv) technological competitiveness and foreign income exert larger effects on high-tech than on low-tech exports; (v) price competitiveness is more relevant for low-tech exports; (vi) technological competitiveness exerts similar impacts on the exports of all country groups, but income elasticities are higher for Latin American countries.

Keywords: Innovation; Export performance; Export demand functions.

J.E.L.: F10, O30.

Acknowledgements: The authors would like to thank Rafael Ribeiro and Gustavo Britto for their helpful comments. The usual disclaimer applies. Funding from CAPES and FAPEMIG is gratefully acknowledged.

1 Introduction

There is little dispute about the relevance of international trade for long-term growth. International trade allows domestic firms to access foreign markets, contributing to boost local production. Meanwhile, free trade increases competition, generating strong incentives for innovation and productivity growth (Helpman and Krugman, 1985). Moreover, trade facilitates the access to inputs and technology, while allowing consumers to access a broader variety of goods at lower prices (Grossman and Helpman, 1991).

Nonetheless, trade imbalances can generate adverse effects on growth under certain conditions. In standard trade theory, trade imbalances are resolved via changes in the nominal exchange rate. Trade deficits generate a decrease in the supply of dollars, leading to a devaluation of the local currency. Exchange rate devaluations improve the price competitiveness of domestic products *vis-à-vis* foreign products, reducing imports and increasing exports until trade equilibrium is restored. For this adjustment to work, however, the Marshall-Lerner condition must be fulfilled. If the sum of the price elasticities of exports and imports is not above unit, a devaluation would not restore current account equilibrium. The evidence regarding the Marshall-Lerner condition, however, is ambiguous. Bahmani *et al.* (2013) carried out a vast review of the studies that have estimated export and import functions, and found that the condition is fulfilled in only half of the 91 cases analysed. According to Thirlwall (1979) and Thirlwall and Hussain (1982), since trade deficits cannot be financed indefinitely, if the Marshall-Lerner condition does not hold, persistent trade deficits could force governments to adopt contractionary policies aiming at improving the balance of trade. Alternatively, exchange restrictions and protectionist measures could also be implemented. In this case, the resulting reduction in imports could also constrain the growth of domestic output, especially in underdeveloped economies, where a considerable share of investment goods is not produced locally. Moreover, trade deficits can also lead to sudden stops and debt crises, as happened in several Latin American countries during the 1980s, leading to sharp reductions in output growth (Obstfeld, 2012; Lane and Milesi-Ferretti, 2012; Catão and Milesi-Ferretti, 2014).

If exchange rate devaluations are not sufficient to bring the current account back to equilibrium, it becomes crucial to understand the determinants of export performance in order to avoid the adoption of protectionist or contractionary policies. Governments from countries with persistent trade deficits often end up adopting import regulations to prevent

sharp exchange rate depreciations and/or debt crises. Nonetheless, promoting policies that foster increases in export performance not only lead to higher domestic growth, but it also allows local producers and consumers to benefit from foreign imports.

Most studies find technology, foreign demand and relative prices as the main determinants of export performance. Traditional export demand functions take into account only relative prices and foreign income as determinants of exports, assuming that the income elasticity of demand captures the non-price competitiveness of each country's production (e.g. Houthaker and Maggee, 1968; Goldstein and Khan, 1985). When it comes to price competitiveness, empirical evidence reveals weak or insignificant effects (Bairam, 1988; McCombie and Thirlwall, 1994; Carlin, Glyn and Van Reenen, 2001; Bahmani *et al.*, 2013). The Schumpeterian approach to international trade, however, provides strong evidence in support of the hypothesis that technological competitiveness is a particularly relevant determinant of export performance (e.g. Fagerberg, 1988; Greenhalgh *et al.*, 1994; Madsen, 2008; Ang *et al.*, 2015). Nonetheless, in spite of the large number of studies that have sought to investigate the determinants of trade performance, some specific questions have not yet received enough attention.

The purpose of this paper is to shed new light into the relationship between innovation, export performance and trade elasticities. The specific contributions of this paper to the existing literature are threefold. First and foremost, only a few studies have investigated empirically the relationship between technological competitiveness and the magnitude of income and price elasticities of exports (e.g. Madsen, 2008; Romero and McCombie, 2018). This paper aims to investigate whether income elasticities indeed capture technological competitiveness, as Houthaker and Maggee (1969) conjectured, examining also Krugman's (1989) argument that income elasticities are in fact proportional to each country share of product variety. Second, the paper seeks to analyse if technological and price competitiveness exert the same effects on the exports of low-tech and high-tech products. Although a few studies have already compared the relevance of the two types of competitiveness across sectors, most of these studies do not consider the effect of foreign demand on exports, or adopt export shares as the dependent variable. Third, to the best of our knowledge, no paper has yet tested the relative importance of technological competition between different groups of countries.

This paper's empirical investigation explores a unique database, which combines export volume, relative prices and foreign income with patent data used to calculate technological competitiveness. Bilateral trade weights were used to generate the measures

of foreign income, price and technological competitiveness, as carried out by Ang *et al.* (2015). The novelty of the database is that patent data classified according to the International Patent Classification was transposed into the International Standard Trade Classification using the methodology developed by Lybert and Zolas (2014), allowing to calculate technological competitiveness in low-tech and high-tech industries. The final sample used here comprises data for 15 countries (5 developed, 5 Asian and 5 Latin American countries) between 1976-2012.

The paper is organized as follows. Section 2 discusses the theories and the evidence regarding the determinants of exports. Section 3 presents the data and the methodology used to investigate the determinants of export performance. Section 4 discusses the results found using aggregate data, dividing the sample into technological sectors, and into country groups. Section 5 presents the concluding remarks of the paper.

2 Innovation and trade

2.1 Traditional export demand function

The first works to investigate empirically the determinants of trade performance sought to estimate basic export and import demand functions (e.g. Houthakker and Magee, 1969). In this approach, export growth depends on income growth and changes in price competitiveness. Formally, the linearized demand function is:

$$\hat{X} = -\eta(\hat{P}_d - \hat{P}_f - \hat{E}) + \varepsilon\hat{Z} \quad (1)$$

where X is exports, E is the exchange rate, P_d and P_f are the domestic and foreign prices levels, respectively, and Z is the foreign income level. Moreover, η is the price elasticities of demand for exports, while ε is the income elasticity of demand for exports. The circumflex denotes growth rates.

A large number of works have estimated export demand functions like equation (1), and most of them find that income elasticities are highly significant, while price elasticities are often not significant. Using data from 15 OECD countries for the period 1951-66, Houthakker and Magee's (1969) seminal paper provided initial evidence that income elasticities are highly significantly different from zero and vary widely between countries, while price elasticities are most often not significant. Similarly, Bairam (1988) estimated export demand functions for 19 OECD countries and found that while income elasticities are again highly significant, price elasticities are most often not significant. Using cointegration techniques, Andersen (1993) found similar results employing relative unit labour costs to measure relative prices. Using data from 8 OECD countries for the period

1955-70, however, Goldstein and Kahn (1978) provided evidence that price elasticities become significant when demand functions are estimated jointly with supply functions. In spite of that, income elasticities remain highly significant in their estimates.

In equation (1), non-price competitiveness is captured in the income elasticity of demand. In general terms, it encompasses all the factors other than price that determine consumption choices, such as quality differences, merchandising, quality of distributions networks, etc. (McCombie and Thirlwall, 1994).

Evidently, aggregate income and price elasticities are weighted averages of the sector-specific elasticities, so that:

$$\hat{X} = -\sum_{i=1}^k \varphi_i \eta_i (\hat{P}_{ai} - \hat{P}_{fi} - \hat{E}) + \sum_{i=1}^k \varphi_i \varepsilon_i \hat{Z} \quad (2)$$

where $i = 1, 2, \dots, k$ are the sectors and φ_i are the associated sectoral shares in total exports, so that $\sum_{i=1}^k \varphi_i = 1$. Hence, aggregate elasticities are partially determined by the sectoral composition of the economies' exports (Araújo and Lima, 2007). Thus, structural change, by altering sectoral weights, can therefore change the growth rate of a country's exports, even if elasticities, relative prices and world income growth remain unchanged.

Seeking to investigate the differences in price and income elasticities of demand across sectors, some works have estimated basic export demand functions for different groups of industries. Gouvêa and Lima (2013) estimated sectoral export demand functions using a fixed effects panel data estimator for a sample of 90 countries between 1965 and 1999. Using Leamer's (1980) sectoral classification, they found that machinery has the highest income elasticity of demand, followed by labour intensive manufactures and petroleum. Primary products presented the lowest income elasticities. They used real exchange rates to measure relative prices, which turned out not significant in most regressions. Romero and McCombie (2016), in turn, used cross-product panels to estimate export demand functions for Lall's (2000) technological sectors in 14 OECD countries separately. The authors used an instrumental variables estimator to control for simultaneity between export quantities and prices, while using industry-specific price indexes calculated by Feenstra and Romalis (2014). Yet, price elasticities were still most often not significant. The results revealed, however, that medium- and high-tech industries present higher income elasticities than primary products and low-tech manufactures.

2.2 Technological competitiveness and product variety

According to Schumpeter (1943, p. 107-8), "as soon as quality competition and sales effort are admitted into the sacred principles of theory, the price variable is ousted

from the dominant position. (...) This kind of [technological] competition is as much more effective than the other as a bombardment is in comparison with forcing a door.” This short passage summarizes the Schumpeterian approach to the impact of innovation and development of new product varieties on export performance.

Several decades after Schumpeter’s seminal books, the author’s emphasis on the importance of innovation, creative destruction, quality improvements and increase in product variety resurfaced in the new theory of international trade (Krugman, 1979; 1980; Helpman and Krugman, 1985). In this approach, trade in differentiated intermediate goods is equivalent to an increase in the number of innovations, which increases the productivity of the final goods sector (e.g. Funke and Ruhwedel, 2002; Ang *et al.*, 2015). Hence, countries improve their trade performance and increase their growth rates by expanding the range of goods they produce (Magnier and Toujas-Bernate, 1994; Hübler, 2015). In this framework, therefore, traditional export demand functions are augmented to take into account technological competitiveness associated with improvements in product variety or quality:¹

$$\hat{X} = -\eta(\hat{P}_a - \hat{P}_f - \hat{E}) + \varepsilon\hat{Z} + \mu(\hat{T}_a - \hat{T}_f) \quad (3)$$

where T denotes the level of technological competitiveness and μ is the technology elasticity of demand for exports.

A large portion of the works that sought to assess the relationship between innovation and trade performance, however, adopted specifications different from equation (3). Fagerberg (1988), Magnier and Toujas-Bernate (1994), Amendola *et al.* (1993) and Amable and Verspagen (1995), for example, found evidence of positive and significant impacts of price and technological competitiveness on export shares of OECD countries using R&D- and/or patent-based measures of technology.² Carlin *et al.* (2001), however, found that while price competitiveness partially explains the export market shares of OECD countries, relative technology intensity is not significant. Adopting a somewhat different approach, Greenhalgh (1990) and Greenhalgh *et al.* (1994) found evidence that patent-based measures of technological competitiveness have a significant impact on the UK’s net exports.

Nonetheless, there is now a considerable number of studies that have estimated equation (3). Using Feenstra’s (1994) theory-based methodology to calculate the export

¹ As Feenstra (1994, p. 161) shows, “a change in the number of varieties within a country acts in the same manner as a change in the taste or quality parameter for that country’s imports”.

² Soete (1981), Hughes (1986), Wakelin (1998) and Montobio and Rampa (2005) found similar results using different specifications for the determinants of export shares.

variety of 15 OECD countries, Funke and Ruhwedel (2002) found evidence that increases in relative product variety exert positive and significant impact on export growth even when controlling for changes in foreign income and prices. Similar results were found by León-Ledesma (2005) using R&D stocks to measure home and foreign technological competitiveness for a panel of 21 OECD countries.³ In his study, changes in income and prices impact significantly on export growth, while the estimated technology elasticity is also positive and significant, and larger than the figures found by Funke and Ruhwedel (2002).⁴ Madsen (2008) estimated equation (3) using both patent and R&D stocks to measure technological competitiveness in a panel of 18 OECD countries. Interestingly, his estimates of the technology elasticity using R&D stocks were similar to the figures found by Funke and Ruhwedel (2002), while the estimates found using patent stocks were similar to the figures found by León-Ledesma (2005). Finally, using panel data for six Asian countries for the period 1953-2010, Ang *et al.* (2015) assessed the relevance of innovation stocks and technological competitiveness for the countries' export growth. Their results indicate that both innovation stock and technological competitiveness are significant determinants of export growth, as well as changes in income and prices.

There are also works that sought to investigate the impact of technological competitiveness and product variety on trade performance across different sectors. Investigating the determinants of trade performance in 43 sectors, Greenhalgh *et al.* (1994) found evidence that income as well as technological and price competitiveness are significant determinants of net exports in most sectors. Wakelin (1998) and Amable and Verspagen (1995), however, found that technological competitiveness has a positive impact on changes in export shares across different sectors, while price competitiveness (measured by relative unit labour costs) was most often significant in low-tech sectors. Similarly, Carlin *et al.* (2001) found that industries with high R&D intensity are less sensitive to price competitiveness. In addition, Romero and McCombie (2018) found evidence that technological competitiveness (measured by relative productivity) has a higher impact on export growth in high-tech industries than in low-tech industries.

2.3 Income elasticities, technological competitiveness and product variety

³ León-Ledesma (2005) tested the effect of foreign innovation on domestic export growth. The author found evidence that an increase in the foreign stock of knowledge has a positive effect on the export growth of the less developed countries in his sample, while the effect is negative for G7 economies.

⁴ Similar results were found by Anderton (1999), who estimated expanded import demand functions analogous to equation (3) for Germany and the UK.

One decade after the publication of Houthakker and Magee's (1969) seminal estimates of basic import and export demand functions, Thirlwall (1979) called attention to the fact that differences in countries' long-term growth rates could be predicted highly accurately using Houthakker and Magee's (1969) income elasticities of demand. According to Thirlwall (1979), provided that relative purchasing power parity is valid in the long-term, and that trade deficits cannot be financed indefinitely, trade must be balanced in the long term.⁵ Nonetheless, since income elasticities of demand are different between countries, some countries will be more susceptible to incur in trade deficits than others. In other words, in countries where the income elasticity of demand for imports is higher (lower) than the one for exports, long-term trade deficits (surpluses) will emerge whenever domestic and foreign incomes experience the same growth rates. As a consequence, as Krugman (1989) also pointed out, there is a long-term 45-degree relationship between the ratio of income elasticities of exports and imports, and the ratio of domestic and foreign growth rates.

According to Thirlwall (1979), the long-term 45-degree relationship between growth ratios and elasticity ratios would be sustained via adjustments in the domestic income growth rate. In countries where the growth ratio is higher than the elasticities ratio, domestic income growth would have to be reduced in order to reduce import growth and re-equilibrate the trade balance. Thirlwall (1979) argued, therefore, that differences in income growth rates are explained by differences in the balance-of-payments constraint imposed by the differences in income elasticities of demand.

According to Krugman (1989), however, the stability of the 45-degree rule is explained by adjustments in income elasticities of demand. Krugman (1989, p. 1039) argues that "fast growing countries expand their share of world markets, not by reducing relative prices of their goods, but by expanding the range of goods that they produce as their economies grow". In other words, output growth would generate product differentiation, which would lead to an increase in the income elasticity of exports and a decrease in the income elasticity of imports, bringing the 45-degree rule back to equilibrium. His argument is that the income elasticities are proportional to the number of product varieties produced in each country. Formally:

$$\varepsilon = \varepsilon_1 + \varepsilon_2 \left[\frac{T_d}{T_d + T_f} \right] \quad (4)$$

⁵ Pedroni (2001) and Taylor and Taylor (2004) provide recent evidence that suggest the validity of relative purchasing power parity in the long term.

According to Krugman (1989), therefore, the income elasticities are entirely endogenous in relation to the domestic share of the world's product varieties, which means that $\varepsilon_1 = 0$ and $\varepsilon_2 = 1$ in equation (4). Substituting equation (4) into equation (1) allows testing Krugman's (1989) hypothesis indirectly. This type of test, however, was never been carried out.

Thirlwall (1991) highlighted two major problems in Krugman's (1989) arguments. Firstly, Thirlwall (1991: 26) stressed that Krugman's (1989) model does not explain what generates faster growth rates, except for population growth. Secondly, he also emphasises that faster-growing countries will not necessarily export more independently of the goods they produce, given that it is highly implausible that diversification in the production of primary commodities will increase a country's income elasticity for exports in the same magnitude as diversification in the production of manufacturing goods.

An alternative interpretation of Krugman's (1989) argument is to consider that introducing measures of product variety or quality into basic export demand functions would eliminate part of the differences in income elasticities of demand across countries, while the technology elasticities would still be different.

In spite of the large number of works that have tested both the traditional and the technology-expanded export demand functions, there is relatively little discussion about the changes observed in income and price elasticities when technological competitiveness is introduced. Madsen (2008) and Romero and McCombie (2018) are some of the few exceptions.

Madsen (2008) analysed the impact of technological competitiveness on export growth using a sample of 18 OECD countries and focusing especial attention on the changes in the magnitude of the income elasticity of demand for exports. He pointed out that estimates using basic export demand functions generate income elasticities much higher than one, as neoclassical theory would predict. According to him, this could be a sign of omitted variable bias. Madsen (2008, p. 157) showed that introducing lags of the dependent and the independent variables as well as time dummies and measures of technological competitiveness turns the short-term income elasticity not significant. In spite of that, however, the income elasticities of demand for exports remained significant for some of the countries under investigation.

Using disaggregate data for seven European countries between 1984 and 2006, Romero and McCombie (2018) assessed the impact of technological competitiveness, measured by relative total factor productivity, on the export growth of low- and high-tech

industries. Interestingly, the authors found that both income and technological elasticities are positive and significant, and, most importantly, considerably larger in high-tech industries. The authors' results show also that while introducing domestic technological growth might reduce the income elasticity of demand for exports, introducing foreign technological growth may lead to an increase in the elasticity, consistently with a negative omitted variable bias. Moreover, Romero and McCombie (2018, p. 18) call attention to the fact that similar movements in income elasticities were found by Ang *et al.* (2015), who estimated expanded export demand functions such as equation (3) for a sample of 6 Asian economies. Despite the fact that they do not discuss changes in the magnitude of income elasticities, their results show that income growth is significant in all regressions, with income elasticities much higher than one even when technological competitiveness is controlled for.

The results found by Madsen (2008), Ang *et al.* (2015) and Romero and McCombie (2018) suggest that although introducing technological competitiveness in export demand functions reduces the magnitude of income elasticities, differences in elasticities between countries still persist. These findings indicate that this alternative interpretation of Krugman's (1989) argument about the endogeneity of income elasticities in relation to product variety and technological competitiveness is not necessarily valid. In other words, even if output growth generate increases in product variety, as Krugman (1989) postulates, long-term income elasticities still seem to differ between countries due to differences in other non-price competitiveness factors.

3 Empirical investigation

3.1 Econometric specification

Following the discussion presented in the previous section, four different specifications of export demand functions were estimated: (i) the simple export demand function given by equation (1); (ii) the technology-expanded export demand function, given by equation (3); (iii) an alternative specification of the technology-expanded function, considering only the growth of the technology stock of the local economy; and (iv) Krugman's export function, found substituting equation (4) into equation (1). Hence, the equations estimated in this paper have the following specifications:

$$\ln X_{it} = \beta_0 + \beta_1 \ln YW_{it} + \beta_2 \ln PWx_{it} + u_{it} \quad (5)$$

$$\ln X_{it} = \beta_0 + \beta_1 \ln YW_{it} + \beta_2 \ln PWx_{it} + \beta_3 \ln YW_{it} * PVS_{it} + u_{it} \quad (6)$$

$$\ln X_{it} = \beta_0 + \beta_1 \ln YW_{it} + \beta_2 \ln PWx_{it} + \beta_3 \ln TW_{it} + u_{it} \quad (7)$$

$$\ln X_{it} = \beta_0 + \beta_1 \ln YW_{it} + \beta_2 \ln PWx_{it} + \beta_3 \ln TSTK_{it} + u_{it} \quad (8)$$

where X_{it} is total export volume, YW_{it} is trade weighted real income of export destination countries, PWx_{it} is the trade weighted export price competitiveness, TW_{it} is the trade weighted technological competitiveness, $TSTK_{it}$ is the domestic stock of patents, and the product variety share is calculated as $PVS_{it} = TSTK_{it} / (\sum_{j=1}^{26} TSTK_{jt})$.

Bilateral trade weights consist of the shares of nominal exports from country i at year t to the following 26 destinations j : Argentina, Australia, Belgium, Brazil, Canada, Chile, Colombia, France, Germany, India, Indonesia, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Peru, Singapore, Spain, Switzerland, Thailand, the UK and the US. Taking the year 2012 as reference, these countries altogether are responsible for approximately 70% of the export markets of the countries analyzed. Using these weights contributes to capture the competitiveness aspect of trade using a more refined measure.⁶

Trade weighted income for country i was constructed as:

$$YW_{it} = \sum_{j=1}^{25} \frac{Xn_{jit}Y_{jt}}{Xn_{it}}$$

where Xn_{jit} is nominal exports from country i to country j , Xn_{it} is total nominal exports of country i , both in US dollars, and Y_{jt} is real income of destination country j . The expected result is that an increase in the (trade weighted) income of the export destinations is accompanied by an increase in the export volume from the domestic economy.

Price competitiveness refers to the following bilateral measure:

$$PWx_{it} = P_{it} / \left(\sum_{j=1}^{25} \frac{Xn_{jit}P_{jt}}{Xn_{it}} \right)$$

where P_{it} and P_{jt} are the export prices (in the same currency) of countries i and j , respectively. In this case, an increase in the index corresponds to a deterioration of the price competitiveness of country i .

Finally, technological competitiveness is calculated in a similar form:

$$TW_{it} = TSTK_{it} / \left(\sum_{j=1}^{25} \frac{Xn_{jit}TSTK_{jt}}{Xn_{it}} \right)$$

where $TSTK_{it}$ and $TSTK_{jt}$ are the stocks of patents of countries i and j , respectively. Thus, an increase in the index is related to an improvement in the technological competitiveness of country i .

⁶ See Madsen (2008) for a similar test of the effect of innovation in export performance of OECD countries. Madsen (1998) also uses a similar index in an analysis of the determinants of price elasticities.

Following the standard practice in the literature, the stock of patents $PSTK_{i,j,t}$ was constructed using the perpetual inventory method (Hall, 1999; Madsen, 2007; 2008), which implies the following equation:

$$TSTK_t = T_t + (1 - \delta)TSTK_{t-1}$$

where T_t refers to the patents in the year t and δ is the depreciation rate, which is taken as 15% following Ang *et al.* (2015). This method and magnitude of depreciation rate allow the innovation stock to impact permanently on the overall knowledge stock, although considering that older innovations have a lower impact. Following Ang, *et al.* (2015), the initial stock of patents was computed as $T_o/(g + \delta)$, where T_o is the number of patents in the first year of the series and g is the average annual geometric growth rate over the whole sample period.

Estimating demand functions such as equations (5) to (8) involves a series of econometric issues. First, unobserved fixed country and/or industry specific characteristics of the explanatory variables can cause endogeneity. Second, as Madsen (1999) formally shows, export price elasticities estimated using OLS are biased towards -1 asymptotically due to measurement errors in both export prices and quantities. For example, since volume is measured in weight, moving exports from low-tech to high-tech products can reduce export weight. This artificially increases export unit value prices *ceteris paribus*, forcing the price competitiveness coefficient to reduce. Third, it is important to control for simultaneity related both to technological and price competitiveness. As Madsen (2008) argues, there are reasons to suspect that increased production might result in lower prices or higher technological competitiveness due to static or dynamic increasing returns to scale, respectively. Trade weighted income is considered exogenous. And fourth, although the fixed effects pooled OLS estimator allows for the intercepts to differ across individuals, it might also produce biased and inconsistent coefficients if the coefficients are heterogeneous between the individuals.

A suitable solution for simultaneity and measurement errors in technological and price competitiveness is to employ an instrumental variable estimator, as carried out by Ang *et al.* (2015). Nonetheless, this requires finding a large number of valid external instruments, which is not an easy task. Thus, in order to optimize the validity of both model and instruments, this paper uses the system General Method of Moments (GMM) of Blundell and Bond (1998) as estimator. This method employs lags of included variables as instruments, controlling for endogeneity by estimating a system composed by an equation in levels and one in differences, while instrumenting both differently. The system

GMM estimator has an additional advantage: it allows taking into account the dynamic effects of both dependent and independent variables.

For the instruments to be valid using the system GMM estimator, two requirements must be satisfied. Firstly, as usual, the instruments “must be correlated with the included endogenous variables, and orthogonal to the error process” (Baum *et al.*, 2003, p. 14). Hansen’s J test assesses this hypothesis by testing for the joint validity of the instruments in overidentified regressions. However, as Roodman (2009a) highlights, this test is prone to weakness and cannot be blindly relied upon. More specifically, according to Roodman (2009a, p. 98), “the test actually grows weaker the more moment conditions there are and, seemingly, the harder it should be to come close to satisfying them all”. Thus, as the number of instruments increases with the size of the time dimension of the panel, the proliferation of instruments may overfit the endogenous variables, biasing the estimated coefficients and generating spurious acceptance of the validity of the instruments in Hansen’s J test (Roodman, 2009b). In order to avoid instrument proliferation, the size of the time dimension (T) of the panel was reduced transforming the data into 5-year averages. This also has the advantage of diminishing serial correlation and smoothing cyclical fluctuations. Moreover, to limit the instrument count in the estimation, the lag range of the instruments was restricted instead of using all available lags. Secondly, for the instruments to be valid, it is also necessary to check for serial correlation of the idiosyncratic error term. This hypothesis is assessed using the Arellano-Bond test applied to the residuals in differences from lag two onwards. All of these procedures were performed and the number of instruments and lags used and the tests results are reported along with the estimation results in the next section.

This paper also investigates the long run relationships in equations (5) to (8) using an error correction model that allows for heterogeneous slopes across the individuals within the panel. Non-stationary series can have a common dynamic, which justifies the variables having a long-term and a short-term component. Those components, in turn, can be modelled using an error correction estimator that deals with the short run dynamics of the series influencing their long run equilibrium courses.

Given the large time dimension of the dataset, the pooled mean group (PMG) estimator of Pesaran *et al.* (1999) is a suitable estimator. On the one hand, the PMG estimator is an intermediate estimator between the fixed effects, which assumes that all coefficients are equal, and the mean group (MG), which allows all coefficients to differ. The PMG estimator allows intercepts, short run coefficients and error variances to differ

across countries, while pooling estimates for the long run coefficients. A Hausman test was performed to assess the homogeneity of the long-term parameters. The test results indicated that the PMG estimator is the suitable choice at a 5% significance level.⁷

Moreover, it is important to note that the PMG estimator is less restrictive than the dynamic OLS (DOLS) and fully modified OLS (FMOLS) of Pedroni (2000, 2001), since the latter models require all variables to have the same order of integration for consistency. Applying the Levin *et al.* (2002) test for unit roots in panel data, the variables in equations (5) to (8) turned out to be integrated of order zero or one (i.e. I(0) or I(1)), giving evidence against the use of the DOLS and FMOLS estimators.⁸ The PMG estimator, however, requires only that the variables be integrated of maximum order 1, allowing for both stationary and non-stationary variables⁹. Although the assumption of homogeneous cointegration parameters is relaxed with the PMG estimator, it still considers that there is a long run relationship between the dependent and independent variables among groups. This relationship is captured by a cointegrating vector, whereas the short run dynamics is represented in the use of the deviation of the dependent variable from its long run equilibrium relationship in the estimation. Using the PMG estimator, therefore, allows assessing the results found using the system GMM estimator.

It is important to note, however, that in spite of reporting the results found using FE and PMG, the System GMM estimator is considered the most reliable estimator, since it controls for the most relevant econometric issues. Hence, the discussion of the regression results will be predominantly focused on the System GMM results.

3.2 Data description

Data from different databases were combined to estimate equations (5) to (8) for 15 countries over the period 1976-2012, following the availability of trade and patent data as well as data used to calculate bilateral trade weights. The sample used combines three groups of countries: developed countries (Germany, Italy, the UK, the US, and the Netherlands), Asian economies (India, Japan, Korea, Singapore and Thailand), and Latin American countries (Argentina, Mexico, Brazil, Chile, and Colombia).

⁷ The p-values for the Hausman test of the consistency of the PMG estimates (against the MG estimates) are 0.28 and 0.12 for the estimations with patent stock and patent stock competitiveness, respectively.

⁸ The results the unit roots tests are presented in table A1 in the appendix.

⁹ Panel cointegration tests' results were not reported since they are unreliable when part of the series is stationary. Therefore, this paper focuses on the error correction coefficients presented in the next section to assess a cointegration relationship. A long-run relationship exists when this coefficient is significantly negative.

Disaggregate trade data was obtained from the UN Comtrade, using the Standard International Trade Classification (SITC) (revision 2) 4-digit product categories. These categories were divided into two groups, one with low and another with high technological content, according to the standard OECD classification. Real GDP data in constant 2010 U.S. dollars was gathered from the World Development Indicators for all countries.

Unit value prices were calculated dividing export value (in dollars) by export volume (in kilograms), both from UN Comtrade. Most of the literature uses export unit values or unit labour costs in manufacturing as proxies for export prices and/or price competitiveness. According to Madsen (2008), both have their advantages and disadvantages. Although unit labour costs are less likely to present endogeneity and simultaneity bias than export unit prices, changes in price mark-ups induced by cost variations can bias (toward zero) the coefficient of unit labour costs, not reflecting changes in actual prices. Taking this into account, export unit values were adopted in this paper.

Data on patents granted was gathered from the United States Patent and Trademark Office (USPTO) to avoid possible differences in patent registration laws across countries. It is worth emphasizing that there is not a direct or perfect measure for innovation. As Fagerberg (1996) highlights, innovation derived from learning-by-doing does not have a clear relationship with R&D. The propensity to patent is also known to vary across industries, as well as R&D expenditures, while productivity measures have only an indirect relationship with innovation. In spite of these caveats, as Griliches (1990), Greenhalgh *et al.* (1994) and Madsen (2008) argue, patents are the best available measure of technology. According to Griliches (1990, p. 1661), patents “are by definition related to inventiveness, and they are based on what appears to be an objective and only slowly changing standard”.

Griliches (1990) highlights two major problems in using patents in economic analysis. The first one is classification. The patent classification system does not relate to economically meaningful classifications of industries, focusing often on internal technological principles. The second issue relates to the intrinsic variability that goes back to the fact that patents differ in their technical and economic significance, since they can reflect minor or major innovations.

These issues notwithstanding, patents have the advantage of being measured without errors and also being the output of both formal and informal research activities (Madsen, 2008). The literature also finds a strong relationship between patent counts and R&D expenditures in the cross-sectional dimension (Griliches, 1990; Greenhalgh *et al.*,

1994; Madsen, 2008). This suggests that patents can be good indicators of differences in innovative activity across firms and/or countries. Furthermore, according to Griliches (1990), whereas propensity to patent varies across industries, the relationship between patents and R&D is almost proportional. Most importantly, patent data has higher availability than R&D data. Hence, although imperfect measures of innovation, as Griliches (1990, p. 1700) argued, “patent statistics remain a unique resource for the analysis of the process of technical change”.

To deal with the problem of classification, patent grants registered at the USPTO were collected individually, allowing the extraction of the first four digits of the International Patent Classification (IPC) codes, the country of origin of the first author, and the year. These IPC codes were transposed into the SITC (revision 2) 4-digit product categories using the methodology proposed by Lybbert and Zolas (2014).

4 Results

4.1 Main results

Tables 1 and 2 present the regression results for equations (5) to (8), aggregating all exports and considering the entire sample of countries. In all GMM regressions the Arellano-Bond test does not reject the absence of autocorrelation of second order, while Hansen’s J test of overidentification does not give evidence against the validity of the instruments used, both at a 5% significance level. The number of instruments is also adequate to the size of the test sample and the number of lags used is the minimum possible. In general, these results give evidence in favour of the instrumental estimation strategy.

The results presented in Table 1 indicate that income growth is the most relevant variable in basic export demand functions. As Madsen (2008) pointed out, income elasticities show up higher than 1 both in FE and SYS-GMM regressions. Yet, when the PMG estimator is used and lags of both dependent and independent variables is controlled for¹⁰, the magnitude of the income elasticity is considerably reduced. Nonetheless, income is still the only significant variable in the regression. The error correction term is negative and significant, confirming the cointegration relationship between the variables. Most importantly, columns (4) to (6) show that Krugman’s hypothesis is refuted, and the

¹⁰ The specification adopted in all PMG models employs one lag of the dependent and of each independent variable, since using more lags reduces considerably the regressions’ degrees of freedom.

interaction between the measure of product variety share and income growth is not significant. Meanwhile, the parameters remain relatively stable.

Table 1: Export performance omitting innovation variables

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	SYS- GMM	PMG	FE	SYS_GMM	PMG
Ln of Trade Weighted Income	1.134*** (0.285)	1.468*** (0.398)	0.230* (0.122)	1.141*** (0.288)	1.242*** (0.391)	0.264*** (0.096)
Ln of Price Competitiveness	0.007 (0.042)	0.165 (0.145)	-0.025 (0.016)	0.008 (0.042)	0.072* (0.034)	-0.013 (0.011)
Ln of Trade Weighted Income*Product variety share				0.109 (0.130)	0.339 (0.499)	0.048 (0.081)
Constant	-7.162 (8.117)	-16.477 (11.422)		-7.546 (8.222)	-10.790 (11.193)	
Error-correction Term			-0.228*** (0.072)			- 0.315*** (0.089)
No. Observations	120	120	540	120	120	540
No. Instruments/Lags		7/2-3			13/2-4	
Arellano-Bond AR(2) Test		0.673			0.485	
Hansen's J Test		0.134			0.115	

Notes: The dependent variable is Ln of Export Volume. Robust standard errors are reported between brackets. Values reported for the tests are p-values. Significance: 10%=*; 5%=**; 1%=***.

Source: Authors' elaboration.

Table 2: Export performance - All industries

Model	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	SYS- GMM	SYS- GMM	PMG	PMG
Ln of Trade Weighted Income	0.784** (0.270)	1.099*** (0.276)	0.381** (0.210)	0.903** (0.491)	0.011 (0.087)	0.642*** (0.074)
Ln of Price Competitiveness	-0.054 (0.032)	-0.048 (0.033)	-0.039 (0.038)	-0.142 (0.169)	-0.006 (0.010)	-0.003 (0.010)
Ln of Patent Stock	0.235*** (0.075)		0.312*** (0.056)		0.428*** (0.028)	
Ln of Patent Stock Competitiveness		0.242** (0.082)		0.388** (0.112)		0.461*** (0.031)
Constant	1.085 (7.644)	-5.294 (7.795)	11.919* (6.051)	0.605 (13.669)		
Error-correction Term					-0.347*** (0.086)	-0.333*** (0.084)
No. Observations	120	120	120	120	540	540
No. Instruments/Lags			12/2-5	8/2-3		
Arellano-Bond AR(2) Test			0.304	0.877		
Hansen's J Test			0.183	0.302		

Notes: The dependent variable is Ln of Export Volume. Robust standard errors are reported between brackets. Values reported for the tests are p-values. Significance: 10%=*; 5%=**; 1%=***.

Source: Authors' elaboration.

Table 2 shows that income elasticities decrease considerably in all regressions when technology stocks are introduced. Such changes are similar to the ones found by Ang *et al.*

(2015) and can be explained by omitted variable bias in basic export demand functions, as argued Romero and McCombie (2018). Technology stocks are always significant, with coefficients ranging between 0.2 and 0.4, while price elasticities remain negative but not significant in most regressions.

When technological competitiveness is introduced instead of technology stocks, the technology coefficient remains always positive and significant, while income elasticities increase in all regressions, once again similarly to the results found by Ang *et al.* (2015). As Romero and McCombie (2018) highlighted, this change can be explained by an omitted variable bias associated with the negative effect that increases in foreign technology stocks exert in domestic export performance. According to Ang *et al.* (2015), however, this could reflect the fact that foreign income becomes the main scalar variable in the estimation when only price competitiveness is introduced. Since patent stock is also a scalar variable, its correlation with foreign income is higher, resulting in a greater decrease in the income elasticity. Interestingly, the coefficients of technological competitiveness are very similar to the ones found for technology stocks, as expected following equation (3).

In sum, these findings indicate that income elasticities are overestimated when proxies for non-price competitiveness are not taken into account, suggesting that there is a long-term relationship between innovation and export volume. On the other hand, price competitiveness is not statistically significant, suggesting that price changes and devaluations do not appear to be relevant strategies to promote exports in the long-term. These results suggest also that innovation variables can be used as proxies for non-price competitiveness, which is captured in the income elasticities of demand in the restricted regressions.

4.2 Results by technological sector

Tables 3 to 6 report the results dividing the sample into high-tech and low-tech industries. The results are in general very similar to the ones reported in Tables 1 and 2.

The results reported in Tables 3 and 4 show that income elasticities are larger for high-tech industries (0.9 to 2.5) than for low-tech industries (0.2 to 1.3). Moreover, Krugman's hypothesis is not found to be valid for neither of the two sectors.

It is interesting to note that price elasticities show up positive and significant in high-tech industries, even when instruments are used to control for the endogeneity of relative prices. This probably reflects the fact that quality improvements are normally

associated with price increases. Thus, when no measure of quality changes is employed, price elasticities tend to capture the effect of quality changes on export performance.

Table 3: Export performance omitting innovation variables – High tech

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	SYS- GMM	PMG	FE	SYS_GMM	PMG
Ln of Trade Weighted Income	2.477*** (0.343)	2.126*** (0.495)	0.957*** (0.085)	2.477*** (0.344)	2.299*** (0.448)	0.862*** (0.084)
Ln of Price Competitiveness	0.341 (0.213)	0.946** (0.358)	0.507*** (0.131)	0.340 (0.212)	0.908** (0.324)	0.438*** (0.121)
Ln of Trade Weighted Income*Product variety share				0.005 (0.203)	0.287 (0.266)	-0.056 (0.084)
Constant	- 47.737*** (9.725)	-37.378** (14.219)		- 47.744*** (9.785)	-42.748*** (13.032)	
Error-correction Term			- 0.164*** (0.047)			- 0.189*** (0.053)
No. Observations	120	120	540	120	120	540
No. Instruments/Lags		9/2-4			13/2-4	
Arellano-Bond AR(2) Test		0.737			0.704	
Hansen's J Test		0.204			0.368	

Notes: The dependent variable is Ln of Export Volume. Robust standard errors are reported between brackets. Values reported for the tests are p-values. Significance: 10%=*; 5%=**; 1%=***.

Source: Authors' elaboration.

Table 4: Export performance omitting innovation variables – Low tech

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	SYS-GMM	PMG	FE	SYS_GMM	PMG
Ln of Trade Weighted Income	0.743** (0.302)	0.997** (0.400)	0.238** (0.119)	0.759** (0.297)	1.347* (0.652)	0.250*** (0.095)
Ln of Price Competitiveness	-0.284 (0.182)	0.212 (0.292)	-0.332*** (0.057)	-0.282 (0.182)	0.487 (0.471)	-0.289*** (0.041)
Ln of Trade Weighted Income*Product variety share				0.099 (0.106)	0.418 (0.399)	-0.051 (0.057)
Constant	3.877 (8.563)	-3.275 (11.414)		3.255 (8.402)	-13.930 (18.838)	
Error-correction Term			-0.129*** (0.032)			-0.168*** (0.045)
No. Observations	120	120	540	120	120	540
No. Instruments/Lags		7/2-3			10/2-3	
Arellano-Bond AR(2) Test		0.868			0.952	
Hansen's J Test		0.060			0.151	

Notes: The dependent variable is Ln of Export Volume. Robust standard errors are reported between brackets. Values reported for the tests are p-values. Significance: 10%=*; 5%=**; 1%=***.

Source: Authors' elaboration.

Table 5: Export performance - High-tech

Model	(1) FE	(2) FE	(3) SYS- GMM	(4) SYS- GMM	(5) PMG	(6) PMG
Ln of Trade Weighted Income	1.556*** (0.494)	2.287*** (0.415)	1.144*** (0.308)	2.052*** (0.445)	0.239** (0.118)	1.083*** (0.077)
Ln of Price Competitiveness	-0.141 (0.223)	-0.107 (0.214)	0.099 (0.444)	0.141 (0.425)	-0.482*** (0.077)	0.455*** (0.118)
Ln of Patent Stock	0.529*** (0.151)		0.695*** (0.180)		0.656*** (0.048)	
Ln of Patent Stock Competitiveness		0.546*** (0.163)		0.784*** (0.216)		0.266*** (0.040)
Constant	-25.108* (13.513)	-40.351*** (11.810)	-14.319 (8.460)	-32.633** (12.585)		
Error-correction Term					-0.219*** (0.046)	-0.195*** (0.052)
No. Observations	120	120	120	120	540	540
No. Instruments/Lags			10/2-4	8/2-3		
Arellano-Bond AR(2) Test			0.408	0.299		
Hansen's J Test			0.524	0.468		

Notes: The dependent variable is Ln of Export Volume. Robust standard errors are reported between brackets. Values reported for the tests are p-values. Significance: 10%=*; 5%=**; 1%=***.

Source: Authors' elaboration.

Tables 5 and 6 reinforce the marked differences between the estimated parameters of the two technological sectors. First and foremost, technological elasticities are smaller in low-tech industries (0.3 to 0.4) than in high-tech industries (0.6 to 0.8), revealing that improvements in technological competitiveness exert a stronger impact on the export performance of high-tech goods.¹¹ Second, this difference notwithstanding, income elasticities are still higher in high-tech industries (1.1 to 2.0) than in low-tech (0.2 to 0.8).¹² This important result suggests that demand tends to grow more rapidly for high-tech goods. It is important to note that innovation does not control for all factors comprised in non-price competitiveness. Hence, other non-price factors are still captured in income elasticities of demand. These findings corroborate Romero and McCombie's (2018) study, which reports similar differences in export functions between high- and low-tech sectors, although using total factor productivity as a proxy for non-price competitiveness. Third, price elasticities are more often statistically significant and larger in the low-tech sector (-0.4 to -0.7) than in the high-tech sector (-0.3 to -0.5). This suggests that for less technology intensive industries exchange rate devaluations and cost reductions exert a more relevant

¹¹ Although the high-tech technology elasticity is only 0.27 using PMG, the price elasticity in this regression is positive and significant. This is most likely due to the fact that innovations often result in price increases. Hence, this regression's parameters might be biased due to measurement errors, which are not dealt with in this regression. Therefore, the preferred results are the ones found using the SYS-GMM estimator, which addresses such problem.

¹² When technology stocks are employed, low-tech income elasticities are not significant.

positive impact on exports. This is yet another empirical evidence of the different dynamics that involves the two different types of industries.

Table 6: Export performance - Low-tech

	(1) FE	(2) FE	(3) SYS- GMM	(4) SYS- GMM	(5) PMG	(6) PMG
Ln of Trade Weighted Income	0.327 (0.242)	0.670** (0.268)	0.290 (0.333)	0.834** (0.308)	0.052 (0.081)	0.469*** (0.069)
Ln of Price Competitiveness	-0.700*** (0.156)	-0.697*** (0.156)	-0.541* (0.216)	-0.529** (0.129)	-0.401*** (0.032)	-0.368*** (0.041)
Ln of Patent Stock	0.314*** (0.059)		0.395*** (0.116)		0.293*** (0.029)	
Ln of Patent Stock Competitiveness		0.316*** (0.059)		0.402*** (0.066)		0.273*** (0.030)
Constant	13.777* (7.025)	7.158 (7.495)	14.277 (9.814)	2.632 (8.625)		
Error-correction Term					-0.215*** (0.052)	-0.201*** (0.048)
No. Observations	120	120	120	120	540	540
No. Instruments/Lags			10/2-4	8/2-3		
Arellano-Bond AR(2) Test			0.611	0.476		
Hansen's J Test			0.088	0.382		

Notes: The dependent variable is Ln of Export Volume. Robust standard errors are reported between brackets. Values reported for the tests are p-values. Significance: 10%=*; 5%=**; 1%=***.

Source: Authors' elaboration.

In sum, the results reported in Tables 5 and 6 highlight that non-price and technological competitiveness are more relevant for the export performance of high-tech products, while price competitiveness is a more determinant factor for the exports of low-tech products. As the results found in the previous section, income elasticities are positive and significant in most regressions, and they are always larger when technological competitiveness is employed instead of the domestic technology stock. Interestingly, price elasticities are now larger and most often negative and significant, while technological elasticities are positive and significant in all regressions. Moreover, the sectoral results point out that technological competitiveness influences both the magnitudes of the income and price elasticities. Both of them tend to decrease when technological competitiveness is introduced, revealing an important omitted variable bias in estimates of simple export demand functions.

4.3 Results by country group

Export demand functions were also estimated for three country groups: developed countries; Latin American countries; and Asian countries. In this investigation it was not possible to use the SYS-GMM estimator due to the reduced sample size. Thus, only the

results using the FE and the PMG estimators were reported. PMG is the most suitable estimator for these estimations, since the groups are probably more homogeneous in their long run relationships. Although the FE estimator is also a short-panel technique, as the SYS-GMM, its results were reported to serve as benchmark for comparison with the results of the previous sections. Table 7 reports the results using technological competitiveness as the innovation variable. Similar results were found using technology stocks. Most of the results confirm what was observed in previous sections. Nonetheless, some changes are noteworthy.

Table 7: Export performance and patent stock competitiveness - Country groups

	(1)	(2)	(3)	(4)	(5)	(6)
Model	FE	PMG	FE	PMG	FE	PMG
Country Group	Latin America	Latin America	Developed	Developed	Asia	Asia
Ln of Trade Weighted Income	1.889** (0.536)	1.176*** (0.207)	0.761*** (0.125)	0.603*** (0.119)	0.511* (0.219)	0.646*** (0.116)
Ln of Price Competitiveness	-0.015 (0.015)	-0.003 (0.024)	-0.000 (0.005)	0.013 (0.013)	-0.021 (0.018)	-0.021 (0.018)
Ln of Patent Stock Competitiveness	0.502** (0.154)	0.660*** (0.103)	0.346* (0.149)	0.655*** (0.214)	0.209* (0.093)	0.457*** (0.035)
Constant	-26.348 (15.610)		4.573 (3.477)		11.023 (6.120)	
Error-correction Term		-0.317** (0.149)		-0.271*** (0.078)		-0.465** (0.210)
No. Observations	185	180	185	180	185	180

Notes: The dependent variable is Ln of Export Volume. Robust standard errors are reported between brackets. Significance: 10%=*, 5%=**, 1%=***.

Source: Authors' elaboration.

The coefficients of price competitiveness are not statistically significant in any of the regressions, while income elasticities are always significant. Technology elasticities are similar for all country groups. However, income elasticities are considerably larger for Latin American countries than for the other groups. This result is counterintuitive. Income elasticities should be higher for more developed countries, given that these countries present higher non-price competitiveness. Nonetheless, similar results have been found in other studies (e.g. Romero and McCombie, 2016). An implicit level effect is the most likely explanation for this apparent paradox. In other words, because less developed countries have a small level of high-tech exports, a small increase in exports in absolute terms appears as a high growth rate in such exports. Nonetheless, further work is necessary to fully understand differences in income elasticities between countries.

5 Concluding Remarks

This paper sought to provide new evidence on the role of technological competitiveness for export performance across different sectors and groups of countries. The empirical investigation revealed that technological competitiveness, measured as ratio of domestic technology stock and the trade weighted technology stock of foreign competitors, is in fact a relevant determinant of export performance.

The results suggest that introducing innovation measures in export demand functions is crucial to properly access the determinants of trade. More specifically, the paper showed that the exclusion of such variables inflates both income and price elasticities of demand for exports due to omitted variable bias. Most importantly, the empirical investigation points out that innovation variables exert a direct and consistent influence on the magnitude of the income elasticity of demand, confirming the assumption that this elasticity captures non-price competitiveness. Yet, the results reveal that income elasticities remain significant even when technological competitiveness is introduced. Moreover, Krugman's (1989) hypothesis that income elasticities are proportional to each country's share in the world's total product variety was also tested. The regression results suggest that this hypothesis does not hold considering this paper's sample.

The paper's findings indicate also that technological competitiveness exerts a larger impact on the exports of high-tech products than on low-tech ones. Moreover, in spite of the relevance of technological competitiveness, income elasticities remain positive and significant, and are larger in the high-tech sector. The regression results suggest also that price competitiveness is more relevant in the low-tech sector. Altogether, these findings highlight the importance of moving towards the production of high-tech products in order to achieve higher export growth.

Finally, differences between country groups were assessed estimating export demand functions for three separate country groups: developed, Latin American and Asian countries. The results revealed that technological competitiveness exerts similar impacts on the exports of all country groups. Yet, income elasticities were higher for Latin American countries. This result is counterintuitive, given that income elasticities should be higher in more developed countries due to higher non-price competitiveness. Although this puzzling result could be explained by differences in export levels between the countries, further investigation is necessary to fully understand this result.

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Appendix – Unit root tests

Both Levin, Lin and Chu (2002) (LLC) and Im-Pesaran-Shin (2003) (IPS) tests were employed to test for panel unit roots, and the results are presented in Table A1. These joint tests are more powerful than ordinary cross-section unit root tests. The LLC test performed is adequate for the size of this paper's panel (N between 10 and 250, T between 25 e 250). However, the LLC test assumes the same autoregressive parameter (ρ) for all panel units i . The IPS test relaxes this assumption, allowing each panel unit i to have its own ρ . In both cases, the null hypothesis is that the panel contains unit roots. Table A1 shows that all variables are either $I(0)$ or $I(1)$, which is sufficient for the estimation purpose.

Table A1: Unit Root Panel Tests

	LLC Test		IPS Test	
	Level	First Difference	Level	First Difference
Ln of Export Volume	-2.5017***	-25.0725***	-0.6988	-25.3220***
Ln of Trade Weighted Income	-5.0672***	-11.6432***	-2.4942***	-11.8827***
Ln of Price Competitiveness	-15.7827***	-19.2616***	-17.1773***	-22.4823***
Ln of Patent Stock	-4.6698***	-6.3609***	-0.4620	-8.7806***
Ln of Patent Stock Competitiveness	-0.9677	-8.3530***	1.2439	-11.2164***

Notes: The results for the LLC test are the adjusted t statistics and the ones for the IPS test are the w-t-bar statistics performed for the autoregressive process with an intercept. The Akaike Information Criteria (AIC) is used to select the optimal lag-length. Significance: ***=1%, **=5% and *=10%..

Source: Authors' elaboration.