

Innovation and export performance in different groups of sectors and countries

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Abstract: The aim of this paper is to study, through an empirical investigation, the relationship between innovation, export performance and trade elasticities, by differentiating the results between technological sectors and country groups. The literature of trade recognizes that technology is an important factor of its performance. However, the basic specification of export demand functions accounts only for relative prices and foreign income, not explaining much about the determinants of competitiveness, or whether competitiveness has a technology component. When it comes to price competitiveness, empirical evidence reveals weak or insignificant effects. Hence, influences related to non-price competitiveness are relevant and worth further investigation, as this paper does in a more comprehensive analysis. Broadly speaking, it combines the contributions of the supply-side Schumpeterian approach behind technology and innovation with the demand-side explanation of trade performance across countries. This paper contributes to the literature by reinforcing the results of the impact of innovation, measured by patent stock and patent stock competitiveness, on export performance in different technological sectors, and also analyzing the aforementioned relationship by country groups.

Keywords: Innovation; Export performance; Export demand functions.

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1 Introduction

Traditional export demand functions take into account only relative prices and foreign income, assuming that the income elasticity of demand captures the non-price competitiveness of each country's production. When it comes to price competitiveness, empirical evidence reveals weak or insignificant effects³. Hence, a large part of the empirical literature on the determinants of export performance highlights technology as an important factor of its performance. The influence of innovation on exports is then relevant and worth further investigation, as this paper does in a more comprehensive analysis.

The importance of trade performance for long-term growth was formalized by Thirlwall (1979), who proposed a balance-of-payments constrained growth model based on standard export and import demand functions and a balance-of-payments equilibrium condition. In those equations, non-price competitiveness is summed up in the income elasticities of demand for exports and imports, which in turn are determined by the many supply characteristic of goods, the technological component being one of them. Furthermore, the ratio between export and import income elasticities determines a country's growth on the long run, a relationship known as Thirlwall's Law. However, although non-price factors are identified as the main determinants of long term growth, by being the determinants of income elasticities of demand, most of the original literature does not consider those factors in an explicit manner in their models⁴. Hence, it lacks research concerning those determinants by introducing them in trade equations, in order to investigate the interaction of supply and demand.

The Schumpeterian approach highlights technological innovation, a broad supply-side factor, as the main component of non-price competitiveness. From the literature that considers the importance of this factor, Helpman & Krugman (1985) and Grossman & Helpman (1991) stand out by making a connection with the relationship between trade in intermediate goods and new goods as a source of growth, through the flow of knowledge

³ See, for instance, Bairam (1988), McCombie & Thirlwall (1994) (chapter 4), Carlin, Glyn & Reenen (2001) and Bahmani, Harvey & Hegerty (2013).

⁴ The work of Romero & McCombie (2017) is an exception that combines Schumpeterian elements to the Kaldorian functions, much like what is done in the present paper.

and innovation that allows for more product variety with specialized inputs. Thereby, countries expand their market shares and obtain economic growth.

Nevertheless, the traditional approach does not consider innovative competitiveness in trade functions. But some empirical investigations have incorporated innovation into their trade models, starting with the important specification of Fagerberg (1988) with innovative competitiveness represented by a combined indicator of relative aggregated R&D expenses and patent data. The results indicate significant effects of this supply-side measure of technology on trade. Similar attempts following this paper found similar results, but with different specifications and technological measures, as in Greenhalgh (1990), Magnier & Toujas-Bernate (1994), Amable & Verspagen (1995), Madsen (2008) and Ang, Madsen & Robertson (2015).

This paper aims, therefore, to offer more evidences regarding the impact of the technological component of non-price competitiveness on trade, more specifically on exports, in order to indirectly capture its influence in long-term growth according to Kaldorian theory. Broadly speaking, the paper intends to evaluate whether the supply-side theory behind innovation can add to the demand-side explanation of trade and growth performance across countries. Using patent data and bilateral trade weights, the empirical tests are conducted for a diverse sample of 15 countries, involving developed, Latin American and Asian countries over the period 1976-2012. The tests also differentiate between technological sectors and country groups, specifications not usual in the literature.

The paper is organized as follows. Section 2 discusses the theories and the evidence regarding the determinants of export performance. Section 3 discusses the data and the methodology used to reassess the theories and the evidence on export performance. Section 4 presents the results found using aggregate data, as well as the results found dividing the sample by technological sectors and by 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:

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

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).⁵ 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; Pradhan *et al.*, 2017). In this framework, therefore, traditional export demand functions are augmented to take into account technological competitiveness associated with improvements in product variety or quality:⁶

⁵ Schumpeter's ideas were also incorporated into growth theory (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992; Jones, 2002). Following Schumpeter (1943), in the new growth models of growth with monopolistic competition, innovations result from investments in R&D, and generate temporary monopoly profits.

⁶ 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".

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

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.⁷ 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 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.⁸ 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).⁹ 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

⁷ Soete (1981), Hughes (1986), Wakelin (1998) and Montobio and Rampa (2005) found similar results using different specifications for the determinants of export shares.

⁸ León-Ledesma (2005) evaluated the relevance of knowledge spillovers for trade performance as well, i.e. 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.

⁹ Similar results were found by Anderton (1999), who estimated expanded import demand functions analogous to equation (3) for Germany and the UK.

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

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.¹⁰ 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

¹⁰ Pedroni (2001) and Taylor and Taylor (2004) provide recent evidence of that suggest the validity of relative purchasing power parity in the long term.

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. Thus, Krugman’s (1989) approach implies that introducing measures of product variety or quality into basic export demand functions should eliminate the differences in income elasticities of demand across countries, while the technology elasticity would 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 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 reduces both short- and long-term income elasticities. The elasticities are further reduced when measures of technological competitiveness are introduced, in some cases to the point that the short-term income elasticity becomes 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 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 Empirics

3.1 Econometric specification

Following the discussion presented in the previous section, equation (3) indicates that traditional export demand functions should be complemented with supply-side measures of innovation to capture part of the unobserved non-price competitiveness of goods. Hence, the equation estimated in this paper has the following specification:

$$\ln X_{it} = \beta_0 + \beta_1 \ln YW_{it} + \beta_2 \ln PWx_{it} + \beta_3 \ln TW_{it} + u_{it} \quad (4)$$

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 and TW_{it} is the trade weighted technological competitiveness. 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.¹¹

Trade weighted income for country i was constructed as:

$$YW_{it} = \sum_{j=1}^{26} \frac{Xn_{jit}Y_{jt}}{Xn_{it}} \quad (5)$$

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:

$$PWx_{it} = P_{it} / \left(\sum_{j=1}^{26} \frac{Xn_{jit}P_{jt}}{Xn_{it}} \right) \quad (6)$$

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:

$$TW_{it} = TSTK_{it} / \left(\sum_{j=1}^{26} \frac{Xn_{jit}TSTK_{jt}}{Xn_{it}} \right) \quad (7)$$

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 .

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:

$$TSTK_t = T_t + (1 - \delta)TSTK_{t-1} \quad (8)$$

where T_t refers to the patents in the year t and δ is the depreciation rate, which is taken as 15% following Caselli (2005) and 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 $T_0 / (g + \delta)$,

¹¹ 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.

where T_0 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.

Since technological competitiveness is based on the stock of patents, it is interesting to use it in a second empirical counterpart:

$$\ln X_{it} = \beta_0 + \beta_1 \ln YW_{it} + \beta_2 \ln PWx_{it} + \beta_3 \ln TSTK_{it} + u_{it} \quad (9)$$

where $TSTK_{it}$ is the domestic stock of patents.

Estimating demand functions such as equations (4) and (9) 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.¹² 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 (4) and (9) 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 modeled 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.¹³ A Hausman test

¹² See Roodman (2009b) for a complete discussion of all the problems related to instrument proliferation.

¹³ See Pesaran and Smith (1995) and Blackburne and Frank (2007) for detailed comparisons between the MG and PMG estimators.

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.¹⁴

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 (4) and (5) 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.¹⁵ The PMG estimator, however, requires only that the variables be integrated of maximum order 1, allowing for both stationary and non-stationary variables. 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 (4) and (9) 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).

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

¹⁴ 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.

¹⁵ The results the unit roots tests are presented in Appendix B.

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).

Table 1 presents the descriptive statistics concerning the variables presented in this section. All are within expected range.

Table 1: Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Ln of Export Volume	555	25.11	1.008	21.90	29.23
Ln of Trade Weighted Income	555	28.48	0.543	27.21	30.16
Ln of Price Competitiveness	555	-0.523	2.825	-20.88	2.849
Ln of Technology Stock	555	7.141	3.133	1.072	13.32
Ln of Technological Competitiveness	555	-3.791	3.461	-9.191	3.489

Source: Authors' elaboration.

4 Results

4.1 Main results

Tables 2 and 3 present the regression results for equations (4) and (9) without and with innovation variables, respectively. 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 favor of the instrumental estimation strategy.

Table 2: Export performance omitting innovation variables

	(1)	(2)	(3)
	FE	SYS-GMM	PMG
Ln of Trade Weighted Income	1.075*** (0.267)	1.468*** (0.398)	0.230* (0.122)
Ln of Price Competitiveness	-0.000 (0.009)	0.165 (0.145)	-0.025 (0.016)
Constant	-5.502 (7.613)	-16.477 (11.422)	
Error-correction Term			-0.228***

			(0.072)
No. Observations	555	120	540
No. Instruments/Lags		7	
Arellano-Bond AR(2) Test		0.673	
Hansen's J Test		0.134	

Notes: The dependent variable is Ln of Export Volume. Robust standard errors are reported between brackets. The Arellano-Bond AR(2) is a test of serial correlation, with null hypothesis that there are no serial correlation. The Hansen's J is a test of overidentifying restrictions, with null hypothesis that the instruments are valid. The values reported for the tests are p-values. Significance: 10%=*; 5%=**; 1%=***.

Source: Authors' elaboration.

The results presented in Table 2 indicate that income growth is the most relevant variable in basic export demand functions. As Madsen (2008) pointed out, income elasticities show up higher both in FE and SYS-GMM regressions. Yet, when the PMG estimator is used the magnitude of the income elasticity is considerably reduced, while the error correction term is negative and significant, confirming the cointegration relationship between the variables. Nonetheless, income is still the only significant variable in the regression.

Table 3 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.

Table 3: Export performance - All industries

Model	(1) FE	(2) FE	(3) SYS- GMM	(4) SYS- GMM	(5) PMG	(6) PMG
Ln of Trade Weighted Income	0.785*** (0.275)	1.068*** (0.268)	0.381** (0.210)	0.903** (0.491)	0.011 (0.087)	0.642*** (0.074)
Ln of Price	-0.013* (0.007)	-0.012 (0.007)	-0.039 (0.038)	-0.142 (0.169)	-0.006 (0.010)	-0.003 (0.010)
Competitiveness						
Ln of Patent Stock	0.215** (0.082)		0.312*** (0.056)		0.428*** (0.028)	
Ln of Patent Stock Competitiveness		0.222** (0.088)		0.388** (0.112)		0.461*** (0.031)
Constant	1.213 (7.709)	-4.477 (7.593)	11.919* (6.051)	0.605 (13.669)		
Error-correction Term					-0.347*** (0.086)	-0.333*** (0.084)
No. Observations	555	555	120	120	540	540
No. Instruments/Lags			12	8		
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. The Arellano-Bond AR(2) is a test of serial correlation, with null hypothesis that there are no serial

correlation. The Hansen's J is a test of overidentifying restrictions, with null hypothesis that the instruments are valid. The values reported for the tests are p-values. Significance: 10%=*; 5%=**; 1%=***.

Source: Authors' elaboration.

When technological competitiveness is introduced instead of technology stocks, the variable is 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 4 and 5 report the results dividing the sample into high- and low-tech industries. The results are in general very similar to the ones reported in Table 3. Income elasticities tend to be positive and significant, 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.

Tables 4 and 5 reveal 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.¹⁶ Second, this difference notwithstanding, income elasticities are still higher in high-tech industries (1.1 to 2.0) than in low-tech (0.2-0.8), while in several cases low-tech income elasticities are not significant. 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 & 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 the less technology intensive industries exchange rate devaluations and cost reductions exert a more relevant positive impact on exports. This is yet another empirical evidence of the different dynamics that involves the two different types of industries.

In sum, the results reported in Tables 4 and 5 highlight that non-price and technological competitiveness is 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.

Table 4: Export performance - High-tech industries

Model	(1) FE	(2) FE	(3) SYS- GMM	(4) SYS- GMM	(5) PMG	(6) PMG
Ln of Trade Weighted Income	1.200** (0.432)	1.985*** (0.371)	1.144*** (0.308)	2.052*** (0.445)	0.239** (0.118)	1.083*** (0.077)
Ln of Price Competitiveness	-0.331** (0.146)	-0.303* (0.146)	0.099 (0.444)	0.141 (0.425)	-0.482*** (0.077)	0.455*** (0.118)
Ln of Patent Stock	0.581*** (0.150)		0.695*** (0.180)		0.656*** (0.048)	
Ln of Patent Stock Competitiveness		0.595*** (0.159)		0.784*** (0.216)		0.266*** (0.040)
Constant	-15.377 (11.800)	-31.616*** (10.498)	-14.319 (8.460)	-32.633** (12.585)		
Error-correction Term					-0.219*** (0.046)	-0.195*** (0.052)
No. Observations	555	555	120	120	540	540
No. Instruments/Lags			10	8		
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. The Arellano-Bond AR(2) is a test of serial correlation, with null hypothesis that there are no serial

¹⁶ 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, these parameters are probably biased due to measurement errors. Therefore, the preferred results are the ones found using the SYS-GMM estimator, which controls for such problem.

correlation. The Hansen's J is a test of overidentifying restrictions, with null hypothesis that the instruments are valid. The values reported for the tests are p-values. Significance: 10%=*; 5%=**; 1%=***.

Source: Authors' elaboration.

Table 5: Export performance - Low-tech industries

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	SYS- GMM	SYS- GMM	PMG	PMG
Ln of Trade Weighted Income	0.199 (0.253)	0.537* (0.289)	0.290 (0.333)	0.834** (0.308)	0.052 (0.081)	0.469*** (0.069)
Ln of Price Competitiveness	-0.726*** (0.103)	-0.721*** (0.104)	-0.541* (0.216)	-0.529** (0.129)	-0.401*** (0.032)	-0.368*** (0.041)
Ln of Patent Stock Competitiveness	0.306*** (0.055)		0.395*** (0.116)		0.293*** (0.029)	
Ln of Patent Stock Competitiveness		0.307*** (0.055)		0.402*** (0.066)		0.273*** (0.030)
Constant	17.459** (7.403)	10.884 (8.075)	14.277 (9.814)	2.632 (8.625)		
Error-correction Term					-0.215*** (0.052)	-0.201*** (0.048)
No. Observations	555	555	120	120	540	540
No. Instruments/Lags			10	8		
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. The Arellano-Bond AR(2) is a test of serial correlation, with null hypothesis that there are no serial correlation. The Hansen's J is a test of overidentifying restrictions, with null hypothesis that the instruments are valid. The values reported for the tests are p-values. Significance: 10%=*; 5%=**; 1%=***.

Source: Authors' elaboration.

4.3 Results by country group

Export demand functions were also estimated for the 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. Table 6 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.

The coefficients of price competitiveness are not statistically significant in any of the regressions, while income elasticities are always significant. Technology elasticities are very similar for all country groups. However, income elasticities are considerably larger for Latin American countries than for the other groups. This result is counterintuitive, since 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 a number of studies. An implicit level effect is the most likely explanation for this apparent paradox.

Table 6: 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.

5 Concluding Remarks

This paper sought to provide further evidence on the role of innovation for export performance, while focusing special attention on the relationship between this variable and the magnitudes of trade elasticities. The empirical investigation indicated that innovation, measured as technology stocks and technology competitiveness, is in fact a relevant determinant of export performance.

The results suggest that introducing innovation measures in trade equations is crucial to properly access the determinants of trade. More specifically, the paper shows that the exclusion of such variables from export demand functions inflates the income elasticity of demand due to omitted variable bias. In other words, the empirical investigation points out that innovation variables influence the magnitude of the income elasticity of demand, confirming the assumption that such elasticities capture non-price competitiveness.

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

Finally, differences between country groups were obtained estimating export demand functions for three separate country groups: developed, Latin American and Asian countries. The results revealed that innovation 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 investigations is necessary to correctly understand this result.

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APPENDIX 1 – Unit root test

The Levin, Lin and Chu (2002) test was employed to test for panel unit roots, and its results are presented in Table A1. According to Baltagi (2005), this joint test is more powerful than ordinary cross-section unit root tests that are commonly known for their low power, performing well only in very large samples. The test performed, in turn, is adequate for the size of this paper's panel (N between 10 and 250, T between 25 e 250). However, it is acknowledged that the option of having a unit root or not in all groups is clearly restrictive. The null hypothesis is that the panel contains unit roots. Only the exports and the patent competitiveness variables present unit roots on levels, but both become stationary in first difference. Therefore, the panel presents a mix of I(0) and I(1) variables, which is sufficient for the estimation purpose.

Table A1: Unit Root Panel Tests

	Unadjusted t	Adjusted t	p-value
Ln of Export Volume	-4.1950	-2.0753	0.0190
Ln of Trade Weighted Income	-7.7497	-4.7551	0.0000
Ln of Price Competitiveness	-12.3844	-7.0893	0.0000
Ln of Patent Stock	-5.2870	-4.1792	0.0000
Ln of Patent Stock Competitiveness	-2.7727	-1.0551	0.1457

Source: Authors' elaboration.