The impact of the enlargement process on the export dynamics of the European Union*

Alessandro Antimiani – INEA, National Institute for Agricultural Economics
Valeria Costantini – Department of Economics, University Roma Tre**

Abstract
There have been concerns about the fact that the overall effect of the EU enlargement process would bring to substantial improvement for EU15 export flows towards CEECs rather than increasing trade potential of CEECs. Thus, there is a growing attention to the analysis of the trade effects related to the enlargement process looking at specific sectors rather than on total trade. In this view, a country’s fundamentals, namely its endowments of physical and human capital, labour, and technological capabilities along with the overall quality of its institutions, determine relative costs and the patterns of specialization that go with them. While traditional factors endowments have been deeply analysed, the literature on the potential of the enlargement process in enhancing technological capabilities of CEECs as one of the leading factor fostering the economic performance is still at the beginning. What we will analyse is the impact of the enlargement process on exports dynamics of CEECs, by including in a gravity model the role of technological innovation. Our key finding is that the enlargement process seems to have a larger potential on bilateral trade flows for the CEECs countries than for EU15, and more importantly that a strong impact is detected in economic sectors with higher degree of technological innovation.

Keywords: EU enlargement, Gravity model, International trade, Technological innovation

J.E.L. codes: F14; F15; O14; O33

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** Corresponding author: v.costantini@uniroma3.it
1. Introduction

There seems to be a wide consensus on the fact that CEECs (from now on EU10) have faced as a major challenge during the enlargement process the adoption of the acquis communautaire of the EU, but at the same time this institutional setting has been a leading factor in enhancing the overall economic performance of the new EU members. EU10 have been characterized by high dependence on low-technology sectors, thus being structurally divergent from EU15. There have been concerns about the fact that the overall effect of the EU enlargement process would bring to substantial improvement for EU15 export flows towards EU10 rather than increasing trade potential of EU10. Thus, there is a growing attention to the analysis of trade effects related to the enlargement process looking at specific sectors rather than on total trade.

Previous studies on trade effect related to actions put in place to prepare transition economies for accession in the case of the EU enlargement (in particular Europe Agreements) have found that they have generated a stimulus to trade flows of the EU10.

In this view, a country’s fundamentals, namely its endowments of physical and human capital, labour, and technological capabilities along with the overall quality of its institutions, determine relative costs and the patterns of specialization that go with them. Starting from the idea that not just exports per se matter for growth but that the composition of export is also crucial, we point out, following Feder (1983) that also the technology composition is also relevant (Guaresma, Worz, 2003). Moreover, recent contributes by Hausmann et al. (2007), Lall et al. (2006) and Rodrik (2006) have focused on the large positive impact on economic growth depending on the specialization pattern of export flows in highly sophisticated products.

As well addressed by Dosi et al. (1990) the Hecksher-Ohlin model, which has focused on the relationship between factor endowments and patterns of specialization, has tended to ignore locational questions (by treating trade as costless) and the role of technology (by assuming that it is common to the world). While new trade theories and particularly new economic geography has largely reduce the gap for the first issue, the second question has been extensively considered by economists such as Dosi, Kaldor, Pasinetti, and Pavitt.

To some extent pure neoclassical trade theory finds some difficulties in explaining trade flows, by assuming homogenous technologies among countries. Dosi et al. (1990) and Fagerberg (1994) have strongly criticized this assumption as they have found strong evidence in favour of a patterns of trade essentially determined by technology gaps, as earlier contributions going from Vernon (1966, 1970) to Kaldor (1963, 1981) and the post-Keynesian tradition. Hence, international differences in technological and innovative capabilities play a fundamental role in explaining the differences in both productivity and export competitiveness.

What we analyse is the impact of the enlargement process on exports specialization, by including in a gravity model the role of technological innovation. We have considered initially the 19 industrial sectors as those adopted in the OECD Science, Technology and Industry Scoreboard classified by the degree of technological sophistication, allowing for a full compatibility between bilateral export flows, economic performance and technological innovation of each sector. We have made an effort towards shaping the role of the stock of knowledge by using the number of patents granted for each sector classified by the OECD technology concordance together with the guidelines provided by the European Commissions for linking technology areas to industrial sectors. We have collapsed the 19 sectors into 4 main aggregates (our macro-sectors in the rest of the paper) depending on the technological contents of each sector, thus representing the technological innovative capacity categories proposed by OECD. In this sense, following contributions on the existence of technological revealed comparative advantages as in Archibugi and Pianta (1992), Pavitt and Patel (1988), Pavitt and Soete (1980), where the higher patenting
activities in more advanced sectors produce positive impacts on the international trade dynamics due to increasing export competitiveness.

The econometric strategy here adopted is based on recent works addressing for the role of endogeneity in the trade flows-economic performance relationships which uses Dynamic panel data estimators. Working on a panel dataset allows us exploring the dynamics of export specialization, while considering multiple importing markets. As a consequence, we will be able to provide new insights on the role of the enlargement process in several directions: we argue if the possibility to compete in an integrated market has forced economic structures of new EU countries to specialized into high tech productions, and if this is the case, we will investigate if the European market constitute a privileged importing partner or if the EU10 have reached higher competitiveness on the overall international markets.

While traditional factors endowments have been deeply analysed, the literature on the potential of the enlargement process, i.e. trade increasing, in enhancing technological capabilities of EU10 as one of the leading factor fostering the economic performance is still at the beginning. Furthermore, gravity models on sector-specific trade patterns are rather rare in general, (Baldwin et al. 2005 are the most complete one), but at the best of our knowledge there are no attempts to specifically investigate the role of differences in technological capabilities as a major source of trade performance in a gravity-based model.

Then, what we are interested in is to analyse the impact of the EU enlargement process on the specialization patterns of the EU member states, and particularly if the cohesion and convergence process has promoted export flows in high-technology sectors for the new member states, as a first sign of increasing productivity gains and positive externalities like technology and knowledge spillovers, in spite of less sophisticated activities. At the best of our knowledge, there are no contributions that analyze the impact of the enlargement process on the EU countries, by adopting a gravity model at the sectoral level, while there are no contribution at all in the gravity literature which explicitly consider the role of technological innovation as a leading factor influencing the export dynamics.

2. International trade, technological innovation, economic performance and the EU enlargement

Foreign trade and growth are interrelated through different channels. For Kaldor (1981) Thirlwall (1979) or Fagerberg (1988), international specialisation and growth are related through endogenous technical change. A certain pattern of international specialisation, which manifests itself through particular values for the income and price elasticities of foreign trade, leads to a certain pace of demand growth, which itself induces a certain rate of productivity improvement, which in turn fosters growth through a mechanism of cumulative causation. A direct consequence is that some patterns of international specialisation, associated to high income elasticities for exports for instance, are more favourable for growth than others.1

The relation between trade and growth has also been studied by new growth theory. As argued in Grossman and Helpman (1991), many of the interactions in the global economy generate forces that may accelerate growth: the exchange of technical information and more generally the diffusion of knowledge between technologically advanced countries/sectors/firms and the followers. Trade in commodities may have implications for technical progress and growth, indirectly by facilitating the exchange and generation of ideas, as well as directly, by facilitating access to a wider set of goods which will favour productivity growth. In the context of an

1 See Temple (1999) for a review of all the main issues on this topic as weel as large picture of main empirical approaches.
innovation-based endogenous growth model and apart from any scale effect, trade may prevent, duplication in research and promote the differentiation of innovations (Rivera-Batiz and Romer, 1991), enhancing productivity and/or consumers’ utility. The authors have tested the impact of the pattern of foreign trade on growth using three different variables reflecting the pattern of international specialisation of a country. The results are that international specialisation matters for growth. Countries whose foreign trade structure is more specialised at the inter-industry level have enjoyed a faster productivity growth than less specialised countries. This would tend to give support to the traditional argument, concerning the gains from trade and the consequences on resources reallocation (Amable, 2000).

Being a component of GDP, exports contribute directly to national income growth. There are also indirect impacts due to economies of scale, increased capacity utilization, productivity gains, and greater product variety. Moreover, a greater exposure to international transactions may induce pressure of firms leading to technological innovation and upgrading. All these trade related aspects were firstly put forward in the international economics literature during the ‘80s (Feder 1983; Bhagwati and Srinivasan 1978; Krueger 1980). More recently, the academic literature put emphasis on the role of trade in fostering innovation and facilitating knowledge and technology transfer, as described in the seminal work by Grossman and Helpman (1991).

However, Temple (1999) claims that often empirical researchers do not stress the difference between technical progress and productivity levels, because the same technical progress could have different impacts on the productivity level since the latter is highly influenced by local factors.

The empirical literature which tests the positive impacts of opening to trade flows on the economic performance is rather extensive, from the first contributions by Balassa (1978, 1984), up to the recent growth literature as in Dollar and Kraay (2004), and Winters (2004). Some cautions have been addressed by development economists such as Rodriguez and Rodrik (2001), in the large debate on the potential positive or negative role of the economic globalization process.

More recently, a specific attention has been devoted to the quality of exports, or saying with Hausmann et al. (2007), what you export matters. Drawing on the contributions of Lall et al. (2006) and Rodrik (2006), Hausmann et al. (2007) give a clear picture of the strong impact on economic growth performances related not only to the export dynamics, but more importantly on the changes in the composition of exports. Countries which are experiencing higher growth rates are those with a well defined specialization process towards economic sectors with higher added value, which correspond to the sectors with a more dynamic technological innovation path. In this sense, the recent efforts played by OECD in the policy discussion papers and in the periodical publication of the “OECD Science, Technology and Industry Scoreboard” have produced a significant interest in the linkages between technological innovation and export competitiveness.

Fosu (1990) studies the effect of manufacturing exports on growth for developing countries as compared to primary sector exports, and reaches the conclusion that there is a differential positive impact by the manufacturing export sector. Greenaway et al. (1999) is one of the few existing contributions that directly studies the growth effect of disaggregated exports. Here, certain industries (fuel, metals, and textiles) are identified as having a special importance for developing countries’ growth performance. Amable (2000), Laursen (2000), and Peneder (2003) investigate the effect of trade specialization (in relation to all other countries) in specific industries. All three studies find evidence for an impact of trade specialization on growth. Amable (2000) identifies specialization as such to be growth enhancing, but especially specialization in electronics. Laursen (2000) arrives at similar results, reporting that specialization in fast-growing sectors (which correspond in general to high-tech sectors) is related to GDP. Peneder (2003) finds that specialization in services represents a burden to future growth whereas exports of
technology-driven and high-skill-intensive industries have positive effects on aggregate growth. The last two contributions refer to OECD countries while Greenaway et al. (1999) restrict their analysis to developing countries.

Eaton and Kortum (2002) have clearly shown that countries’ relative productivities vary substantially across industries, so that in a Ricardian model of international trade based on differences in technology, the sectoral technological specialization hardly affects export dynamics and consequently economic growth performances. This last evidence is also confirmed by Greenaway et al. (1999), showing that economic growth is not only associated with export growth, but more importantly export composition hardly influence differences in economic performance at the country level. Moreover, the interpretation of the role of technology in explaining the export dynamics provided by Eaton and Kortum (2002) is quite attractive. Each country’s state of technology influences the absolute advantages, while the heterogeneity of technological specialization governs comparative advantages. In their contribution the authors use a theoretical model for international trade where technology is the parameter to be estimated by using a gravity equation. In our work, we assume that economic integration of EU10 countries into the European Union has brought to a convergence in the technological specialization patterns, and we want to investigate if these changes has influenced the export dynamics of EU member states.

In the context of this wide theoretical literature, the EU enlargement process clearly represents an interesting and useful case study in order to evaluate the relationship between trade and technological innovation.

Many empirical contributions has been focused on the agri-food sector, since its relevance in the economy of EU10, and more importantly the large potential impact related to previous high tariffs profiles. More general analyses on trade patterns of EU10 after during the enlargement are not frequent. As a general consideration, structural features of new accession countries are so distant in some cases that the evolution of single new members state could be hardly dissimilar, so that empirical analyses should take into account carefully differences existing among EU10 (De Benedictis and Tajoli, 2006). In a early report of the European Commission², this aspect has been particularly stressed, underlining the differences among CEECs countries, especially with respect to role of the Agri-food sector. CEECs have been characterized by high dependence on the agricultural sector, thus being structurally divergent from EU-15 and at the same time bringing many difficulties in the CAP setting (Rollo, 1995). Recently, Bartosova et al (2007) use a dynamic panel model to analyze the impact on imports and exports of CEECs due to the enlargement, by using unilateral trade flows for different economic sectors. Drabik and Bartova (2007) use an interesting approach to check the post accession trade specialization of CEECs and they conclude that the EU enlargement have not produced significant changes of trade composition by partners/grouping even if CEECs improve their ability to improve competitive position in trade with all trade groups.

However, one of the main issue of the enlargement process is if it has facilitated knowledge and technology transfer from old to new member states. To the best of our knowledge there are very few contributions on technological innovation for Eastern European countries (Krammer, 2009 is the most recent one) and more specifically on the linkages between technological innovation and catching-up in trade flows (Cavallaro and Mulino, 2008). The two mentioned papers both provide empirical evidence of the positive role of the enlargement process on technological catching-up and vertical innovation for the EU10, but the linkages between innovation and trade are not deeply investigated.

² Analysis of the impact on agricultural markets and income of EU enlargement to the CEECs, march 2002, directorate General for Agriculture.
3. The gravity equation for trade flows

According to the generalized gravity model of trade, the volume of trade between pairs of countries \( X_{ij} \) is a function of their incomes, their populations, their geographical distance, and a set of dummies representing different aspects as the existence of free trade agreements or past colonial relationships or many other specific features, as shown by the equation

\[
X_{ij} = Y_i^\alpha Y_j^\beta POP_i^\gamma POP_j^\delta DIST_{ij}^\epsilon Z_{ij}^\zeta X_i^\rho X_j^\sigma \exp(\alpha_{ij} + \gamma D_{ij})u_{ij}
\]  

[1]

where \( Y_i \) and \( Y_j \) indicate the GDPs of the reporter and the partner, respectively, \( POP_i \) and \( POP_j \) are reporter and partner populations, \( DIST_{ij} \) measures the distance between the two countries’ capitals (or economic centers), \( Z_{ij} \) represents any other factors aiding or preventing trade between pairs of countries. \( X_i \) and \( X_j \) represent specific reporters and partners features which may affects trade flows. The model may also include dummy variables \( (D_{ij}) \) for trading partners sharing a common language, a common border, or the existence of past colonial relationships, as well as trading blocs’ dummy variables which evaluate the effects of preferential trading agreements or integrated economic areas. \( \alpha_{ij} \) represents the specific effect associated with each bilateral trade flow (country pairs fixed effects), as a control for all the omitted variables that are specific to each trade flow and that are time-invariant, while \( u_{ij} \) is the error term.

For estimation purposes, the log-linear transformation is usually adopted, interpreting the coefficient values as elasticities.

Although the theoretical support for the gravity model was originally very poor, since the second half of the 1970s, several theoretical developments have filled this gap. Anderson (1979) made the first formal attempt to derive the gravity equation from a model that assumed product differentiation. Bergstrand (1985, 1989) also explored the theoretical determination of bilateral trade in a series of papers, in which gravity equations were associated with simple monopolistic competition models. Helpman (1987) used a differentiated product framework with increasing returns to scale to justify the gravity model. More recently, Deardorff (1995) has proven that the gravity equation characterizes many models and can be justified from standard trade theories. Anderson and Wincoop (2003) derived an operational gravity model based on the manipulation of the Constant Elasticity of Substitution (CES) system that can be easily estimated and helps to solve the so-called border puzzle. According to these authors, multilateral trade resistance terms (MRTs) should be added into the empirical estimation to correctly estimate the theoretical gravity model. A simple and intuitive way to do this in cross-section studies is to proxy these terms with country dummy variables or, in a panel data framework, with bilateral fixed effects. The empirical contributions by Baldwin and Taglioni (2006) and Baier and Bergstrand (2007) suggest that by including specific country-pairs time-variant fixed effects allows representing the multilateral resistance terms in appropriate way. As we are considering a panel version of a gravity equation, with a temporal dimension added to the cross-section one, the log-linear form of equation (1) accounting for country fixed effects is given by:

\[
\ln X_{ijt} = \alpha_{ij} - \ln D_{it}^{\frac{1-\sigma}{\sigma}} - \ln D_{jt}^{\frac{1-\sigma}{\sigma}} + \gamma D_{ij} + \beta_1 \ln Y_i + \beta_2 \ln Y_j + \beta_3 \ln POP_i + \beta_4 \ln POP_j + \\
+ \beta_5 \ln DIST_{ij} + \beta_6 \ln Z_{ij} + \beta_7 \ln X_i + \beta_8 \ln X_j + \nu_{ijt}
\]  

[2]

where the trade values from country \( i \) to country \( j \) in period \( t \) are expressed in current US$, as the formulation of the multilateral resistance terms requires.

The theoretical gravity equation proposed by Anderson and van Wincoop (2003) requires to consider explicitly the effects of the existence of multilateral resistance terms, which are
represented by $P_{it}^{1-\sigma}$ and $P_{jt}^{1-\sigma}$ as time-varying multilateral (price) resistance terms for each $i$-th reporter and $j$-th partner respectively. As suggested by Baldwin and Taglioni (2006) the MRTs will be proxied with 2NT ($N =$ countries, $T =$ years) dummies for unidirectional trade. Finally, $u_{it}$ denotes the error term.

Recent theoretical advancements have addressed another crucial problem related to the existence of a large number of zero trade flows values which may produce important biases in the statistical procedure. The earlier approaches to handle these estimation biases were: i) to discard the zeros from the sample; and ii) to add a constant factor (equal to 1) to each observation on the dependent variable, so that the log-linearization of $(0+1)$ trade flows gives zero values (Chen, 2004, among the others). As emphasized by Martin and Pham (2008), this strategy is correct as long as the zeros are randomly distributed. However, if the zeros are not random, as is usually the case, this induces to selection bias. Very broadly, recent contributions have proposed two main alternative solutions. The first one consists in the adoption of a non linear estimator as the Poisson-Pseudo Maximum Likelihood estimator as proposed by Santos-Silva and Tenreyro (2006) and Westerlund and Wihelmssson (2006).

The second one is a Heckman’s two stages procedure (Heckman, 1976) consisting in a first-stage probit selection equation where the dependent variable is a binary variable assuming value 0 is there is no trade flows ad 1 otherwise. The estimated parameters are used to calculate the inverse Mills ratio, which is then included as an additional explanatory variable explaining sample selection biases in the second-stage standard gravity model with values of trade flows (Chevassus-Lozza et al., 2008; Olper and Raimondi, 2008). Following Martin and Pham (2008), the Pseudo-Maximum Likelihood procedure with a Poisson estimator is not efficient when there are many zeroes. As in the estimation of the equations for macro-sectors for the EU10 we have many zero values, the two step procedure is rather preferable. Moreover, the theoretical foundation of this procedure has been established by Helpman et al. (2008), which have shown that a great part of biases is not due to selection biases but due to neglecting the impact of firms heterogeneity. The two steps Heckman’s sample-selection procedure may give very poor results when estimated for a single equation with the same variables in the selection and estimation equations. Hence, Helpman et al. (2008) suggest that there are some variables related to the fixed costs of establishing trade flows that should be appropriately excluded from the equation for the level of trade. The model yields a generalized gravity equation that accounts for self-selection of firms into export markets and their impact on trade volumes. It is a more flexible model than Anderson and Wincoop (2003) model since it accounts for the fact that most countries trade only with a fraction of the countries in the world economy. It suggests that the decision to export is not independent of the volume of exports. The authors derive from this theory a two-stage estimation procedure that enables one to decompose the impact on trade volumes of trade resistance measures into its intensive (trade volume per exporter) and its extensive (number of trading firms) margins. They also show that most of the bias is due to the omission of the extensive margin (number of exporters), rather than to selection into trade partners. This last results is confirmed by recent empirical contributions applying the HMR procedure to panel data (Martinez-Zarzoso et al., 2009). As explained by Helpman et al. (2008), in addition to the inverse Mills’ ratio (explaining sample selection bias) a second variable

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3 A common application of the inverse Mills ratio (sometimes also called ‘selection hazard’) arises in regression analysis to take account of a possible selection bias. If a dependent variable is censored (i.e., not for all observations a positive outcome is observed) it causes a concentration of observations at zero values. The inverse Mills ratio is the ratio of the probability density function of the predicted values from probit estimation over the cumulative distribution function of the predicted values.
related to the impact of firms heterogeneity should be included, simply given by $\omega_{ij}$ that is an increasing function of the fraction of country $i$ firms that trade with country $j$. The new variable, $\omega_{ij}$, is an inverse function of firm productivity, constructed as the predicted probability of trade from country $i$ to country $j$, using the estimates from the first stage probit equation.

Last recent development in the gravity equation modelling concerns a dynamic specification of trade flows that allows for addressing two additional problems. The first one arises from the autocorrelation of the residuals caused by a strong hysteresis in trade flows related to the presence of trade sunk costs (Bund and Klaassen, 2002; De Benedictis et al., 2005; De Nardis and Vicarelli, 2007). The second one is given by the existence of endogenous regressors as in the case of Free Trade Agreements (Baier and Bergstrand, 2007; Carrere, 2006).

System GMM proposed by Blundell and Bond (1998) is useful for the estimation of a theoretically founded gravity models allowing for instrumenting endogenous variables and correcting for autocorrelation of the residuals. Compared to the Arellano and Bond (1991) GMM in difference estimator, system GMM allows also to not exclude fixed effects related to importing and exporting countries as well as country pairs and all other time invariant variables. The System GMM adds to GMM in difference untransformed level equations instrumented by first difference and Bond (2002) shows that it is more efficient than the GMM if the panel is short in time ($T$) and large in cross-section units ($N$) and if it includes persistent time series.

Our dataset is large in cross-section units and short in time, trade flows present strong persistence in the short-run thus requiring a dynamic approach. More importantly, the technological innovation variable included among the regressors is typically endogenous, due to the high correlation with trade dynamics. As a general result, it is true that increasing investments in innovation brings to improvement in the production capacity and in the medium-run in the export competitiveness. But it is also true that those sectors which are characterized by an higher openness degree can benefit from international knowledge spillovers resulting in an increased innovative capacity. Considering that the enlargement process has brought to a relatively rapid opening process for the accession countries, the increase in trade flows could have reasonably influenced the technological capabilities of industrial sectors.

4. **Econometric specification and dataset description**

The final equation we have estimated for the trade flows of the European Union countries is based on the Helpman (1995) factor based gravity model, thus considering as dependent variable the export flows. This is a usual assumption when the purpose of the analysis is the understanding of factors driving international competitiveness associated to a certain event, as is the case of the enlargement process.

From a pure econometric point of view, we have adopted a theoretically based gravity model à la Anderson and van Wincoop (2003) by including countries fixed effects, in a slight different way from suggestions by Baldwin and Taglioni (2006) and Baier and Bergstrand (2007), because number of observations for the EU10 sample provides insufficient degrees of freedom for the estimation of $2NT$ ($N$= countries, $T$ = years) dummies for unidirectional trade in a System GMM. Hence, we have adopted the approach suggested by De Benedictis et al. (2005) by including exporting and importing ($\alpha_i$ and $\delta_j$ respectively) countries fixed effects, and a country-pairs time-variant trend variable calculated as the interaction between temporal trends and fixed effects for country pairs ($\text{trend}_{ij}$).

We have also adopted the two stages procedure proposed by Helpman et al. (2008), as the inclusion of a time-variant control variable ($FHET_{ij}$) for firms heterogeneity coming from a first stage probit selection equation is necessary to correct for biases coming from zero export flows in the dataset (especially for the EU10 sample). In order to include a specific transaction cost variable
related to firms heterogeneity that is not included among the regressors of the second stage estimation, we have decided to adopt the Cost of Doing Business variable provided by the World Development Indicators dataset (World Bank, 2008). As described in Helpman et al. (2008) there are a number of alternative measures representing this dimension, but this specific variable is available for the widest j countries sample and it is strongly correlated with the other similar variables, thus well representing this dimension.

We have also addressed dynamics by including lags of our dependent variable, and endogeneity of the technological innovation variable by instrumenting it with lags. As we have already mentioned the best approach to consider all these shortcoming together is the System GMM estimator proposed by Blundell and Bond (1998), which allows to treat autocorrelation of the residuals and endogeneity of the regressor as well as taking in the estimation all time-invariant variables (otherwise dropped by a GMM estimator).

The final equation for our gravity model is given by

\[ x_{ijt} = \alpha_i + \delta_j + \pi_{it} + \sum_{p=1}^{n} \lambda_p x_{ij,t-p} + \beta_1 \text{COL}_{ijt} + \beta_2 \text{CONT}_{ijt} + \beta_3 \text{dist}_{ijt} + \beta_4 \text{land}_{ijt} + \beta_5 \text{mass}_{ijt} + \beta_6 \text{simil}_{ijt} + \]

\[ + \beta_7 \text{endow}_{ijt} + \beta_8 \text{techno}_{ijt} + \beta_9 \text{ENL}_{ijt} + \beta_{10} \text{kpat}_{i,t-q} + \beta_{11} \text{prod}_{ijt} + \epsilon_{ijt} \]  

where lower case letters denote variables expressed in natural logarithms and upper case letters indicate dummy variables.

The country sample here considered is made of 24 exporting countries (the \(i\)-th countries), 14 old EU members (all EU15 members excluding Luxembourg) and 8 new CEECs member states (Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovak Republic, Slovenia). The \(j\)-th importing countries are 145, chosen on the basis of the data availability, and considering that in all cases the export flows from the \(i\)-th countries to the 145 \(j\)-th partners constitute more than 95% share of total export.

The time period analysed goes from 1996 to 2007, thus allowing to include all EU15 as already existing EU member states, while considering only the CEECs as new members. The full sample therefore covers a total of 41.760 potential available observations (24*145*12), of which 24.360 refer to EU15 and 17.400 to EU10.

Trade data on export flows are taken from UNCTAD-COMTRADE database, based on the Harmonised Commodity Description and Coding System (HS 1996) expressed as unilateral export flows in current value (US$) from country \(i\)-th to country \(j\)-th in the period 1996-2007.

The standard gravity variables related to the geographic dimension are taken from CEPII, where \(\text{COL}_{ij}\) and \(\text{CONT}_{ij}\) are dummy variables related to the existence (value 1) or not (value 0) of past colonial relationships and a common geographical border between each country-pairs. The log of distance (\(\text{dist}_{ij}\)) is calculated as the great-circle formula (Mayer and Zignago, 2006) and land, represent the log of surface area of the importing countries. We expect that coefficients for COL and CONT should be positive, while for DIST and LAND should be negative. While distances are considered as a proxy of transport costs, the surface area of the importing countries gives a

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4 Martinez-Zarzoso et al. (2008) do not include this variable in the first stage probit model while Martin and Pham (2008) strongly recommend this procedure.
5 We have not considered countries of the new enlargement wave and potential candidates (i.e., Bulgaria, Romania, Croatia and Turkey) because of lack of data at disaggregated level.
6 This choice is quite necessary considering the availability of patents data, which are not so consistent for CEECS before 1996. Finally, structural data on specific economic sectors are rather difficult to obtained in a long time series, and this is particularly true for CEECs.
dimension to the role of intra-national trade, as well as the larger the country, the higher the intra-national trade share respect to total trade.

Considering our general factor endowments approach, we have adopted some specific combinations of variables explaining the role of the economic dimensions of the trading partners as well addressed by many empirical contributions. In particular, we have included as a standard measure of relative country size the similarity index of the GDPSs of two trading partners (simil$_{ijt}$) firstly proposed by Breuss and Egger (1999), calculated as:

$$
\text{simil}_{ijt} = \ln \left[ 1 - \left( \frac{GDP_{ijt}}{GDP_{it} + GDP_{jt}} \right)^2 - \left( \frac{GDP_{ijt}}{GDP_{it} + GDP_{jt}} \right)^2 \right] \quad [5]
$$

This index is bounded between 0 (absolute divergence in size) and 0.5 (equal country size). The larger this measure and, thus, the more similar two countries in terms of GDP, the higher the share of intra-industry trade. It is also clear that the total volume of trade should be higher, the larger the overall economic space. We have employed a synthetic measure of the impact of country-pair size as a proxy of the “mass” in gravity models, mass$_{ijt}$, calculated as the sum of value added at constant term of the exporting and importing countries (De Benedictis et al., (2005a)):

$$
\text{mass}_{ijt} = \ln(GDP_{it} + GDP_{jt}) \quad [6]
$$

We have also included a measure of the distance between domestic endowment, endow$_{ijt}$, approximated by the standard formula proposed by Egger (2002) and now widely diffused in empirical gravity models the absolute difference in relative factor endowments between country-pairs. This is calculated as:

$$
\text{endow}_{ijt} = \ln \left( \frac{GDP_{it}}{POP_{it}} \right) - \ln \left( \frac{GDP_{jt}}{POP_{jt}} \right) \quad [7]
$$

In line with Helpman (1987), the GDP per capita can be considered as a proxy for the capital-labor ratio of each country as suggested in Breuss and Egger (1999) and Egger (2002). This Heckscher–Ohlin-type interpretation stems from Bergstrand (1985) and is based on Kaldor’s (1963) stylized facts. An increase in the capital labour ratio will increase GDP per capita. The importers’ GDP per capita (GDP$_j$) is usually interpreted as an indicator of the sophistication of demand in the importing country. The coefficient of the importer’s per capita income is its income demand elasticity. If this value is greater than unity, imported goods are classified as so-called luxury goods, if it is less than unity they are so-called necessities. This variable could take a minimum value of 0 (equality in terms of relative factor endowments). According to theory, the larger this difference, the higher the volume of inter-industry trade, and the lower the share of intra-industry trade. Data on GDP and population come from World Development Indicators online database.

When we explore trade patterns for different sectors, there are other factors than pure border effects which affect bilateral trade flows. A type of distance rarely used is the technological distance, that allows to better shaping what is normally attributed to undistinguished country fixed effects. Intuitively, assuming that the technological gap can be a check on trade and remembering that similar countries have more intensive commercial relations (intra-industry trade), we expect a negative correlation between the technological distance and the bilateral
export flows. In the contribution by Filippini and Molini (2003) technological distance is a general variable for each country, while we would like to investigate the role of such distances at the sector level. In order to catch the propensity of \( j \)-th countries to import goods with different technological characteristics, we have computed a technological distance variable (TECDIS) as the absolute difference of values assumed by the ARCO technological capabilities index developed by Archibugi and Coco (2004).

Starting from the catching-up hypothesis by Abramovitz (1986), where the level of education may be one way to measure social and technological capability, the theoretical and empirical analyses have considered several ways to measure technological capabilities. One of the most complete and recent work in this sense is the contribution of Archibugi and Coco (2004).

We have built a technological distance index (tecdis\(_{ijt}\)) based on only two out of the four components proposed by Archibugi and Coco (2004). In order to represent the diffusion of technological infrastructures we have accounted for internet and telephone penetration (number of internet, fixed and mobile telephone lines per 1,000 persons) and per capita electricity consumption. The second dimension related to the creation of human capital resources is the average of two components associated to the domestic efforts in human capital accumulation, expressed as the secondary gross enrolment ratio, and to influence produced by Foreign Direct Investments (FDI) inflows. This second dimension draw on results provided by Eaton and Kortum (1996), which have estimated that a country’s level of education significantly facilitates its capability to adopt technology. The final formulation of the ARCO index is given by

\[
ARCO_{jt} = \frac{1}{2} \left[ \frac{1}{3} \left( \frac{\ln(TEL_{jt})}{\ln(TEL_{\text{max}})} + \frac{\ln(INTERNET_{jt})}{\ln(INTERNET_{\text{max}})} + \frac{\ln(ELECAP_{jt})}{\ln(ELECAP_{\text{max}})} \right) + \frac{1}{2} \left( \frac{\ln(EDU_{jt})}{\ln(EDU_{\text{max}})} + \frac{\ln(FDI_{jt})}{\ln(FDI_{\text{max}})} \right) \right]
\]

while the final index for technological distance between each pair of \( ij \) countries at time \( t \) is computed as the absolute value of the difference between ARCO\(_{jt}\) and ARCO\(_{ij}\).\(^7\)

In order to investigate if the enlargement process has produced some effects on trade patterns on EU member states we have introduced a dummy variable for the “EU membership” effect. Countries joining EU should have benefited from European trade integration process, thus the variable assumes values 0 up to the moment when the country enter in the EU, and then value 1. As in (De Benedictis et al., 2005; Paas, 2001, Sapir, 2001) we have computed three different variables, namely CEFTA, BAFTA and ENL\(_{ijt}\)= a dummy variable embodying the ‘announcement effect’ of the entrance of the eight new member countries into the EU. This announcement corresponds to the date of European Council meeting of Laeken in December 2001; the dummy assumes the value of 1 since 2002 for all country pairs in the sample.

A stock of knowledge is created as an explanatory variable in the gravity model for the four macro-sectors. The knowledge stocks are defined following the stock of knowledge function considering only the accumulation issue and the related decay rate of the stock, while excluding the

\(^7\) As we can see, the formulation of the ARCO index is based on the same methodology adopted for the Human Development Index (HDI), where the observed values are normalised by a minimum and maximum value. In this case the minimum value is always equal to zero whereas the maximum value has been taken in the whole time period/countries sample considered in this work. This formulation gives us the possibility of accounting for temporal changes at country level as well as the methodology adopted by UNDP for the HDI. Following the UNDP methodology, all the component have been considered in a logarithm form, creating a threshold above which the technological capacity of a country is no longer enriched by the increase of single components.
component related to diffusion (Popp, 2001, 2002, 2005). This choice is related to the fact that Popp accounts for the diffusion of technologies by assigning patents also to the end-user sectors rather than only the innovation producer. Our data allow us to assign 4 digit patents codes to the inventing industries so that our stock of knowledge function is defined as:

\[
K_{PAT}^k = \sum_{s=0}^{t} PAT^k_{is} e^{-\beta_1(t-s)}
\]

where \( K_{PAT}^k \) represents the knowledge stock in industry \( k \) for each \( i-th \) exporting country at time \( t \), and \( s \) represents an index of years up to and including year \( t \), \( PAT^k_{is} \) represents the number of patents produced by industry \( k \) in country \( i \) in year \( t \), and \( \beta_1 \) represents a rate of decay, and we have taken an average value of 0.3 as a mean value from the literature. The stocks allow us to estimate an overall knowledge production function, considering that in most of the cases the capacity to apply for a patent to a patent office (and more importantly to an international patent office such as EPO) hardly depend on previous experience, so that the higher the number of patents granted to a certain firm, the higher the probability that this specific firm will apply for new patents. Moreover, the skills acquired during first applications can be considered as sunk costs, while the marginal cost of succeeding application is rather lower than in the beginning (we are not referring to the R&D costs but only to transactional costs for filling patents).

The year of the patent application is used because patents sorted by application years are closely correlated with R&D expenditures (Griliches, 1990).

We use a stock of knowledge function instead of a pure patents count approach because there exists convincing empirical evidence that cumulative domestic innovative efforts is an important determinant of productivity and competitiveness (Coe and Helpman, 1995).

As already mentioned, by using patent counts as a measure of the stock of knowledge allows us to avoid some of the pitfalls encountered when using R&D expenditures. Patent data also offer other advantages. Unlike other data on inventive activity, such as R&D expenditures, patent data are available in highly desegregated forms. Furthermore, using patent data allows us to construct a longer time series, as data on R&D by industry for the CEECs are not available until 2001.

It is a reasonable assumption to adopt patents as a measure of the inventive capacity and the accumulation of patents in specific sectors as a proxy of the stock of knowledge available for each sector, as clearly explained by Griliches (1990), and recently adopted by Eaton and Kortum (1996) and Coe and Helpman (1995) specifically for the analysis of the linkages between technological innovation and international trade. The high correlation between R&D efforts and patenting activity is now widely accepted, while some problems may arise when we consider the decreasing returns to investments especially for mature sectors. If we consider a patent indicator built on a specialization patterns rather than on pure patents count, we partially reduce this problem. What we argue here is that we are investigating the specialization of producing innovation in each sector compared to the general efforts, thus adopting a patent indicator that is partially disentangled from the R&D patterns. Nonetheless, some cautions must be adopted in the interpretation of the results, especially when comparing EU15 with EU10. Moreover, patent data have been widely used to analyse the competitiveness of various countries at the international level by constructing revealed technology advantage indexes, and describing the international location of inventive capacity in different industries (Archibugi and Pianta, 1992; Coe and Helpman, 1995; Dosi et al., 1990; Eaton and Kortum, 1996, 2002; Fegerberg, 1994; Pavitt and Patel, 1988; Pavitt and Soete, 1980).
Moreover, as we are conscious that RD productivity expressed as patent to RD ratios is decreasing over time especially after the sector has become mature (or it is well developed in a country), by taking the stock we are implicitly evaluating the accumulation of the stock of knowledge in the followers (EU10) with an higher weight than those of the leaders (EU15). Considering that an RD effort in a follower produces, ceteris paribus, an higher output (number of patents), by accounting of the accumulation of knowledge stock, we are considering increasing returns to scale for EU new member states investments in new technologies.

Patenting activities are costly, requiring the publication of the specification of the invention in the local language in the country granting protection, and the payment of a filing fee. As well as we consider only patents applied into the European Patents Office, which is generally more expensive than patenting in domestic patents offices, assuming that the marginal benefits from patenting are at least equal to marginal cost, we are assuming that firms apply to EPO only for economically valuable inventions.

However, when working with patent data, it is important to be aware of its limitations. The existing literature on the benefits and drawbacks of using patent data is quite large. An important concern is that the quality of individual patents varies widely. Some inventions are extremely valuable, whereas others are of almost no commercial value. This is partly a result of the random nature of the inventive process. Accordingly, the results of this paper are best interpreted as the effect of an “average” patent, rather than any specific invention. However, there are other reasons for variation in the quality of patents that can be controlled. For example, the propensity to patent varies widely by industry. In some industries, secrecy is a more important means of protection. In these industries, the cost of revealing an idea to competitors is often not worth the gains from patent protection. Moreover, not all inventions are patentable, and not all inventions are patented, because the magnitude of the inventive output differ greatly due to specific sectoral and firms characteristics (Griliches, 1990). This specific point is hardly linked with the different propensity to export due to firms heterogeneity. In this sense, the adoption of the two step procedure suggested by Helpman et al. (2007) especially with the inclusion of an ad hoc variable referred to firms heterogeneity in the first selection estimation allows us reducing possible biases related to the technological innovation dimension.

As a result, the correlation between R&D and patents varies across industries. It is for this reason that separate regressions are done for each industry. Estimating different regressions for each industry controls for variations in the propensity to patent across industries. Another possible problem is that the propensity to patent may vary over time. Historically, the ratio of patents to R&D expenditures has fallen in the United States (as well as in other industrialized nations). Some researchers, such as Evenson (1991) and Kortum and Lerner (1998), consider the falling ratio to be evidence of diminishing returns to R&D. Other researchers, most notably Griliches (1989, 1990), claim that research opportunities have not declined, but rather that the fall in the patent-to-R&D ratio is due to changes in the willingness of inventors to patent new inventions. As stressed by Popp (2002), using patents weighted by the patent-to-R&D ratio as an attempt to control for possible changes in the quality of patents over time has no effect on the final results, so we have used patents counts and stock of knowledge. In order to control for sectors heterogeneity, we have run a second estimation by using a stock of knowledge weighted by the number of employees or alternatively by the sectoral production value. In both cases results remain robust and coherent.

The macro-sectors here considered are 4, classified by OECD Technology Scoreboard into high-technology, medium-high-technology, medium-low-technology, and low-technology industries. The sectors are classified by using the ISIC Rev.3 classification as described in Table 1, and the linkages between ISIC Rev.3, NACE and IPC codes are also reported.
In this way it is possible to put together data coming from different sources, such as the STAN database, the structural economic data form EUROSTAT and data for patents from PATSTAT. The classification of patents data is taken from Johnson (2002) and Schmoch et al. (2003), referring to 46 industrial sectors classified by using ISIC Rev.3 which are related to the International Patents Classification codes by WIPO. We have collapsed the original 46 sectors into the 19 sectors and the 4 macro-sectors used for the Annual OECD Technology Scoreboard Report, thus obtaining a set of industrial sectors where data on trade flows, structural characteristics and patents are fully comparable. In the last column Table 1 we have reported the original patents fields used by Schmoch et al. (2003) for linking patents codes with industrial sectors.8

Table 1 – Classification of industrial sectors and concordance with patents fields

<table>
<thead>
<tr>
<th>Macro sector</th>
<th>Sector</th>
<th>ISIC Rev. 3</th>
<th>NACE</th>
<th>PATENTS FIELD*</th>
</tr>
</thead>
<tbody>
<tr>
<td>High-technology industries (SEC-TEC1)</td>
<td>1. Aircraft and spacecraft</td>
<td>353</td>
<td>35.3</td>
<td>43</td>
</tr>
<tr>
<td></td>
<td>2. Pharmaceuticals</td>
<td>2423</td>
<td>24.4</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>3. Office, accounting and computing machinery</td>
<td>30</td>
<td>30</td>
<td>28</td>
</tr>
<tr>
<td></td>
<td>4. Radio, TV and communications equipment</td>
<td>32</td>
<td>32</td>
<td>34-35-36</td>
</tr>
<tr>
<td></td>
<td>5. Medical, precision and optical instruments</td>
<td>33</td>
<td>33</td>
<td>37-38-39-40-41</td>
</tr>
<tr>
<td>Medium-high-technology industries (SEC-TEC2)</td>
<td>6. Electrical machinery and apparatus</td>
<td>31</td>
<td>31</td>
<td>29-30-31-32-33</td>
</tr>
<tr>
<td></td>
<td>7. Motor vehicles, trailers and semi-trailers</td>
<td>34</td>
<td>34</td>
<td>42</td>
</tr>
<tr>
<td></td>
<td>8. Chemicals excluding pharmaceuticals</td>
<td>24 excl. 2423</td>
<td>24 excl. 24.4</td>
<td>10-11-12-14-15-16</td>
</tr>
<tr>
<td></td>
<td>9. Railroad equipment and transport equipment</td>
<td>352 + 359</td>
<td>35.2-35.4-35.5</td>
<td>44</td>
</tr>
<tr>
<td></td>
<td>10. Machinery and equipment, others</td>
<td>29</td>
<td>29</td>
<td>21-22-23-24-25-26-27</td>
</tr>
<tr>
<td>Medium-low-technology industries (SEC-TEC3)</td>
<td>11. Building and repairing of ships and boats</td>
<td>351</td>
<td>35.1</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td>12. Rubber and plastics products</td>
<td>25</td>
<td>25</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td>13. Coke, refined petroleum products and nuclear fuel</td>
<td>23</td>
<td>23</td>
<td>09</td>
</tr>
<tr>
<td></td>
<td>14. Other non-metallic mineral products</td>
<td>26</td>
<td>26</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>15. Basic metals and fabricated metal products</td>
<td>27-28</td>
<td>27-28</td>
<td>19-20</td>
</tr>
<tr>
<td>Low-technology industries (SEC-TEC4)</td>
<td>16. Manufacturing, others; Recycling</td>
<td>36</td>
<td>36</td>
<td>46</td>
</tr>
<tr>
<td></td>
<td>17. Wood, pulp, paper, paper products, printing and publishing</td>
<td>20-21-22</td>
<td>20-21-22</td>
<td>06-07-08</td>
</tr>
<tr>
<td></td>
<td>18. Food products, beverages and tobacco</td>
<td>15-16</td>
<td>15-16</td>
<td>01-02</td>
</tr>
</tbody>
</table>

Notes: * The figures reported in column “Patent fields” refer to the 46 fields where patents are classified by Schmoch et al. (2003) in order to provide a correspondence between IPC codes and ISIC Rev.3 industrial sectors. The full list of IPC codes for each patent field is described in the Appendix of Schmoch et al. (2003) paper.

Finally, in order to consider the dimension of the production for each sector we have included data on the value added per sector (prod_ii) deflated with overall manufacturing producer prices as suggested in Baldwin et al. (2005), in order to better shape the sectoral dimension of our investigation. Data on production volume rather than value added would be better to represent the production capacity of each sector, but data availability for this measure was very poor. On the

8 While patent data are now readily available for most nations, these data are still of minimal use for economic analysis due to their mode of presentation. Patents are recorded for administrative purposes using the International Patent Classification (IPC) system, which categorises inventions by product or process. Instead, most economic researchers and analysts are interested in the particular sectors of the economy responsible for the invention or its subsequent use. There are many contributions on concordance techniques for the assignment of the patent data by field of technology to a classification by economic sector, mapping patent product or process categories into the economic sectors responsible for their creation and subsequent use. The OECD Technology Concordance (OTC) described in Johnson (2002), like its predecessor the Yale Technology Concordance as originally presented by Kortum and Putnam (1997), is a tool that bridges definitions, allowing researchers to transform IPC-based patent data into patent counts by sector of the economy. In our paper we have adopted the version proposed by MERIT (Verspagen et al., 2004), and SPRU (Schmoch et al., 2003), specifically oriented to the EPO patents. Considering that we work with European Union countries and with EPO patents statistics, we have chosen for this approach.
importer side, we have not considered specific sectoral data on domestic consumption due to poor data availability. We have considered mass and similarity as proxies for bilateral demand at the general level. As in Baldwin et al. (2005) by taking data for specific sectors for the importing countries substantially reduce the observations, producing inconsistent results.

5. First empirical evidences from descriptive statistics

Graphs 1 and 2 draw a first picture of the of the changes occurred between 1996 and 2006 in terms of relative specialization respect to sectoral patents registered and trade flows towards world, by using TRCA and RCA indexes for technology and trade respectively, for EU10 and EU15 separately.

To characterize the extent of specialization for technological innovation in each sector we have computed the so-called Technological Revealed Comparative Advantage (TRCA) index firstly proposed by Archibugi and Pianta (1992), which is defined as a country’s share of patents in a specific sector relative to its share of all patents in all sectors,

\[
TRCA_{ij} = \frac{\sum_i P_{ij}}{\sum_j \sum_i P_{ij}},
\]

where \(P_{ij}\) denotes the number of patents of country \(i\) in the sector \(j\).

For trade flows we have computed the standard Revealed Comparative Advantages index developed by Balassa (1965).

Graph 1 – RCA and TRCA for EU12 in 19 sectors (1996 and 2006)

Focusing on the EU10, and looking at the picture of EU15 as reference, there are some sectors, namely, 02, 06, 11 and 17, which show significantly changes between 1996 and 2006. In two cases,

\[\text{In the text 1996 and 2006 refer to the two year period, respectively, 1996-97 and 2006-07.}\]
sectors 11 and 06, while the specialization in terms of trade flows remains similar, the TRCA strongly decrease. In both cases, results depend on the strong increase in the patents registered for these sectors in the world. However, in the case of “building and repairing of ships and boats” (11) it seems that a partial “patent diversion” occurred between EU10 and EU15.

For “pharmaceuticals” (02) the enlargement process has reduced both trade and patenting specialization while for “wood, pulp, paper products, printing and publishing” (17) the TRCA increased: while 02 is a high technology sector, 17 is classified as low.
Between 1996 and 2006, in the EU10, sectors 04 and 07 show an increase of trade, both in terms of RCA and as share on total trade (Graph 3) even if, relatively to the world, technological specialization of EU10 is low for both. On contrary, while sectors 14 and 17 increase their technological specialization between 1996 and 2006 as mentioned above, trade shares decrease both.

Looking at the Graph 4, after the enlargement, sectors with low TRCA are the strongest in the competition extra EU. At the same time, looking at the intra-EU trade, the shares for sectors 09 and 16 increased between 1996 and 2006 and these sectors are the ones with highest TRCA. Generally speaking, it seems that EU10 countries do not compete, out of Europe, in terms of technological contents. On the contrary, however, the extra-EU trade increased in sector 01, 03 and, in a low extent, in 04, which are high technology industries. At the same time, it must be noted that sectors 14 and 17 slightly increase their share on extra-EU trade simultaneously to the increase in their TRCA.

In the graph 5 and 6, we further analyze the convergence between EU10 and EU15, evaluating the ratio between the share of export of single sector on total trade, both to intra-EU and to Extra-EU, on the same share evaluated for the world.

\[
\frac{X_{ij}}{\sum_j X_{ij}} / \frac{X_{i, \text{world}}}{\sum_j X_{j, \text{world}}}, \quad [11]
\]

where \( X_{ij} \) is the export of country \( i \) of sector \( j \) to intra and Extra-EU.

We evaluated this ratio for the two years period 1996-97 and 2006-07 and for EU10 and EU15. EU15, since 1996, do not show a specialization in exporting towards intra-EU rather than extra-EU. It is a little bit surprising that EU15 do not show any high specialization in exporting more to the European Union, relatively to the world trade, which is used to normalize the numerator. Similarly, for EU10, while in 1996 some sectors were intra-EU oriented, mainly “wood, pulp, paper, paper products, printing and publishing” (17), “textile, textile products, leather and footwear” (19), “electrical machinery and apparatus” (06), “building and repairing of ships and boats” (11), “other
non metallic mineral products” (14), “basic metals and fabricated metal products” (15) and “manufacturing, other, recycling” (16), after the enlargement the “geographic specialization” has been reduced with sectors, like 06, 14, 17, 16 and 19 that showed a reduction in the value for the intra-EU value.

Graph 5 – Sectoral share in EU10 end EU15 normalized by the value for World (1996)

Graph 6 – Sectoral share in EU10 end EU15 normalized by the value for World (2006)

On other hand, sector like “medical, precision and optical instruments” (05), “coke, refined petroleum products and nuclear fuel” (13) and “radio, TV and communication” (04) “moved” towards higher value for the intra-EU specialization.
Finally, for the “building and repairing of ships and boats” (11), enlargement process pushed strongly towards extra-EU specialization the EU10 countries. For this sector, it is worth to know that the TRCA index strongly reduced between 1996 and 2006. Considering EU10 as the followers and the EU15 as the leaders as in Abramovitz (1986) catching-up hypothesis, we can see from Graphs 7 and 8 that the economic integration process has brought to a sudden reduction in diffusion barriers allowing the followers to upgrade their technological contents at the existing capital stock at a rate that is substantially higher than productivity growth rate of EU15.

**Graph 7 – Technological specialization for macro sectors, EU10 (1996 2006)**

The picture for EU15 clearly represent an increasing patent activity specialization for the high-tech sector with a growing stock of knowledge, while for the other three macro-sectors the technology specialization pattern is rather stable. Turning to EU10 the picture changes, and the specialization increases for three out of the four macro-sectors. This trend is particularly evident for the high-tech sector which has experienced a structural break after year 2001, closely linked to the enlargement process. As affirmed by Dosi et al. (1990), the technological gap framework allows us to emphasize that rather than inter-industry variations in the technological endowment of a specific country, it is the variation across countries in innovativeness within each sector which seems to be crucial for the dynamics of trade patterns (and economic growth). Hence, our assumption is close to Fagerberg (1994), as we argue that differences between countries in trade patterns are explained in terms of differential endowments, but more importantly these differences relate to the country-sector-specific conditions of technological learning and accumulation.
6. **Empirical results from the econometric estimation of the gravity equation**

We report in the Tables the results of the more robust estimations, while we have tried many different models by including several explanatory variables such as the bilateral real exchange rate calculated as suggested by Carrere (2006), the relative endowment calculated by using capital labour ratios instead of GDP per capita, or dummy variables related to the enlargement process such as those suggested in Paas (2001) and De Benedictis et al. (2005) related to countries in CEFTA and BAFTA, and other standard gravity instruments such as countries sharing common language or religion. We have decided not to consider a variable related to Rule of Law because it is strongly correlated with two regressors which are the technological diffusion as expressed by the ARCO index, and more importantly the cost of doing business variable included in the Probit first stage model as suggested by Helpman et al. (2008).

In this paper we have considered the one lag value of stock of knowledge, instrumenting it with its two periods back value. The choice of the one lag in the regression is based on several tests that have showed this is the most appropriate (and statistically robust) estimation.

Results in Table 2 clearly show that estimating a gravity model by using standard OLS produces results that are not statistically robust, while it is worth noticing that the coefficient related to lagged dependent variable is always positive and statistically robust. So that we have to correct both for autocorrelation of the residuals and for endogeneity of the regressors. In fact, if technological capability, here expressed by the stock of knowledge (KPAT) is a necessary condition for achieving higher economic opportunities, and if it hardly depends on a number of conditions such as the institutional capacities, the establishment and operation of new firms, and among the others the openness to competition, it is quite obvious that technological capabilities are mutually correlated with the export dynamics. Empirical results in Eaton and Kortum (2002) confirm that trade does allow a country to benefit from foreign technological advances. Hence, endogeneity could be a source of statistical bias if it is not appropriately treated, both for domestic technological innovation and for international technological diffusion.

Moreover, if we account for the impact of firms heterogeneity (FHET) by using a two step procedure proposed by HMR the coefficient related to FHET is positive and statistically robust.
Even though an instrumental variable estimator allows correcting for endogeneity, it gives still biased results due to the autocorrelation of the residuals, and the evidence is provided by the AR(1) and AR(2) tests for the System-GMM. From Table 2 it seems clear that in our panel dataset System-GMM correcting for firms heterogeneity by using a two step procedure is the most appropriate estimation method.

Table 2 – Estimation of the enlargement effect on EU25

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>XTIVREG</th>
<th>XTIVREG-HMR</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>EXPt-1</td>
<td>0.714***</td>
<td>0.584***</td>
<td>0.686***</td>
<td>0.433***</td>
<td>0.273***</td>
<td>0.183***</td>
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<tr>
<td></td>
<td>(155.79)</td>
<td>(116.45)</td>
<td>(73.89)</td>
<td>(17.58)</td>
<td>(9.77)</td>
<td>(7.62)</td>
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<tr>
<td>COL</td>
<td>0.373***</td>
<td>0.606***</td>
<td>0.389***</td>
<td>0.767***</td>
<td>0.606***</td>
<td>0.947***</td>
</tr>
<tr>
<td></td>
<td>(14.88)</td>
<td>(11.50)</td>
<td>(7.25)</td>
<td>(9.42)</td>
<td>(3.65)</td>
<td>(4.53)</td>
</tr>
<tr>
<td>CONT</td>
<td>-0.116***</td>
<td>-0.321***</td>
<td>-0.401***</td>
<td>-0.210</td>
<td>-0.425</td>
<td>-0.174</td>
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<td></td>
<td>(-2.84)</td>
<td>(-3.71)</td>
<td>(-4.55)</td>
<td>(-1.57)</td>
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<td>DIST</td>
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<td>-0.688***</td>
<td>-0.525***</td>
<td>-0.616***</td>
<td>-0.965***</td>
<td>-1.098***</td>
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<tr>
<td></td>
<td>(-22.37)</td>
<td>(-18.35)</td>
<td>(-13.67)</td>
<td>(-16.01)</td>
<td>(-10.00)</td>
<td>(-6.78)</td>
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<td>LAND</td>
<td>0.000</td>
<td>0.012</td>
<td>-0.133***</td>
<td>-0.219***</td>
<td>-1.530***</td>
<td>-1.187***</td>
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<tr>
<td></td>
<td>(0.00)</td>
<td>(0.09)</td>
<td>(-5.84)</td>
<td>(-3.14)</td>
<td>(-6.44)</td>
<td>(-3.24)</td>
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<td>MASS</td>
<td>0.777***</td>
<td>1.304***</td>
<td>0.543***</td>
<td>0.456***</td>
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<tr>
<td></td>
<td>(16.23)</td>
<td>(13.05)</td>
<td>(15.17)</td>
<td>(9.46)</td>
<td>(7.87)</td>
<td>(4.18)</td>
</tr>
<tr>
<td>SIMILARITY</td>
<td>0.334***</td>
<td>0.323***</td>
<td>0.173***</td>
<td>0.523***</td>
<td>-0.119</td>
<td>0.111</td>
</tr>
<tr>
<td></td>
<td>(13.87)</td>
<td>(6.49)</td>
<td>(6.57)</td>
<td>(9.98)</td>
<td>(-0.77)</td>
<td>(0.62)</td>
</tr>
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<td>ENDOWM</td>
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<td>-0.054***</td>
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<td>(-2.74)</td>
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<td>(7.59)</td>
<td>(11.66)</td>
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<td>(10.56)</td>
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<tr>
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</tr>
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<td></td>
<td>(6.16)</td>
</tr>
<tr>
<td>ENL</td>
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<td>0.114***</td>
<td>0.213***</td>
<td>0.120***</td>
<td>0.145***</td>
<td>0.164***</td>
</tr>
<tr>
<td></td>
<td>(7.80)</td>
<td>(3.54)</td>
<td>(8.02)</td>
<td>(9.31)</td>
<td>(6.91)</td>
<td>(7.45)</td>
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<tr>
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<td>(-0.22)</td>
<td>(12.67)</td>
<td>(14.31)</td>
<td>(3.63)</td>
<td>(5.20)</td>
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<td>WALD</td>
<td>451775.7</td>
<td>2.62E+06</td>
<td>233677.1</td>
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<tr>
<td>F-STAT</td>
<td>125618.7</td>
<td>19208.94</td>
<td>14736.82</td>
<td></td>
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<td></td>
</tr>
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<td>AR(1)</td>
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<td>-12.04 (0.00)</td>
<td>-12.87 (0.00)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AR(2)</td>
<td>1.22 (0.22)</td>
<td>0.31 (0.76)</td>
<td>-1.39 (0.16)</td>
<td></td>
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<tr>
<td>OBS</td>
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<td>23,324</td>
<td>22,324</td>
<td>24,393</td>
<td>23,564</td>
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</tbody>
</table>

Notes: robust t-statistics in absolute value are reported in parenthesis, *, **, *** significant at the 10%, 5%, 1%, respectively.

AR(1) and AR(2) are tests – with distribution N(0, 1) – on the serial correlation of residuals.

More importantly, by using System-GMM we reach consistent and robust estimates for the technological variables, both related to the stock of knowledge of the exporting countries and the technological capabilities of the importing partners.

As we are interested in understanding the effects of the enlargement process on the quality of the export dynamics of the European countries, we have adopted the four macro-sectors disaggregation proposed by OECD (2008), thus comparing the effects of the enlargement process on the EU15 and the EU10.

Results for the EU15 and EU10 samples are quite different, allowing to make some interesting comment on divergences between the two samples, but more importantly on the impact of the
enlargement process and the technological catching up by the new member states. As we can see from Tables 3-4, using Sys-GMM results remain statistically robust for both samples.

### Table 3 – Estimation of the enlargement effect on EU15 for different macro-sectors

<table>
<thead>
<tr>
<th>EXP TOT</th>
<th>SEC-TEC1</th>
<th>SEC-TEC2</th>
<th>SEC-TEC3</th>
<th>SEC-TEC4</th>
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<tr>
<td>EXPt-1</td>
<td>0.335***</td>
<td>0.256***</td>
<td>0.060</td>
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<td>(5.44)</td>
<td>(4.67)</td>
<td>(1.13)</td>
<td>(0.65)</td>
</tr>
<tr>
<td>COL</td>
<td>0.763***</td>
<td>1.329***</td>
<td>1.619***</td>
<td>1.876***</td>
</tr>
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<td></td>
<td>(4.51)</td>
<td>(6.07)</td>
<td>(6.82)</td>
<td>(7.18)</td>
</tr>
<tr>
<td>CONT</td>
<td>-0.213</td>
<td>0.025</td>
<td>0.837</td>
<td>0.296</td>
</tr>
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<td></td>
<td>(-0.45)</td>
<td>(0.03)</td>
<td>(1.02)</td>
<td>(0.38)</td>
</tr>
<tr>
<td>DIST</td>
<td>-0.423***</td>
<td>-0.400***</td>
<td>-0.702***</td>
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</tr>
<tr>
<td></td>
<td>(-4.36)</td>
<td>(-3.11)</td>
<td>(-5.55)</td>
<td>(-3.40)</td>
</tr>
<tr>
<td>LAND</td>
<td>-0.580***</td>
<td>-1.021***</td>
<td>-0.585**</td>
<td>-1.059**</td>
</tr>
<tr>
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<td>(-3.93)</td>
<td>(-3.04)</td>
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<tr>
<td>MASS</td>
<td>0.291***</td>
<td>0.721***</td>
<td>0.420***</td>
<td>0.736***</td>
</tr>
<tr>
<td></td>
<td>(3.90)</td>
<td>(4.03)</td>
<td>(2.52)</td>
<td>(4.76)</td>
</tr>
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<td>SIMILARITY</td>
<td>0.293***</td>
<td>0.606***</td>
<td>0.868***</td>
<td>0.895***</td>
</tr>
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<td>(2.66)</td>
<td>(4.81)</td>
<td>(7.02)</td>
<td>(6.01)</td>
</tr>
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<td>ENDOMW</td>
<td>1.103***</td>
<td>-0.689***</td>
<td>-0.990***</td>
<td>-0.997***</td>
</tr>
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<td>(8.37)</td>
<td>(-2.95)</td>
<td>(-3.78)</td>
<td>(-3.60)</td>
</tr>
<tr>
<td>TECDIS</td>
<td>-1.626***</td>
<td>-1.761***</td>
<td>-1.138***</td>
<td>-2.100***</td>
</tr>
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<td>(-9.57)</td>
<td>(-7.03)</td>
<td>(-4.50)</td>
<td>(-9.79)</td>
</tr>
<tr>
<td>FHET</td>
<td>0.448**</td>
<td>0.521***</td>
<td>0.545***</td>
<td>0.457***</td>
</tr>
<tr>
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<td>(1.84)</td>
<td>(4.78)</td>
<td>(2.85)</td>
<td>(2.87)</td>
</tr>
<tr>
<td>ENL</td>
<td>0.189***</td>
<td>0.108***</td>
<td>0.074***</td>
<td>0.058*</td>
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<td>(5.37)</td>
<td>(3.58)</td>
<td>(2.68)</td>
<td>(1.77)</td>
</tr>
<tr>
<td>PATt-1</td>
<td>0.219***</td>
<td>0.392***</td>
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</tr>
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<td>(4.47)</td>
<td>(7.22)</td>
<td>(2.36)</td>
<td>(4.94)</td>
</tr>
<tr>
<td>PROD</td>
<td>0.414***</td>
<td>1.076***</td>
<td>0.949***</td>
<td>0.479***</td>
</tr>
<tr>
<td></td>
<td>(3.07)</td>
<td>(9.82)</td>
<td>(7.13)</td>
<td>(7.13)</td>
</tr>
<tr>
<td>OBS</td>
<td>15,148</td>
<td>17,766</td>
<td>17,765</td>
<td>17,764</td>
</tr>
<tr>
<td>F-STAT</td>
<td>32698.91</td>
<td>9644.61</td>
<td>8679.57</td>
<td>5690.88</td>
</tr>
<tr>
<td>AR(1)</td>
<td>-5.33 (0.00)</td>
<td>-10.67 (0.00)</td>
<td>-7.74 (0.00)</td>
<td>-10.66 (0.00)</td>
</tr>
<tr>
<td>AR(2)</td>
<td>0.96 (0.33)</td>
<td>1.6 (0.67)</td>
<td>1.53 (0.13)</td>
<td>1.4 (0.16)</td>
</tr>
</tbody>
</table>

Notes: robust t-statistics in absolute value are reported in parenthesis, *, **, *** significant at the 10%, 5%, 1%, respectively.

AR(1) and AR(2) are tests – with distribution N(0, 1) – on the serial correlation of residuals.

The coefficients related to distance are much lower for the EU15 than for the EU10 at the general level, but the gap is quite larger corresponding to the high-tech sectors. This means that for CEECs trade barriers related to trade costs, in terms of transactional and sunk costs are still a great constraint for exporting goods with high economic value. This result is reinforced by the higher values assumed by the coefficients associated to the lagged dependent variable, which is considered the sign of a strong persistence in trade patterns and a proxy of the existence of sunk costs. As we can see these sunk costs operates for CEECs exports especially in the high and medium technology sectors, while for the low tech sector the coefficient is positive but no statistically significant.

For EU15 the coefficients for the MASS are positive and statistically significant for all sectors but the low tech one, where the coefficient is not robust. MASS is a variable representing the role of global bilateral demand, the higher the value the greater the influence of demand factors in the
export dynamics. As we can see from Table 4 results for EU10 are less homogeneous and robust, meaning that factors from the demand side influence less the capacity to export. In particular, we have to consider how this variable is composed, as the sum of GDP of each pair of exporting and importing countries. Typically, the EU15 countries have large economic dimensions, where the domestic demand play a crucial role in sustaining production capacity at the earlier stages of development for a certain industry. On the contrary, for EU10 the domestic demand could be very small so that exports are explained by external demand and supply characteristics.

Another difference is related to the role of the similarity in the economic dimension of each country pair (SIMILARITY) and relative endowment between exporting and importing countries. The variable SIMILARITY is an index bounded between 0 (absolute divergence in size) and 0.5 (equal country size). The larger this measure and, thus, the more similar two countries in terms of GDP, the higher the share of intra-industry trade. For EU15 coefficients are always positive and statistically robust, with the exception of low tech sector, where we find negative values. On the contrary, for the variable ENDOW, we find positive coefficient for total export and for the low tech export for EU15, while negative values for sectors with higher technological contents. In this case, a negative coefficient means that the closer the trade partners in terms of capital intensity, the higher the potential trade. Both results can be interpreted as a clear sign of the larger importance of intra-industry trade in the first three sectors, typically occurred between countries with similar factors endowment as in the early explanations of Linder (1961) and Grubel and Lloyd (1975).

On the contrary, for the EU10 sample coefficients for ENDOW are always positive and statistically significant for three out of the four sectors, and they are larger for the two high tech sectors than for the other two lower tech sectors. In this case, we can interpret our results in a traditional Heckscher-Ohlin framework, where different factor endowments bring to different specialization patterns, where inter-industry flows will be more important the greater the difference between countries in terms of their endowments. Our results seem to be confirmed both by the absence of a clear impact associated to similarity in the economic size, but more importantly by the large difference between the coefficients associated to technological distance (TECDIS) for the two samples. It is worth noticing that technological distance plays a crucial role for the export dynamics of both country samples, but for the Eastern Europe countries it is quite important especially for the first two sectors, high-tech and medium-high-tech, meaning that in this case intra-industry trade is less important than specialization patterns. But more importantly the specialization patterns toward high-tech sectors are strongly affected by differences in factor endowments and technological capabilities, while for the EU15 the intra-industry trade seems to be predominant.

The impact of the enlargement process is clearly stronger for the new accession countries than for the older EU member states. The coefficients for EU15 are always lower than EU10 for all sectors, and they progressively decrease with the reduction of the technological content of the sector. It is also interesting to note that the highest coefficient for EU10 is related to the low tech sector, and this could be explained by the increasing export share in this sector oriented toward the European Union market. The enlargement process in this case has brought to a rapid convergence in the production standards of CEECs in the agri-food sector, allowing new member states to enter in an highly protected sector, characterised by higher market prices than in the rest of the world. Nonetheless, the effect of the enlargement process on the high-tech sector seems to be quite high, and this result is also consistent with the role of technological innovation.

In fact, moving to the technological upgrading process of the EU10 that the enlargement process has fostered, the impact of the stock of knowledge on the export dynamics is clearly positive and it is favouring sectors with the higher technological contents, thus helping new member states to reduce the technological gap but more importantly to converge to higher economic development.
level by increasing growth rates. As we can see from the results obtained for EU15, the accumulation of a stock of knowledge has a strong positive impact on export capacity especially in the high-tech sector. This result confirms the importance of the enlargement process in the inducement of a technological upgrading of the whole economy as a major source of economic growth.\(^{10}\)

| Table 4 – Estimation of the enlargement effect on EU10 for different macro-sectors |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| EXP\(_{t,2}\)                    | 0.154           | 0.312***        | 0.235***        | 0.175**         | 0.220           |
|                                 | (1.44)          | (4.33)          | (3.58)          | (2.19)          | (1.31)          |
| COL                             | 1.195           | 0.094           | 1.097***        | 1.505***        | 1.082**         |
|                                 | (1.03)          | (0.17)          | (2.01)          | (2.60)          | (1.89)          |
| CONT                            | 1.527           | 0.395           | 0.588           | 1.148           | -0.740          |
|                                 | (0.96)          | (0.30)          | (0.75)          | (0.94)          | (-0.99)         |
| DIST                            | -1.224***       | -1.340***       | -0.963***       | -0.654***       | -0.717***       |
|                                 | (-3.61)         | (-6.09)         | (-4.93)         | (-3.38)         | (-3.28)         |
| LAND                            | -1.556***       | -0.273          | -0.681          | -1.432***       | -1.054*         |
|                                 | (-2.95)         | (-0.89)         | (-1.67)         | (-2.89)         | (-1.81)         |
| MASS                            | 1.852***        | 0.384*          | 0.131           | 0.849***        | 0.340           |
|                                 | (4.71)          | (1.70)          | (0.55)          | (2.29)          | (0.80)          |
| SIMILARITY                      | -0.194          | 1.076*          | -0.127          | 0.520           | 0.847           |
|                                 | (-0.33)         | (1.79)          | (-0.26)         | (0.64)          | (1.23)          |
| ENDOWM                          | 0.327*          | 0.559***        | 0.444***        | 0.123           | 0.394**         |
|                                 | (1.64)          | (3.01)          | (3.66)          | (0.60)          | (2.28)          |
| TECDIS                          | -2.654***       | -3.149***       | -2.830***       | -2.554***       | -2.358***       |
|                                 | (-3.84)         | (-5.95)         | (-5.51)         | (-3.64)         | (-3.39)         |
| FHET                            | 0.548**         | 0.621***        | 0.525***        | 0.857           | 0.569***        |
|                                 | (2.04)          | (4.78)          | (2.85)          | (0.87)          | (3.62)          |
| ENL                             | 0.137**         | 0.387***        | 0.278***        | 0.353***        | 0.485***        |
|                                 | (1.97)          | (4.25)          | (3.42)          | (3.88)          | (4.15)          |
| PAT\(_{t,1}\)                   | 0.214**         | 0.146**         | 0.113**         | 0.084***        | -0.010          |
|                                 | (2.30)          | (2.16)          | (1.73)          | (3.07)          | (-0.37)         |
| PROD                            | 0.435***        | 0.772***        | 0.483***        | 0.664***        |                  |
|                                 | (4.10)          | (8.58)          | (3.39)          | (3.92)          |                  |
| OBS                             | 8,416           | 6,657           | 7,045           | 5,764           | 4,224           |
| F-STAT                          | 925.99          | 995.46          | 1485.06         | 1010.33         | 1409.43         |
| AR(1)                           | -8.46 (0.00)    | -11.36 (0.00)   | -11.15 (0.00)   | -8.45 (0.00)    | -7.51 (0.00)    |
| AR(2)                           | 0.42 (0.67)     | 2 (0.10)        | -1.19 (0.12)    | -1.8 (0.17)     | 0.84 (0.40)     |

Notes: robust t-statistics in absolute value are reported in parenthesis, *, **, *** significant at the 10%, 5%, 1%, respectively.

AR(1) and AR(2) are tests – with distribution \(N(0, 1)\) – on the serial correlation of residuals.

The lower impact of the existing stock of knowledge for the EU10 can also be explained in a Vernon context, where product differentiation is primarily demand-determined: high levels of income and sophisticated demand patterns induce innovative responses of domestic firms. Considering that per capita income levels in EU10 countries are still much lower than in the EU15, the domestic demand is not sufficient to pulled (induce) technological innovation and production.

\(^{10}\) In order to control for sectors heterogeneity, we have run a second estimation by using a stock of knowledge weighted by the number of employees or alternatively by the sectoral production value. In both cases results remain robust and coherent.
specialization in highly sophisticated goods. In this sense the enlargement process should act as an external demand factor by widening the destination market. In this sense, our work is rather preliminary, and a deeper investigation at more disaggregated sector level, and with an expanded time series should bring to more insightful results.\(^{11}\)

7. Conclusions
We have evaluated the impact of the enlargement process on the export dynamics of the European Union members by a disaggregated analysis based on 4 macro-sectors classified by technological content as proposed by the OECD Technology Scoreboard.

We have developed a new empirical estimation of the gravity equation for bilateral trade flows by including specifically the role of technological innovation as a source of international competitiveness. Hence, we have classified IPC patents codes by aggregating on the basis of the OECD Technology Concordance in order to compute specific stock of knowledge for each manufacturing sector. Then, we have aggregated data for 19 industrial sectors on bilateral export flows, production value, and patents into four macro-sectors.

We have adopted a dynamic estimator such as System GMM in order to consider both autocorrelation of the residuals and endogeneity of some regressors, while allowing to maintain time invariant regressor which are necessary for estimating a gravity equation.

Our main findings are that the enlargement process produced a positive impact on the export dynamics of the European Union. This impact seems to be larger for new member states than for EU15 and it is much more evident for high-tech sectors than for low tech sectors.

Technological innovation plays a crucial role in explaining export performance of EU, more consistently for EU15 than for EU10. This last result give us some advice on the possibility to better explore the relationships between technological change and international trade at a more disaggregated level, by considering also the impact of international technological spillovers related to the enlargement process, and more broadly to the gradual integration of EU10 into international markets.

References
Archibugi, D., Pianta, M., 1992, Specialization and size of technological activities in industrial countries: The analysis of patent data, Research Policy, n. 21, pp. 79-93.

\(^{11}\) Somewhere specify how we have decided to include KPAT with one temporal lag (we have considered both KPAT synchronized with exports and with two lags. As we expected, the coefficient for the KPAT with no lags were not statistically significant, while for the two periods back the coefficients were closed to results with one lag. Considering that adopting a temporal dynamics with two lags produces loss of information, we have taken KPAT with one lag.


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