Technology and costs in international competitiveness: from countries and sectors to firms

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Abstract

This paper examines the determinants of international competitiveness at the level of sectors and firms. It does so within the broader "technology gap" perspective whereby wide technological and organizational differences ultimately shape the patterns of trade within sectors across countries and their dynamics. First, we take stock of the incumbent evidence on the relation between cost-related and technological competition at country and sectoral level. The overall picture indeed suggests that the countries' sectoral market shares are mainly shaped by technological factors while cost advantages/disadvantages do not seem to play any significant role. But within any sector, within any country, firms widely differ. Hence the question: does this property apply also at a micro level? Here, we attempt to identify the underlying dynamics at the firm level using a large panel of Italian firms, over nearly two decades. Results show that also at micro level in most sectors investments and patents correlate positively both with the probability of being an exporter and with the capacity to acquire and to increase exports, whereas labour costs show a negative effect only in some sectors. The result is reinforced when separating the short- and long-run effects, highlighting the predominant impact of technological proxies and basically the irrelevance of wage costs.

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JEL classification: D22, F10, F14, F19, L25, O32.

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1. Introduction

In order to appreciate that countries are vastly different in terms of technological and organizational capabilities, to paraphrase Lucas (1988), one does not need an economist but just a vaguely informed turist. And of course this is reflected by equally vast differences in productivities and per capita incomes. However - much less appreciated in the economic theory - this is also reflected by the patterns of trade and their dynamics over time. This relative neglect is probably due to a considerable extent to the early very neat representation by David Ricardo of the determination of trade flows in terms of comparative advantages, indeed one of the pieces of his work nearest to a contemporary, albeit rudimentary, general equilibrium theory whereby allocations are basically determined by opportunity costs under a long list of conditions including the fully employment of all resources in every country, absence of dynamic increasing returns, perfect capital and labour mobility across sectors, no idiosyncratic firm-specific or sector-specific technological capabilities, and a few others.

What happens if these latter conditions are not met? Or, somewhat dramatizing, as we argue in Cimoli et al. (2009), in turn paraphrasing Reinert (2009), what happens if, say, one opens up trade between a "Stone Age economy" and an ICT-based one? Most likely, if there will be bilateral trade at all, the "Stone intensive" economy will be more likely to export "stone intensive" products. However, will it? Maybe, the more advanced ICT economy will produce almost anything worth trading irrespective of the stone- or ICT-intensities of the products. What matters might be ultimately technological capabilities and not relative prices (and even less so shadow prices).

Indeed, at least since the seminal work of Posner (1961), a stream of analyses has been arguing that one of the main sources of (absolute) advantage of a country comes from its relative technological position against its competitors in any one activity, rather than from intersectoral opportunity costs within the same country. The roots of such a perspective date back to 18th and 19th centuries pre-Ricardian or anti-Ricardian theories of trade - including largely forgotten authors like Ferrier and List - and refined in modern technology-gap theories of international trade and related product-cycle views (in addition to Posner, 1961; see Freeman, 1963; Hirsch, 1965; Vernon, 1966; Hufbauer, 1970; Cimoli, 1988 and the preliminary attempt to get together the whole view in Dosi et al., 1990). In such a perspective, trade flows are primarily driven from sector-specific absolute advantages, in turn stemming primarily from widespread technological asymmetries between countries which relate in first instance to the capability of some countries to produce innovative commodities (i.e. commodities which other countries are not yet capable of producing, irrespective of relative costs) and to use process innovations more efficiently or more quickly thus reducing input coefficients.

In the following, we first try to offer a concise but hopefully exaustive overview of the empirics of such literature, whose theoretical underpinnings rest, of course, upon, at least, *partial disequilibrium* assumptions, and more generally upon evolutionary notions of international dynamics of industries and trade. In turn, the "partial disequilibrium" (and most likely "general") perspective allows to easily disentangle *technological factors* from cost factors as determinants of trade flows. Again in the foregoing caricature, there will not be any cost adjustment that will induce the substitution of a stone-based product to a microprocessor in any economy, let alone the most advanced ones! Being less crude, one ought to ask, in tune with the seminal but neglected Kaldor (1978)'s question, what is the relative role of technological *vs.* cost conditions as determinants of trade flows. And this is what the sectoral "technology gap" literature does with quite robust results on the dominant role of the former (Fagerberg, 1988; Dosi et al., 1990; Amendola et al., 1993; Laursen and Meliciani, 2010). Granted that, what happens *within* sectors?

After all, intra-industry differences are large. Firms within each sector, irrespectively of the level of industry disaggregation, are highly heterogeneous on whatever measure chosen, both on the input and output sides, their efficiencies, degrees of innovativeness, market performances, even in presence of the same input prices (see, within an expanding literature, from Hildenbrand, 1981 and Nelson, 1981 to Bartelsman and Doms, 2000; Dosi and Grazzi, 2006; Dosi, 2007; Dosi and Nelson, 2010; Syverson, 2011). And the available evidence supports also at least equally deep degrees of heterogeneity in the participation on the export markets (see the review in Bernard et al., 2012; Melitz and Trefler, 2012). Hence one needs to discard any 'representative firm' like hypothesis and study what is the underlying micro evidence to the aggregate macro or 'meso' patterns.

Overlapping but distinct from new-new (micro) theories of international trade (see Melitz, 2003; Bernard et al., 2007a; Melitz and Ottaviano, 2008), we address the microeconomics of competitiveness and export performance. In line with the technology gap tradition, we address the distinct effects of technological and cost variables in shaping firm's exports. This is the second and central task of this work.

Employing several sources of Italian firm level data we investigate the effects of technological and cost variables in affecting export market participation and trade volumes. Whether technology, as proxied by the firm's pool of patents, appears to matter, there is no widespread evidence that a lower cost of labor is a significant factor for international competitiveness. These results are robust to a number of controls and robustness checks. More in particular, the effectiveness of patents in shaping firm-level exports - as well as the limited impact of cost variables - is also confirmed when adapting a traditional technology gap framework which enables to spell out the short and long run effects of the determinants of international competitiveness. Our results still hold when employing variables proxying for the output of innovation activities, such as product and process innovation, as available through Community Innovation Survey (CIS). Finally, the paper also marginally contributes to the emerging literature on quality sorting and trade (Crozet et al., 2012; Manova and Zhang, 2012) by investigating the channels which are responsible for the different patterns that we observe in the exports of innovating and non-innovating firms. Employing the volume of exports of firms to any given product-country destination we find that exports of firms engaged in innovative activities decrease less in response to an exogeneous shocks as a real exchange rate appreciation, and this is mostly due a smaller reduction in the quantity sold.

Our contribution provides a framework in which to explicitly link technology-gap and evolutionary theories to the observed dynamics at the firm-level. Indeed, the separate analysis of technological and cost factors at the most disaggregate level statistically available is one of the distinguishing features of this work with respect to most of the recent firm level contributions studying the determinants of export status and export volumes. Sectors differ in terms of dominant technologies of production, patterns of innovation, competition mechanisms. And unlike any "Ricardian hypothesis", financial capitals are very mobile but capabilities are very sticky: one can switch from an investment into biscuits to microprocessors, but firms may hardly do the same in terms of what they are able to do. This also highlights a fundamental time dimension. Firms' capabilities are quite sticky (within a huge litarature, see the overview in Dosi and Nelson, 2010) while cost are less so - think for example of a devaluation of a currency -. Hence, the investigation of the long-run as distinguished from the shorter-term one is crucial.

The paper is organized as follows. Section 2 addresses the state-of-the-art on technology-gap interpretation of trade flows at country and sector levels, and also reviews the literature on export and innovation at the micro level. Section 3 describes the data upon which our analyses are based. Section 4 presents the methodology and results. Section 5 adds further evidence on the role of product and process innovation using data from two waves of CIS surveys. Section 6 concludes.

2. Technology and costs in international competitiveness

2.1. Conceptual framework and findings at the country and sector level

Competitiveness is determined by several factors. One is certainly labour costs, the labour being the - relatively more - immobile factor among countries. However, the aggregate, sectoral, and micro literature within but also outside the "technology gap" tradition on international trade have debated the extent to which technological innovation is affecting trade performance, in addition to, or even against changes in labour costs.

Following Dosi et al. (1990), one can specify sectoral trade performance as a function of both technological absolute advantage (T_{ij}) and variable costs (C_{ij}):

$$X_{ij} = f(T_{ij}, C_{ij}) \tag{1}$$

where X_{ij} is some indicator of international competitiveness (say the market share of exports in sector i by country j); T_{ij} represents an indicator of technological levels (both product and process technologies in the same sector i for country j) and C_{ij} represents a proxy for variable costs, typically labour costs.

In the technology-gap and evolutionary account of international trade, equation (1) is consistent with macroeconomic disequilibrium: for example, it does not imply any clearing on factors' and commodities' markets and, indeed, it requires an implicit assumption on some "stickiness" in the reallocation of resources from one sector to another. More generally, it implies changes in trade and technology unpegged to some underlying equilibrium and imperfect adjustments in macroeconomic variables to continuously changing technological "fundamentals" (see Amendola et al., 1993).

The estimates of (1) have been generally undertaken, mostly due to data constraints, at the aggregate country, or industry-country, level. One of the first test of technological gap theory is in Soete (1981) (see also Soete, 1987) who shows that, among OECD countries and across several industries, there is a close relationship between technological performance, as proxied by patenting activity, and export performance, as proxied by export market shares. Following this first evidence, an important stream of literature has investigated the role of both technological (including not only patents, but also investments and R&D) and cost-price factors in affecting international market shares, both at the country (Fagerberg, 1988; Amendola et al., 1993) and at the country-industry level (Dosi et al., 1990; Magnier and Toujas-Bernate, 1994; Amable and Verspagen, 1995; Landesmann and Pfaffermayr, 1997; Wakelin, 1998b; Carlin et al., 2001; Laursen and Meliciani, 2000, 2002, 2010). Most of this literature is summarized in Table 1, where we also report the main results emerging from the studies, as well as the differences in terms of period, number of countries and sectors analyzed, and empirical methodology. Here, let us flag some of the main themes running through these investigations.

At the country level, Fagerberg (1988) finds that factors related to technology, in particular investments, patents and R&D, explain most of the growth in export market shares, whereas cost-competitiveness, as proxied by unit labour costs, plays a limited role. The result about unit labour costs was also meant as an explanation for the "Kaldor paradox" (Kaldor, 1978), highlighting the evidence on the fact that the *fastest growing countries* in terms of exports and GDP in the post-war period have at the same time experienced much *faster growth in relative unit labour cost* than other countries, and viceversa. This finding is corroborated by Amendola et al. (1993) who, within an autoregressive distributed lag model, are able to show that technological variables have mainly a long-run effect on export shares, while unit labour costs have some effect only in the short run.

These results have been largely confirmed by the analysis at the country-industry level, where, however, the importance of technology and costs is usually found to be heterogeneous across sectors. Greenhalgh (1990), Magnier and Toujas-Bernate (1994), and Amable and Verspagen (1995) use an error correction model to estimate long-run relationships. In Greenhalgh (1990), relative prices seem to affect negatively UK exports only in few sectors; notably, traditional sectors like textiles are also found to be non-price sensitive. On the other hand, the number of innovations affects exports positively in most sectors, even if some core innovative sectors like engineering ones are not in the list. Magnier and Toujas-Bernate (1994) and Amable and Verspagen (1995) find similar heterogeneous patterns for a larger group of countries using different proxy for innovation (R&D and investments in the first case, and patents and investments in the second case). In particular, Amable and Verspagen (1995) point out that the sectoral differences in the estimation can only partly fit within the taxonomy proposed in Pavitt (1984). Indeed, the importance of patents is much broader than just in the science-based sectors. This is consistent with Wakelin (1998b) who, focussing on bilateral trade flows, shows that R&D intensity and patents are important both in high and low technology sectors, whereas costs, as proxied by wages, are significant only in low and medium technology sectors. The sectoral heterogenity can help also in interpreting the evidence in Carlin et al. (2001) whereby, we suggest, pooling across all sectors blurs the "true" effect of technological factors.

On the methodological side, a few of the foregoing studies try to estimate both short-run and long-run effects, using a cointegration specification, like Greenhalgh (1990), Magnier and Toujas-Bernate (1994) and Amable and Verspagen (1995), or a distributed lag specification, like Amendola et al. (1993) and Carlin et al. (2001). A somewhat different framework is used in Landesmann and Pfaffermayr (1997), who develop an "almost ideal demand system" to investigate how export demand is shaped by unit labour costs and R&D expenditures. Dosi et al. (1990), based mainly on a cross-sectional analysis for a dataset similar to Soete (1981, 1987), estimate several functional specifications relating proxies of export performance (export market shares, export per capita, export over gdp) to innovation proxies (patent shares, investment per employee) and cost proxies (wages and unit labour costs). By and large, the results confirm that the international composition of trade is explained by different degrees of innovativeness. In Appendix A we provide a reassessment of some of these results on the grounds of a sectoral dataset on most OECD countries over nearly two decades.

A more recent stream of literature have started to study the role of technological spillovers in international market share dynamics. Laursen and Meliciani (2000), using a dynamic model similar to Amendola et al. (1993) , show that domestic upstream and downstream R&D linkages affect export shares in scale-intensive and specialized-supplier industries, respectively. Using the same dataset, Laursen and Meliciani (2002) find that international linkages do not have any impact on trade balance. Finally, Laursen and Meliciani (2010) find that in ICT industries both domestic and international ICT knowledge flows have a positive impact on export market shares, while in non-ICT industries only domestic flows are significant.

Table 1: Country- and sector-level studies

Authors	Period	Countries	Sectors	Methodology	Main results
Soete (1981, 1987)	1963-1977	20	40	cross-sectional estimation of four equations in 1977	Patents (+)
Fagerberg (1988)	1961-1983	15	aggregate economy	2SLS estimation of a six equations model	R&D-Patents (+), Investments (+), Costs ()
Dosi et al. (1990)	1963-1977	20	40	cross-sectional analysis	Investments (+), Patents (+), Costs ()
Greenhalgh (1990)	1954-1981	1 (UK)	31	error correction model	#Innovations (+), Prices ()
Amendola et al. (1993)	1967-1987	16	aggregate manufacturing	autoregressive-distributed lag model	Patents (+), Investments (+), Costs ()
Magnier and Toujas-Bernate (1994)	1975-1987	5	20	error correction model	R&D (+), Investments (+), Prices (-)
Amable and Verspagen (1995)	1970-1991	5	18	error correction model	Patents (+), Investments (+), Costs (-)
Landesmann and Pfaffermayr (1997)	1973-1987	7	2	almost ideal demand system	R&D (+), Costs (-)
Wakelin (1998b)	1988	9	22	OLS estimation of pooled and sectoral data	R&D (+), Patents (+), Investments (), Costs(-)
Carlin et al. (2001)	1970-1992	14	12	distributed lag model	Patents (), R&D (), Investments (+), Costs (-)
Laursen and Meliciani (2000, 2002)	1973-1991	9	19	dynamic model	R&D linkages (+), Costs (-)
Laursen and Meliciani (2010)	1981-2003	14	16	dynamic model	ICT knowledge flows (+), Costs (-)

Note. The Main results column reports whether a variable has, on average, a positive and relevant effect (+), a negative and relevant effect (-), or is not significant ().

2.2. Findings at the firm-level

Many empirical studies point to a positive impact of innovation as such on exports at the firm level. Using mostly survey data specifically designed to measure innovation activity (e.g. the European framework of the Community Innovation Survey), the relationship has been tested for direct proxies of product and process innovation (Wakelin, 1998a; Basile, 2001; Lachenmaier and Wöß mann, 2006; Cassiman et al., 2010; Van Beveren and Vandenbussche, 2010; Becker and Egger, 2013) as well as for broader set of variables, including measures of innovation inputs like R&D expenditures (Aw et al., 2007; Castellani and Zanfei, 2007; Harris and Li, 2009; Caldera, 2010; Damijan et al., 2010; Ganotakis and Love, 2011) and various proxies of spillovers and interaction effects (Roper and Love, 2002; Barrios et al., 2003; Beise-Zee and Rammer, 2006; Álvarez et al., 2009). The evidence is based on firms active mainly in manufacturing sectors, even if recent contributions have started to investigate the relationship between export and innovation also for firms in services sector (see Eickelpasch and Vogel, 2011). A related issue, that is the contribution of services firms to manufacturing firms, has been analyzed at the sectoral level in Evangelista et al. (2013). Table 2 summarizes the main characteristics of these studies, including the coverage in terms of countries and number of firms, the main data sources, and the structure of the data.

Notably, this literature is mainly focussed on the role of innovation and in most cases it fails to account also for the role of cost-competition in international trade. Among the few exceptions, Wakelin (1998a) shows that unit labour costs do not influence export performance whereas Basile (2001), Beise-Zee and Rammer (2006), and Aw et al. (2007) do find a negative and significant effect of labour costs. Barrios et al. (2003) and Eickelpasch and Vogel (2011) provide evidence for positive effects of wage in a sample of manufacturing Spanish and services German firms. These contrasting evidences can be due, to some extent, to sector-specific absolute advantages (or disadvantages), which are not controlled for in studies that typically estimate pooled (across sectors) regressions.

As mentioned before, most of the empirical literature addressing the relationship between innovation and export behaviour at the firm level employs survey data that present a cross-sectional structure, or only a limited time-series variation (see Table 2). This implies that the effects over time of innovation and costs have seldom received the deserved consideration. And this applies also to studies that employ relatively long panel, like Caldera (2010).

Equation (1) may be forced into some "microfounded" equilibrium rationalization as in new trade theories models (Krugman, 1979, 1980) and, more recently, into "new-new" theories rooted in Melitz (2003), using a monopolistic competition framework, and taking firms' differential efficiency as one of the main determinant of firms' partecipation on international markets in presence of fixed costs (see also Bernard et al., 2007b; Melitz and Ottaviano, 2008). These heterogeneous-firms models usually assume some equilibrium wage equal for all firms, and let all the different degree of export partecipation be driven by different productivities in presence of some (unobserved) sunk entry costs into foreign markets.

Below, our firm-level story is grounded into the technology-gap interpretation of equation (1), in within-country, within-sector estimates. This is indeed a distinctive feature of this analysis. First of all, equilibrium models, while powerful in analyzing the outcomes of uneven technological activities in term of resulting steady states, appear to be much less suited to study the relationship between relative changes in technological activities and relative changes in trade flows - both being plausibly far-from-equibilibrium phenomena. Second, with respect of trade models *à la* Melitz, we do not restrict heterogeneity at the level of differential production efficiency, but we also look at the difference technological activity that characterize firms, and at their influence over firms' trade partecipation.

In this paper, we aim at estimating the distinct effects of technological and cost variables on firms export performance. Using a long panel of Italian firms, we shall consider the role of wage costs, labour productivity, and two proxies of product and process innovations, i.e. patents and investment intesity. Investments are a proxy for whatever goes under the heading of "embodied technical change" and "process innovation". Patents stand mainly for the "disembodied technical change" and "product innovation". These two forms of innovation can affect the trade performance in several ways. Process innovations involve the acquisition of machineries necessary to produce goods at a lower cost. Product innovation is related to different forms of product differentiation or quality improvement which help firms to gain market shares in a world where consumers have a taste for differentiated and high quality products, or new products altogether.

As for the cost variable, it is common in the empirical literature (see 2.1) to look at unit labour costs. Here, we will look at labour productivity and wage separately: this has the advantage that we do not impose that an increase in productivity has the same effect of a decrease in wage. Moreover, it allows us to separate more clearly pure cost effects (wage) from efficiency-related effects.

We shall also assess the short and long run effects of these variables, and the robustness of the results to unobserved heterogeneity and endogenity of both innovation and costs. In the second part of the paper, we will also use proxies of product and process innovation as available through Community Innovation Survey (CIS). This makes our results more comparable to the ones surveyed above. Finally, employing the volume of exports of firms to any given product-country destination, we will consider, in a quite new way, whether innovative and non innovative firms do react in different ways to exogeneous shocks as a real exchange rate.

Table 2: Firm-level studies

Authors	Country	Data source	Structure	Firms
Wakelin (1998a)	UK	SPRU innovation survey	cross-section	320
Sterlacchini (1999)	Italy	field study	cross-section	143
Basile (2001)	Italy	3 Mediocredito surveys	panel	around 6000
Roper and Love (2002)	Germany and UK	product development survey(PDS)	cross-section	1087(UK) and 1190(Germany)
Barrios et al. (2003)	Spain	ESEE survey	panel	around 2000
Beise-Zee and Rammer (2006)	Germany	CIS	cross-section	4786
Lachenmaier and Wöß mann (2006)	Germany	IFO innovation survey	cross-section	981
Aw et al. (2007)	Taiwan	Statistical Bureau's census and R&D survey	panel	between 518 and 1311
Castellani and Zanfei (2007)	Italy	CIS2 and ELIOS	cross-section	785
Álvarez et al. (2009)	Spain	survey in four industries	2 cross sections	134
Harris and Li (2009)	UK	CIS3 and Annual Respondents Database (ARD)	cross-section	3303
Caldera (2010)	Spain	ESEE survey	13-years panel	around 1900
Cassiman et al. (2010)	Spain	ESEE survey	8-years panel	around 1000
Damijan et al. (2010)	Slovenia	CIS1, CIS2, CIS3 and firm accounting data	panel	9148
Van Beveren and Vandenbussche (2010)	Belgium	2 CIS surveys	cross-section	189
Eickelpasch and Vogel (2011)	Germany	German business services statistics	3-years panel	53876
Ganotakis and Love (2011)	UK	survey of new technology based firms (NTBFs)	cross-section	412
Becker and Egger (2013)	Germany	IFO innovation and Business surveys	3-years panel	1212

3. Data and Descriptive statistics

3.1. Dataset description

In order to investigate the sources of firm-level competitiveness several sets of micro-data have to be linked together.

The first is MICRO.3, a databank developed within a collaboration between the Italian Statistical Office (ISTAT) and members of the Laboratory of Economics and Management (LEM) of Scuola Superiore Sant'Anna in Pisa.[1]

[1]The database has been made available for work after careful censorship of individual information. More detailed information on the database Micro.3 is in Grazzi et al. (2013b).

Micro.3, our main source of firm level variables, is based on the census of Italian firms conducted yearly by ISTAT and contains information on firms with more than 20 employees in all sectors of the economy for the period 1989-2006. Starting in 1998 the census of the whole population of firms only concerns companies with more than 100 employees, whereas in the range of employment 20-99, ISTAT directly monitors only a "rotating sample" which varies every five years. Hence, in order to complete the coverage of firms in that range from 1998 onward, Micro.3 resorts to data from the financial statement that limited liability firms have to disclose, in accordance to Italian law.[2] This legal requirement provides us virtually with the universe of limited liability companies bigger than 20 employees. In the end, Micro.3 contains data for 148604 Italian firms, of whom 71437 are active in the Manufacturing sectors. As far as the representativeness of the sample is concerned, Micro.3 covers around 50-60% of the value added generated by all Italian firms in the manufacturing sectors, which are, according to the Nomenclature statistique des Activités économiques dans la Communauté Europénne (NACE) Revision 1.1, sectors 15 to 37.

Micro.3 has been linked to two other sources of microdata. The first is the number of patents granted to Italian firms in the US (USPTO) and in Europe (EPO). After the link, performed by matching the name of the firms, a total of 23477 patents turn out to be matched to 1735 firms in Micro.3. This relatively small number reflects the general fact that the percentage of firms holding patents in any sector is a small share of the total. Other studies on similar database do confirm this trend. Malerba and Orsenigo (1999) employs a dataset which contains 15175 patents *application* by 3805 firms (Malerba and Orsenigo, 1999, p. 646), while Cefis and Orsenigo (2001), who still consider patents application, rely on 1369 firms (Cefis and Orsenigo, 2001, p. 1142). On the contrary, we consider here only granted patents as a more meaningful proxy of innovation activity. Notice also that the process of linking data on granted patents to other database, such as Micro.3, is usually rather difficult. The classification used by the patent office and that implemented by the national office for structural business statistics are different, hence the comparison and linking of the two database requires some pattern recognition techniques.

The second set of microdata that we link to Micro.3 is COE (Statistiche del Commercio Estero), which registers the export activity of all Italian firms. Micro.3 and COE are both provided by ISTAT, hence, using the unique identification code of the firm, it is possible to link the firm-level export data to Micro.3. This allows us to obtain data on exports volume for all the period of analysis. Further, the data for the more recent time window (1998-2006) can be disaggregated at the firm-product-country level. Obviously, the necessity to

[2]Limited liability companies (società di capitali) have to provide a copy of their financial statement to the Register of Firms at the local Chamber of Commerce.

Table 3: Observations by manufacturing sectors in year 2000

	(I)	(II)	(III)	(IV)	(V)
All manufacturing	30,599	100.00	100.00	75.87	100.00
Food, beverages, tobacco	2,049	6.70	7.75	74.33	4.80
Textiles, wearing, leather	5,379	17.58	13.70	72.91	13.94
Wood	776	2.54	1.49	66.88	0.67
Paper & printing	1,709	5.59	5.06	69.28	2.56
Coke & petroleum	108	0.35	0.90	41.67	2.61
Chemicals	1,174	3.84	6.67	91.99	10.11
Rubber & plastics	1,863	6.09	5.15	86.74	4.68
Other non-metallic	1,697	5.55	5.09	64.76	3.34
Basic metals	866	2.83	4.57	82.56	4.99
Fabricated metal	4,668	15.26	9.66	63.52	5.27
Machinery	4,433	14.49	15.22	87.95	20.70
Computing & electrical	2,681	8.76	10.41	74.67	9.93
Transport equipment	1,023	3.34	9.57	77.61	11.07
Other manufacturing	2,173	7.10	4.74	85.18	5.33

Note. (I) Number of firms; (II) percentage share of firms within each sector; (III) shares of employment; (IV) percentage of exporting firms within each sector; (V) shares of export volumes.

link COE to MICRO.3 limits the sample of firms to those with 20 or more employees. Depending on the years, these firms represent between 75% and 80% of Italian exports.

The resulting dataset is used for the empirical analysis of section 4. Table 3 reports, for each sector and for the aggregate manufacturing in 2000, number of firms, the percentage shares of firms in each sector, shares of employment, percentage of exporting firms, share of export volumes. We observe (column II) that almost one half of firms with more than 20 employees are active in three sectors: textile, machinery, and fabricated metal, whereas the distribution in terms of employment (column III) is a little bit less skewed (the three biggest sectors account for around 40% of the total employment).

As for the international activity of the firms, one notices differences in the export propensity (column IV): the machinery and the chemical industries have around 90% exporting firms, while sectors like textiles, food, and transport equipment report significantly lower figures, around 75%. Notice that these percentages refer to the export propensities of firms bigger than 20 employees.[3] Column V shows that the machinery sector alone accounts for around one fifth of export volumes: this is not surprising, given the importance of this sector in the international specialization of Italian manufacturing. Also relevant is the export share of the chemical sector, which account for around 6.5% of employment but for more than 10% of export volumes. Textiles, computing, and transport equipment, account for another one third of export volumes.

Table 4: Descriptive statistics in year 2000

	VOLUME OF EXPORTS		WAGE		PRODUCTIVITY		INV		PATENT	
	Mean	(Std.Dev.)	Mean	(Std.Dev.)	Mean	(Std.Dev.)	Mean	(Std.Dev.)	Mean	(Std.Dev.)
All manufacturing	5814.76	(42494.50)	27.64	(12.28)	45.24	(30.82)	0.11	(0.23)	0.04	(0.20)
Food, beverages, tobacco	4168.39	(17625.17)	28.60	(10.20)	52.80	(34.51)	0.16	(0.25)	0.01	(0.10)
Textiles, wearing, leather	4610.01	(20714.46)	22.18	(7.78)	34.78	(21.93)	0.09	(0.22)	0.01	(0.10)
Wood	1547.65	(4587.60)	22.59	(5.85)	36.49	(16.42)	0.13	(0.24)	0.01	(0.12)
Paper & printing	2662.37	(15492.91)	30.76	(14.20)	49.97	(36.41)	0.14	(0.29)	0.01	(0.11)
Coke & petroleum	42992.41	(223717.29)	37.65	(12.27)	86.56	(60.50)	0.16	(0.16)	0.01	(0.10)
Chemicals	15318.63	(62288.25)	37.26	(12.62)	72.88	(60.59)	0.14	(0.26)	0.12	(0.32)
Rubber & plastics	4467.90	(21290.59)	26.92	(7.26)	45.86	(28.60)	0.13	(0.20)	0.05	(0.22)
Other non-metallic	3505.68	(12135.63)	28.90	(30.92)	49.03	(50.89)	0.12	(0.19)	0.03	(0.16)
Basic metals	10257.20	(49867.96)	31.25	(14.29)	55.52	(30.75)	0.18	(0.33)	0.02	(0.15)
Fabricated metal	2007.87	(6250.15)	27.31	(7.69)	42.42	(19.35)	0.10	(0.17)	0.03	(0.16)
Machinery	8309.26	(35881.70)	31.70	(9.29)	49.50	(24.82)	0.07	(0.24)	0.10	(0.31)
Computing & electrical	6590.90	(44967.35)	28.62	(10.88)	44.96	(26.82)	0.07	(0.12)	0.07	(0.25)
Transport equipment	19245.22	(160219.26)	28.25	(9.20)	44.94	(26.90)	0.10	(0.20)	0.06	(0.23)
Other manufacturing	4366.32	(16258.90)	23.10	(6.39)	36.77	(19.86)	0.08	(0.24)	0.03	(0.17)

Note. VOLUME OF EXPORTS, WAGE and PRODUCTIVITY are in thousands of euros. INV is defined as investments in tangible fixed assets over value added. PATENT is a dummy variabile taking value one if the firm's stock of patents is non empty.

3.2. Variables

We shall relate the propensity to export and export volumes to firm's average labour cost per employee ($WAGE$); labor productivity ($PROD$), defined as the ratio between value added (at constant prices) and employment; investment intensity (INV), defined as the ratio of acquired tangible assets to the firm's value added; and finally, a dummy for patents (PAT), taking value one if the firm's stock of patents is non empty.

Investment intensity measures the degree to which a firm devotes resources to the acquisition of machineries and other kinds of industrial equipment which is likely to embody new technologies and thus new (cost-reducing) ways of producing goods. It is a normalized measure (with respect to value added) since the amount of investments greatly depends on the size of the firm. The dynamics of firms' investment and its relation to performance are analyzed at length in Grazzi et al. (2013a) on the same set of data, finding a rather small, but positive and significant relation between so-called investment spikes and firms' productivity.

Some explanation is required for the patent dummy variable. As already mentioned, only a tiny fraction of Italian firms do patent. Hence, in our sample, in 2000 out of 30599 firms, only 1297 (4.2%) reported to have one or more patents and a mere 735 firms had two or more patents. Not only there are very few patenting firms overall, we also observe very low rates of transition into the status of innovation as proxied by patents. Out of the 71437 firms that we are able to track for at least some years, the vast majority (71304) enters the sample holding no patents, and only 1332 (1.9%) firms registered at least one patent during the period of observation. Given the observed patterns, a dummy variable enables to capture most of the information about patenting activity.[4] Table 4 reports

[3]Export propensity for the whole population of Italian firms is much lower. For the aggregate manufacturing is around 20% (see, ICE-ISTAT, 2011, pag. 256).

[4]Also notice that there exists some relation between patenting activity and international trade. 82%

some descriptive statistics of the main variables used in the empirical analyses.

4. Technology and cost competion: analysis on firm-level integrated data

4.1. Econometric strategy

In this section, we resort to integrated firm-level data to analyze the determinants of Italian manufacturing exports within the traditional framework of the empirical micro literature on trade and innovation (see section 2.2). In our baseline specification, we relate the (1-year lagged) technological and cost variables to the main dependent variable, in two different steps. A first one relates to the probability of the firm of being an exporter (the so called "extensive margin"). A second one concerns the performance of exporting firms in terms of levels of exports (the so called "intensive margin"). In this setting, we use pooled tecniques, respectively, probit and OLS estimation. For our baseline specification (levels of exports), we perform a first robustness analysis by controlling for time-variant omitted variables that could bias the estimates (inverse mills ratio in the Heckman selection model). This rather simple regression framework enhances the comparability of our results to those at the country and sector level (section 2.1) as well as to the firm level findings reviewed in section 2.2.

Next, we resort to a dynamic distributed lag model, common within the literature at the macro and sectoral level (see section 2.1) and adapt it to firm-level analysis. This enables us to estimate both the short-run and the long-run effects of technological and cost variables. At least as important, this regression framework also allows to control both for unobserved heterogeneity and for endogeneity of all our main regressors through a "system GMM" estimation.

4.2. Selection into export markets

Consider the factors affecting firm's decision to enter foreign markets. Here, due to data constraint, one can only investigate the propensity to export of firms bigger than 20 employees (see table 3 and section 3.2). Among these firms, there are many that export and other that sell only on domestic markets: export status is not randomly assigned, but rather reminds of firms' specific "identity cards", that determine also their differential exporting behaviour. Export status is indeed quite stable: on the same dataset of Italian firms, Grazzi (2012) calculates a probability of around 0.9 that a firm exporting in year t is still exporting in year $t+1$.

We estimate the following equation (all variables are expressed in log):

$$\begin{aligned} P(D_{EXP_{it}} = 1) = \Phi(&\alpha WAGE_{it-1} + \beta PROD_{it-1} \\ &+ \gamma INV_{it-1} + \delta PATt_{it-1} + \phi EMP_{it-1} + d_t + \epsilon_{it}) \end{aligned} \tag{2}$$

of all patenting firms are also exporters (compared to a 57% of exporters among non patenting firms).

Table 5: Selection into export markets

Dependent variable: export dummy						
	WAGE	PROD	INV	PAT	Obs.	firms
All manufacturing	0.034^a	0.119^a	0.011^a	0.115^a	181524	39761
	(0.008)	(0.005)	(0.001)	(0.007)		
Food, beverages, tobacco	-0.007	0.132^a	0.009^b	0.144^a	14136	2941
	(0.030)	(0.016)	(0.004)	(0.044)		
Textiles, wearing, leather	-0.052^a	0.253^a	-0.017^a	0.053	32356	8030
	(0.020)	(0.013)	(0.003)	(0.070)		
Wood	0.044	0.204^a	0.010	0.206^a	4854	1028
	(0.062)	(0.038)	(0.007)	(0.061)		
Paper & printing	-0.274^a	0.131^a	0.023^a	0.122^c	10635	2268
	(0.038)	(0.023)	(0.004)	(0.066)		
Coke & petroleum	0.335^b	-0.041	-0.014	-0.085	915	158
	(0.149)	(0.073)	(0.015)	(0.056)		
Chemicals	0.038^c	0.014	0.004	0.025	9261	1714
	(0.021)	(0.012)	(0.003)	(0.016)		
Rubber & plastics	0.107^a	0.068^a	0.009^a	0.007	9846	2074
	(0.023)	(0.013)	(0.003)	(0.022)		
Other non-metallic	0.283^a	-0.106^a	-0.008^c	0.285^a	12685	2532
	(0.043)	(0.023)	(0.004)	(0.030)		
Basic metals	0.105^a	0.063^a	0.012^a	0.163^a	7108	1236
	(0.039)	(0.019)	(0.004)	(0.010)		
Fabricated metal	0.067^b	0.218^a	0.034^a	0.216^a	21541	5011
	(0.029)	(0.019)	(0.003)	(0.024)		
Machinery	0.054^a	0.070^a	0.009^a	0.066^a	24312	5010
	(0.014)	(0.008)	(0.002)	(0.007)		
Computing & electrical	0.095^a	0.150^a	0.041^a	0.114^a	15294	3624
	(0.023)	(0.015)	(0.003)	(0.014)		
Transport equipment	0.169^a	0.051^a	0.012^a	0.140^a	5725	1244
	(0.042)	(0.020)	(0.004)	(0.015)		
Other manufacturing	0.001	0.075^a	0.001	0.094^a	12856	2891
	(0.024)	(0.014)	(0.003)	(0.024)		

Note. Probit estimation. Marginal effects computed at means (discrete change from 0 to 1 for patent dummy) with robust standard errors clustered at the firm level in parentheses. Coefficient on EMP omitted. Sector-year dummies are included in the first regression (All manufacturing) and year dummies in the sectoral regressions. ^{a} $p < 0.01$, ^{b} $p < 0.05$, ^{c} $p < 0.10$.

where D_{EXP} is a binary variable taking value one if the firm exports, and zero otherwise. EMP denotes the (log) number of employees and it is added as a control for possible size effects, d_t controls for year fixed effects. Results from the probit estimation of equation (2) are presented in Table 5.

Patents are significant and with a positive sign, in 10 out of 14 sectors. Among these, it is worth mentioning the machinery, the computing, and the transport sectors, in which the highest percentage of patenting firms is registered (respectively 12%, 7%, and 7% in 2006). A bit more surprising is the result for the chemical sector, in which patents, as proxies for innovativeness, seem to play no significant role.[5]

[5]This is plausibly due to the very heterogeneity of the sector, which includes segments - like basic

A similar pattern is observed also for investment intensity, our proxy for process innovation, which does not turn out to be positive and significant only in 5 out of 14 sectors, whereas productivity is not significant in just two sectors.

The $WAGE$ variable is often positive and significant, except in the paper and textiles sectors, where it is negative and significant, and in three other sectors (Food, wood and other manufacturing) where it is not significant. Hence, it would appear that not only cost of labour is not a general deterrent to export participation, but in many sectors firms with a higher cost per employee are more likely to export. Indeed wages are obviously an element of cost for the firm, but they also capture differential skills and, possibly, also that part of the "innovation rent" distributed to workers. This evidence is in agreement with much of the empirical work on the selection into export markets: exporting firms pay higher wages than non exporting firms (see Bernard and Jensen (1999) for evidence on manufacturing firms in USA and Serti et al. (2010) for evidence on Italy based on a previous version of the dataset used here).

The coefficient on the (log) number of employees, not reported in Table 5 is, as expected, positive and significant in all sectors: other things being equal larger firms are more likely to export.

Two clear messages emerge from the evidence presented above. First, total labour compensation does not appear to be a hindrance to export participation. Given our baseline specification we hold back from deriving strong causal relationships from a single regression but the correlation is there and widespread. Second, labour productivity alone is able to capture only a part of the technological heterogeneity existing among firms withinin an industry. In fact, both the degree of investment intensity (a proxy for capital-embodied process innovation) and the propensity to patent (standing mostly for product innovation) are positively correlated with the probability to export in most sectors, even among firms with similar productivity levels.

Technology seems to be a crucial dimension that allows firms to take part or not to the export markets. In the next paragraph, we will investigate to what extent, among exporting firms, technology and costs shape the dynamics of exports.

4.3. Levels of exports

Let us now analyze the determinants of trade volumes of Italian firms during the period 1989-2006. The baseline model describing the determinants of levels of exports read as follows (all variables are in logs):

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chemicals and plastics - where innovation-based advantages are not likely to influence export activities, and others - such as drugs and many organics chemicals - where it does. Further disaggregation would critically reduce the number of observations within each sub-sector.

Table 6: Levels of exports

Dependent variable: trade volumes						
	WAGE	PROD	INV	PAT	Obs.	firms
All manufacturing	-0.002	0.920^{a}	0.086^{a}	0.551^{a}	138241	31255
	(0.053)	(0.029)	(0.006)	(0.041)		
Food, beverages, tobacco	0.333^{c}	0.876^{a}	0.152^{a}	1.057^{a}	9931	2310
	(0.184)	(0.089)	(0.026)	(0.401)		
Textiles, wearing, leather	-0.046	1.182^{a}	-0.066^{a}	0.614^{a}	23326	5778
	(0.117)	(0.060)	(0.014)	(0.141)		
Wood	-0.332	0.486^{b}	0.025	1.825^{a}	3226	743
	(0.387)	(0.233)	(0.042)	(0.253)		
Paper & printing	-1.438^{a}	1.004^{a}	0.217^{a}	1.365^{a}	7249	1719
	(0.263)	(0.143)	(0.027)	(0.347)		
Chemicals	0.199	0.801^{a}	0.307^{a}	0.161	8153	1578
	(0.210)	(0.106)	(0.029)	(0.143)		
Rubber & plastics	0.948^{a}	0.922^{a}	0.074^{a}	0.381^{a}	8492	1848
	(0.205)	(0.110)	(0.024)	(0.110)		
Other non-metallic	1.655^{a}	-0.238	-0.041	0.762^{a}	8178	1755
	(0.255)	(0.149)	(0.027)	(0.226)		
Basic metals	0.114	1.023^{a}	0.080^{a}	0.099	5743	1064
	(0.303)	(0.124)	(0.029)	(0.343)		
Fabricated metal	-0.009	1.135^{a}	0.120^{a}	0.706^{a}	14647	3531
	(0.160)	(0.098)	(0.017)	(0.121)		
Machinery	0.094	0.918^{a}	0.039^{a}	0.413^{a}	21544	4531
	(0.108)	(0.064)	(0.012)	(0.056)		
Computing & electrical	-0.279^{c}	0.842^{a}	0.193^{a}	0.540^{a}	12056	2796
	(0.152)	(0.093)	(0.022)	(0.112)		
Transport equipment	0.320	0.922^{a}	0.150^{a}	0.941^{a}	4680	1041
	(0.349)	(0.169)	(0.034)	(0.173)		
Other manufacturing	-0.740^{a}	1.214^{a}	0.066^{a}	0.545^{a}	10562	2471
	(0.182)	(0.111)	(0.023)	(0.158)		

Note. Pooled OLS estimation with robust standard errors clustered at the firm level in parentheses. Coefficient on EMP omitted. Sector-year dummies are included in the first regression (All manufacturing) and year dummies in the sectoral regressions. ^{a} $p < 0.01$, ^{b} $p < 0.05$, ^{c} $p < 0.10$.

$$
\begin{aligned}
EXP_{it} =& \alpha WAGE_{it-1} + \beta PROD_{it-1} + \gamma INV_{it-1} \\
&+ \delta PAT_{it-1} + \phi EMP_{it-1} + d_t + \epsilon_{it}
\end{aligned} \tag{3}
$$

where EXP denotes the trade volumes and EMP is added, again, to control for size effects, d_t controls for year fixed effects. Equation (3) is estimated with pooled OLS for the reason explained above. Results are reported in Table 6[6].

Patenting firms report, on average, higher exports, with a “premium” that varies across sectors and is significant in all sectors except for basic metals and chemicals. Labour

[6] Here, and in the following analysis, the coke & petroleum sector is not taken into account due to the small number of exporting firms.

productivity is always positive and significant, with the exception of the non-metallic sector, where it is not significant. Investment intensity is positive and significant in all industries but wood products and non-metallic minerals, where it is not significant, and textile, where somewhat puzzlingly investment shows a negative sign. The coefficient on the number of employees, not reported in the table, is positive and significant in all sectors.

The coefficients accounting for labour compensation display a more ambiguous picture. In three industries (paper and printing, computing & electrical, other manufacturing), the negative and significant values suggest that wages might be a factor in hindering international competitiveness. However, it is either not significant or positive in the majority of sectors. As it was the case with the selection equation, also in this case total labor compensation appears to capture, at least partly, different qualities of the workforce across firms, and possibly some sharing by workers of any "competitiveness rent".

So far, the analysis has assumed that the effects of costs and technologies are homogeneous over time. In order to control for possible structural breaks, and in particular for changes brought about by the Euro introduction, we estimate equation (3) on two separate samples, 1989-1995 (pre-Euro) and 2000-2006 (post-Euro).[7] Results, not shown here, are much similar to those presented in Table 6, as far as the pre-Euro period is concerned, with the exception of the coefficient on wage in the first period, which is negative and significant for the aggregate manufacturing, and in textiles, fabricated metal and machinery sectors. In the years following the Euro introduction, the coefficient on wage becomes positive and significant in the aggregate regression and in textiles, basic metals, fabricated metal and machinery sectors (and not significant in computing and other manufacturing were it was negative and significant). These results hint at the possibility that cost competition became less important in some sectors after the Euro introduction. We also observe that in some sectors (food, transport, other manufacturing) there has been an increased importance of technological competition, as put forward by the patent dummy coefficient: it is not significant in the first period and becomes positive and significant in the second period. This result is consistent with the findings on a sample of Italian firms in Basile (2001) showing that in a period of potential and/or actual devaluation, innovation is a less effective tool of non-price competitition.

4.4. Robustness

As we have shown in Section 4.2, exporting firms tend to have specific characteristics that enable them to engage in competition with foreign firms on world markets. As a first robustness analysis, and as standard in the "new-new" trade literature (see review in section 2.2), we adopt here a version of the Heckman selection framewrok in order to

[7]Refer to Dosi et al. (2012) for an exercise on the same dataset taking into account the Euro introduction.

Table 7: Levels of exports: Heckman selection model

Dependent variable: trade volumes						
	WAGE	PROD	INV	PAT	Obs.	firms
All manufacturing	-0.049	0.758^a	0.072^a	0.499^a	181524	39761
	(0.048)	(0.027)	(0.006)	(0.038)		
Food, beverages, tobacco	0.256	0.690^a	0.143^a	1.026^b	14136	2941
	(0.167)	(0.084)	(0.025)	(0.415)		
Textiles, wearing, leather	-0.054	0.909^a	-0.039^a	0.668^a	32356	8030
	(0.107)	(0.058)	(0.013)	(0.145)		
Wood	-0.362	0.205	0.009	1.828^a	4854	1028
	(0.350)	(0.216)	(0.039)	(0.206)		
Paper & printing	-0.853^a	0.777^a	0.165^a	1.310^a	10635	2268
	(0.243)	(0.130)	(0.025)	(0.295)		
Chemicals	0.153	0.764^a	0.291^a	0.118	9261	1714
	(0.196)	(0.098)	(0.026)	(0.137)		
Rubber & plastics	0.733^a	0.800^a	0.062^a	0.404^a	9846	2074
	(0.190)	(0.102)	(0.023)	(0.100)		
Other non-metallic	1.210^a	-0.057	-0.018	0.567^a	12685	2532
	(0.228)	(0.134)	(0.025)	(0.207)		
Basic metals	-0.071	0.943^a	0.073^b	-0.031	7108	1236
	(0.283)	(0.117)	(0.029)	(0.326)		
Fabricated metal	-0.094	0.885^a	0.072^a	0.596^a	21541	5011
	(0.147)	(0.091)	(0.016)	(0.115)		
Machinery	0.014	0.795^a	0.028^b	0.336^a	24312	5010
	(0.101)	(0.060)	(0.012)	(0.053)		
Computing & electrical	-0.351^b	0.673^a	0.142^a	0.462^a	15294	3624
	(0.142)	(0.087)	(0.021)	(0.107)		
Transport equipment	0.111	0.796^a	0.126^a	0.777^a	5725	1244
	(0.308)	(0.151)	(0.031)	(0.168)		
Other manufacturing	-0.706^a	1.055^a	0.057^a	0.508^a	12856	2891
	(0.170)	(0.107)	(0.022)	(0.144)		

Note. Maximum likelihood estimation of Heckman selection model with robust standard errors clustered at the firm level in parentheses. The excluded selection variable is the firm's export status at time $t-1$. Coefficient on EMP omitted. Sector-year dummies are included in the first regression (All manufacturing) and year dummies in the sectoral regressions. ^{a} $p < 0.01$, ^{b} $p < 0.05$, ^{c} $p < 0.10$.

check if the results about the determinants of exports are heavily driven by a selection bias.

In Table 7 we report the results obtained from the maximum likelihood estimation of a Heckman model in which the equation describing the selected sample is our equation (3) and the selection variable, excluded from the level equation, is the export status of the firm at time $t-1$. The number of firms and observations refer both to the censored and uncensored regression.

Based on the Wald test for the correlation of the error term of the selection and the level equation (not reported in the table), we reject in all sectors the hypothesis that the decision to export is independent from the volume of exports. As for the coefficients, most of the results obtained in section 4.3 through pooled OLS are qualitatively unchanged. The main difference concerns the wage variable in the food sector and the productivity variable in the wood sector: their coefficients are still positive but not significant anymore. In all the other sectors, the pattern is the same observed in the previous section even if point estimates tend to be on average slightly smaller.

4.5. Short-run vs. *long-run*

In this section, we provide estimates of both short-run and long-run coefficients on wage, productivity, investment intensity, and patents. The exercise fits within the empirical framework used in most studies at the country and sector level (see section 2.1), and it aims to offer a novel evidence about exports' determinants at the firm level.

Adapting the empirical framework of Amendola et al. (1993) to firm-level data, we specify an autoregressive distributed lag model (ADL) which reads as follows:

$$\begin{aligned} EXP_{it} = & \sum_{l=1}^{K} \eta_l EXP_{it-l} + \sum_{l=1}^{L} \alpha_l WAGE_{it-l} + \sum_{l=1}^{L} \beta_l PROD_{it-1} + \sum_{l=1}^{L} \gamma_l INV_{it-1} \\ & + \sum_{l=1}^{L} \delta_l PAT_{it-1} + \sum_{l=1}^{L} \phi_l EMP_{it-1} + d_t + \epsilon_{it} \end{aligned} \tag{4}$$

Equation (4) is similar to the specification in Carlin et al. (2001) who, however, do not estimate the autoregressive term ($\eta = 0$). Here, similarly to Amendola et al. (1993), we choose $K = 1$ and $L = 3$.

In order to identify the short-run coefficients, we employ a "twostep system GMM" estimator, which allows to control both for unobserved heterogeneity and for the potential endogeneity of cost and technology variables. In particular, we use, where possible, less distant lags (typically at $t - 2$ and $t - 3$) to instrument, in the first difference equation, both the lagged value of the dependent variable (EXP_{it-1}) and the variables that we take as endogeneous, that is wage, productivity, investment intensity, and patents. Long-run coefficients are calculated from the short-run ones according to the formula:

$$x_{long-run} = \frac{\sum_{l=1}^{3} x_l}{1 - \eta_1} \tag{5}$$

where $x \in \{\alpha, \beta, \gamma, \delta\}$.

Table 8: ADL model for levels of exports: short-run coefficients

Dependent variable: trade volumes												
	WAGE			PROD			INV			PAT		
	$t-1$	$t-2$	$t-3$	$t-1$	$t-2$	$t-3$	$t-1$	$t-2$	$t-3$	$t-1$	$t-2$	$t-3$
All manufacturing	-1.360^c	0.330	0.150	1.211^a	0.165	-0.400^a	0.179^b	0.093	−0.022	3.375^b	−0.465	-2.690^b
	(0.785)	(0.670)	(0.177)	(0.306)	(0.281)	(0.145)	(0.078)	(0.071)	(0.013)	(1.468)	(1.405)	(1.196)
Food, beverages, tobacco	0.442	0.089	−0.173	0.038	0.117	0.068	0.001	0.006	−0.050	−0.120	−0.099	−0.215
	(0.271)	(0.302)	(0.245)	(0.094)	(0.088)	(0.115)	(0.031)	(0.025)	(0.031)	(0.318)	(0.348)	(0.224)
Textiles, wearing, leather	−0.042	−0.099	-0.492^c	0.281^a	0.129^b	0.413^a	0.035	0.030	0.032	0.017	−0.011	0.145
	(0.175)	(0.151)	(0.284)	(0.076)	(0.064)	(0.137)	(0.021)	(0.019)	(0.022)	(0.158)	(0.166)	(0.138)
Wood	−0.133	0.081	−0.085	0.204	0.104	−0.048	0.026	0.034	0.073	0.980	0.005	−0.073
	(0.351)	(0.324)	(0.351)	(0.175)	(0.168)	(0.250)	(0.064)	(0.046)	(0.065)	(0.725)	(0.418)	(0.468)
Paper & printing	−0.224	−0.184	−0.486	0.395^b	0.157	0.076	0.079^b	0.066^c	0.035	0.287	0.620	0.208
	(0.362)	(0.317)	(0.379)	(0.190)	(0.154)	(0.192)	(0.038)	(0.035)	(0.040)	(0.315)	(0.463)	(0.212)
Chemicals	0.115	0.207	−0.301	0.212^b	−0.041	0.256^c	0.057^c	0.064^b	0.097^a	−0.034	0.073	0.009
	(0.324)	(0.281)	(0.243)	(0.108)	(0.087)	(0.141)	(0.030)	(0.030)	(0.032)	(0.164)	(0.147)	(0.242)
Rubber & plastics	−0.007	0.161	−0.367	0.143	−0.078	0.254	0.048^c	0.062^b	0.040	−0.279	0.142	0.076
	(0.297)	(0.224)	(0.283)	(0.115)	(0.130)	(0.173)	(0.026)	(0.026)	(0.029)	(0.299)	(0.510)	(0.304)
Other non-metallic	0.031	0.269	−0.205	0.017	−0.024	0.116	−0.009	−0.021	0.009	−0.117	0.520	0.188
	(0.249)	(0.276)	(0.282)	(0.123)	(0.105)	(0.176)	(0.032)	(0.030)	(0.040)	(0.395)	(0.768)	(0.416)
Basic metals	0.084	0.357	-0.736^c	0.105	0.073	−0.009	0.009	0.051	0.049	0.013	0.261	−0.401
	(0.429)	(0.411)	(0.413)	(0.137)	(0.126)	(0.159)	(0.043)	(0.038)	(0.052)	(0.472)	(0.518)	(0.398)
Fabricated metal	−0.158	−0.026	−0.095	0.027	0.046	0.150	0.036	0.007	0.010	−0.005	0.172	−0.216
	(0.233)	(0.208)	(0.266)	(0.096)	(0.123)	(0.213)	(0.025)	(0.024)	(0.025)	(0.097)	(0.139)	(0.176)
Machinery	0.109	0.276	0.127	0.452^a	0.040	-0.276^c	−0.006	0.104^b	−0.004	0.155	−0.226	0.196
	(0.531)	(0.558)	(0.167)	(0.201)	(0.250)	(0.147)	(0.032)	(0.043)	(0.013)	(0.291)	(0.287)	(0.296)
Computing & electrical	0.198	0.059	-0.918^a	0.267^b	−0.022	0.266	0.077^b	0.057^c	0.078^b	0.371^a	−0.239	0.545^b
	(0.168)	(0.263)	(0.318)	(0.123)	(0.109)	(0.175)	(0.031)	(0.030)	(0.038)	(0.107)	(0.204)	(0.220)
Transport equipment	−0.206	0.404	-1.065^b	0.205	-0.484^b	0.800^a	0.010	−0.011	0.028	0.215	0.058	0.014
	(0.313)	(0.275)	(0.419)	(0.153)	(0.196)	(0.309)	(0.035)	(0.031)	(0.043)	(0.240)	(0.456)	(0.251)
Other manufacturing	−0.511	-0.628^b	−0.509	0.571^a	0.567^a	0.413^b	0.034	0.018	−0.002	−0.096	0.055	0.136
	(0.402)	(0.288)	(0.350)	(0.151)	(0.183)	(0.182)	(0.038)	(0.033)	(0.042)	(0.276)	(0.573)	(0.557)

Note. Twostep system GMM estimation. Coefficients on EXP_{t-1} and EMP_{t-l} omitted. Sector-year dummies are included in the first regression (All manufacturing) and year dummies in the sectoral regressions. Robust standard errors in parentheses. ^{a} $p < 0.01$, ^{b} $p < 0.05$, ^{c} $p < 0.10$.

Table 9: ADL model for levels of exports: long-run coefficients

Dependent variable: trade volumes							
	WAGE	PROD	INV	PAT	Obs.	firms	AR(2)
All manufacturing	-3.468^c	3.841^a	0.983^a	0.869^a	60669	15738	0.198
	(1.866)	(0.867)	(0.338)	(0.278)			
Food, beverages, tobacco	1.456	0.907	−0.176	−1.763	4275	1103	0.998
	(1.721)	(0.992)	(0.325)	(2.112)			
Textiles, wearing, leather	−2.142	2.788^a	0.326	0.511	9677	2664	0.246
	(1.568)	(0.671)	(0.198)	(0.557)			
Wood	−0.459	0.868	0.445	3.052^b	1428	369	0.503
	(1.757)	(1.309)	(0.486)	(1.338)			
Paper & printing	−2.943	2.067^b	0.592^c	3.667^b	3167	876	0.408
	(1.984)	(1.040)	(0.323)	(1.433)			
Chemicals	0.078	1.683^c	0.855^a	0.188	3825	879	0.421
	(1.977)	(0.887)	(0.292)	(1.127)			
Rubber & plastics	−0.967	1.451	0.683^c	−0.280	3897	1004	0.334
	(2.646)	(1.255)	(0.363)	(1.021)			
Other non-metallic	0.375	0.431	−0.079	2.338^b	3796	937	0.006
	(1.800)	(1.048)	(0.373)	(1.159)			
Basic metals	−0.917	0.526	0.337	−0.394	2755	620	0.520
	(2.445)	(0.947)	(0.381)	(1.476)			
Fabricated metal	−2.371	1.905	0.455	−0.410	6315	1727	0.042
	(3.215)	(1.855)	(0.587)	(1.599)			
Machinery	4.646	1.953	0.856^c	1.137^b	9736	2422	0.093
	(3.041)	(1.871)	(0.466)	(0.581)			
Computing & electrical	−1.387	1.071^c	0.444^b	1.418^a	5076	1316	0.753
	(0.981)	(0.555)	(0.195)	(0.524)			
Transport equipment	−3.155	1.898	0.095	1.042	2039	524	0.643
	(2.446)	(1.284)	(0.330)	(1.084)			
Other manufacturing	-4.689^c	4.415^a	0.144	0.270	4464	1240	0.798
	(2.470)	(1.260)	(0.301)	(1.034)			

Note. Twostep system GMM estimation. Long-run coefficients calculated as from formula (5). Sector-year dummies are included in the first regression (All manufacturing) and year dummies in the sectoral regressions. Robust standard errors in parentheses. ^{a} $p < 0.01$, ^{b} $p < 0.05$, ^{c} $p < 0.10$.

To ease the reading of the results, short-run and lon-run coefficients are reported in two different tables, respectively 8 and 9. In Table 9, we also report the number of observations and firms for each regression, as well as the p-value of the Arellano-Bond test for second-order autocorrelation in the error term of the first difference equation. Notice that in three sectors (other non-metallic, fabricated metal, machinery) the test rejects the hypothesis of no autocorrelation. In these sectors, we instrument the lagged dependent variable with deeper lags ($t-4$ and $t-5$). The same set of instruments is used for the rubber and plastics sector and the aggregate manufacturing, where the AR(2) test was unsatisfactory when using lags $t-2$ and $t-3$. The p-value of the Hansen test (not reported in table) is usually well above 0.10, with the only exception of textile sector and aggregate manufacturing.

In the tables, we do not report the coefficient on EXP_{t-1} which is significant in all sectors, with an average value of 0.7. Labour costs display some negative and significant effects in the short-run (usually with a 3-years lag) in five sectors (textiles, basic metals, computing, transport and other manufacturing). However, this effect vanishes in the long-run: it is apparent from Table 9 that the negative effect of wage is significant only in the residual sector of other manufacturing.

Technology variables show quite a different pattern. Investment intensity turns out to have a positive and significant effect in the short-run, usually in two or in all three lags, in five sectors (paper and printing, chemicals, rubber and plastics, machinery and computing). In these sectors, investments intensity is a significant driver of export performance also in the long-run. The patent variable, on the contrary, does not seem to have any effect in the short-run, with the significant exception of the computing and electrical sector, where it is positive and significant in the first and in the third lag. The effects of patents show up in the long-run: indeed, the dummy variable is positive and significant in five industries (wood, paper and printing, other non-metallic, machinery, computing and electrical).

Summing up, the most general finding concerns the long-term competitive effect of innovation both in its disembodied form, as captured by patents, and embodied into investments. Conversely, changes in wages appear to display only short-run effects, which are reabsorbed in the longer term. In this respect, results are rather consistent with the aggregate evidence reviewed in Section 2.1.

5. Product versus process innovation: CIS surveys

The analyses of the previous section rest on an integrated firm-level database. In this respect, one of the main advantage of Micro.3 was the large and representative sample of business firms. Compared to many previous firm-level studies it was possible to employ a much bigger set of firms, see for instance the figures in Table 2. However, that comes together with some constraints on the choice of the variables of interests. Process innovation had to be proxied with investment and product-related innovation with registered patents. In this section, and as standard in many innovation studies (again, refer to Table 2), we resort to the Italian section of the Community Innovation Survey (CIS) for complementary measures of product and process innovation. We employ both the 2000 (CIS3) and 2004 (CIS4) waves. The CIS3 dataset is a cross-sectional survey of innovation activities performed by firms during the 1998-2000 period. The survey covers all the firms with 250 or more employees in 2000 and a sample of firms in the range of employment 10-250. In the end, there are 15512 firms in CIS3, of which 9034 are active in manufacturing sectors. The CIS4 survey covers the 2002-2004 period and employs the same methodology as the CIS3. It offers information about 21854 firms, of which 7586 are manufacturing firms.[8] Notice that only 5923 firms are present in both surveys (3194 for manufacturing).When linked to Micro.3, the sample is further reduced because some firms surveyed by CIS are below the 20 employee threshold of Micro.3. For the analysis on manufacturing sectors, we can use information about 5434 firms for CIS3 and 4206 for CIS4: of these, only 1845 are present in both surveys.

The CIS surveys report answers provided by the firms to a questionnaire concerning various aspects of their innovative activities. They have been already employed to investigate the relation between innovation and firm performance, both in Italy (see among the others Vivarelli et al., 1996; Castellani and Zanfei, 2007) and in other European countries (see Belderbos et al., 2004; Harris and Li, 2009; Van Beveren and Vandenbussche, 2010, for the Netherlands, UK, and Belgium respectively; and see Table 2). In particular, we will use three different variables. The first one indicates whether the firm introduced new products during the reference time period (1998-2000 for CIS3 and 2002-2004 for CIS4); the second one indicates whether the firm introduced new processes over the same periods; while the third one selects, among the firms that introduced a new product, those which introduced a product that was perceived as new also for the reference market.[9]

Table 10 reports the differences between innovators in terms of the propensity to export and levels of exports among exporting firms. Notice that as the number of observations is greatly reduced with respect to previous specifications, we run a pooled regression for all manufacturing sectors, controlling for industry fixed effect by means of dummy variables. Columns (1) and (3) report the innovation premia estimated from the following regression:

$$X_i = \alpha INN_i + \beta sector_i + \epsilon_i \tag{6}$$

where INN is one of the two measures of innovation, product or process and X is either an export dummy or the (log) of trade volumes. Columns (2) and (4) estimate the same equation also including an additional control for size, measured in terms of employment. Note that we run two separate regression on the two CIS waves, CIS3 and CIS4, because, as shown above, there is a very small overlap between the firms that are surveyed both waves.

Looking at coefficients in Table 10 one finds out that among innovators there is a higher percentage of exporting firms, ranging between 14.8% (Col. 1) and 13.2% (Col. 3) in the case of product innovation, and between 10% (Col. 1) and 11.7% (Col. 3) in the

[8]The lower proportion of manufacturing firms over the total in CIS4 with respect to CIS3 is mainly due to the fact the CIS4 covers also the construction sector, NACE Rev.1.1 45.

[9]The questionnaires sent to firms are available online at `http://epp.eurostat.ec.europa.eu/portal/page/portal/microdata/cis`. The variables that we use in this work are related to question 1.1, 1.4, and 2.1 in CIS3 questionnaire and to question 2.1, 2.3, and 3.1 in CIS4 questionnaire.

Table 10: Innovation premia

	CIS3		CIS4	
	(1)	(2)	(3)	(4)
Panel A: Product innovation premia				
Exporting firms	14.8	10.9	13.2	9.4
Levels of exports	116.4	55.0	115.2	51.5
Panel B: Process innovation premia				
Exporting firms	10.0	6.4	11.7	8.3
Levels of exports	80.4	23.1	84.2	25.0

Note. The table reports innovation premia, in percentage, estimated from equation 6. Columns (2) and (4) control for total employment. All differences are significant at the 1% level.

case of process innovation. The premia are lower when the size of the firm is taken into account (Col. 2 and 4) , but they are still significant, both from a statistical and from an economic point of view. Among exporting firms, the ones that introduced a product or a process innovation report levels of exports that, after controlling for firm employment, are much higher than those of non innovating firms: the difference ranges between 55% (Col. 2) and 51.5% (Col. 4) for product, and between 23.1% (Col. 2) and 25% (Col. 4) for process innovation. A robust feature emerging from the two waves of CIS is that, on average, product innovation premia are higher than process innovation premia.

Next, let us proceed to verify the robustness of the findings of the previous section on the impact of innovation on propensity to export and on trade volumes. For the sake of comparability of results, we keep the regression models as close as possible to those of the previous section, only refining the measures for product and process innovation. In particular, we follow Becker and Egger (2013) in defining three dummy variables denoting respectively firms that introduced only a product innovation ($INPDT$), firms that introduced only a process innovation ($INPCS$), and firms that introduced both ($BOTH$). These variables are mutually exclusive so that we can better identify the different innovation strategies of the firms; at the same time, we avoid that the high correlation between product and process innovation introduce problems of multicollinearity in the regressions.[10] Further, in a different model specification, we also include the categorical variable accounting for the introduction of product which are new also for the reference market. In this setting, we are able to distinguish, among firms that introduced only a

[10]For example, in CIS3, of 2141 (2038) firms reporting the introduction of a new product (process), 1463 firms introduced both a product and a process innovation: that is, around 70% of product innovators are also process innovators. Figures are similar for CIS4.

product innovation or both product and process innovations, those whose product was new also for their reference market (respectively, $INPDT\_MKT$ and $BOTH\_MKT$), from those whose product was new only for the firm (respectively, $INPDT\_FIRM$ and $BOTH\_FIRM$).[11]

We start to investigate the impact of innovation on the propensity to export in a setting similar to that of equation (2) and we estimate two probit models

$$\begin{aligned} D_{EXPi} =& \alpha WAGE_i + \beta PROD_i + \gamma INPCS_i + \delta INPDT_i \\ &+ \zeta BOTH_i + \phi EMP_i + \epsilon_i \end{aligned} \tag{7}$$

where the new innovation dummy variables replace INV and PAT. Estimates are reported in columns (1) and (3) of Table 11, whether columns (2) and (4) refer to the specification that includes the possibility to discriminate between innovation new to the reference market, or only to the firm. Variables are not indexed by t as we run two different regression on the two waves of the CIS. In order to minimize simultaneity biases, the regressors and the dependent variable are measured at different time periods. Regressors refer respectively to 1998-2000 and 2002-2004 for CIS3 and CIS4 (they are averages in the case of continuous variables), while the dummy for export status refers to 2001 and 2005.

We then investigate the impact of innovation on firms' trade volumes in a setting that is similar to that of equation (3), and we now exploit CIS variables to estimate the following models:

$$\begin{aligned} EXP_i =& \alpha WAGE_i + \beta PROD_i + \gamma INPCS_i + \delta INPDT_i \\ &+ \zeta BOTH_i + \phi EMP_i + \epsilon_i \end{aligned} \tag{8}$$

where trade volumes refer to 2001 and 2005, and regressors, as before, to 1998-2002 and 2002-2004. As before, results are reported in columns (1) and (3) of Table 12, whether columns (3) and (4) refer to the specification that distinguishes the relevance of the product innovation.

Results from Tables 11 are largely consistent with those of the previous section, which were obtained employing a larger set of firms, as that available in Micro.3, and different proxies for innovation activities. Productivity levels are positively correlated with the propensity to export, and the same positive effect holds for the three innovation variables. We find that the simultaneous introduction of a product and process innovation has an

[11] Among firms introducing a product innovation, 82% and 69% are the percentage of firms that considered the product new also for the market, in CIS3 and CIS4 respectively.

Table 11: Selection, CIS3 and CIS4

	CIS3		CIS4	
	(1)	(2)	(3)	(4)
WAGE	−0.046	−0.045	−0.005	−0.005
	(0.028)	(0.028)	(0.031)	(0.031)
PROD	0.142[a]	0.141[a]	0.120[a]	0.119[a]
	(0.021)	(0.021)	(0.019)	(0.019)
INPDT	0.092[a]		0.092[a]	
	(0.011)		(0.011)	
INPCS	0.025[c]	0.025[c]	0.050[a]	0.049[a]
	(0.014)	(0.014)	(0.012)	(0.011)
BOTH	0.077[a]		0.093[a]	
	(0.011)		(0.011)	
INPDT_FIRM		0.071[a]		0.091[a]
		(0.019)		(0.014)
INPDT_MKT		0.094[a]		0.085[a]
		(0.011)		(0.013)
BOTH_FIRM		0.043[b]		0.053[a]
		(0.019)		(0.016)
BOTH_MKT		0.081[a]		0.105[a]
		(0.011)		(0.011)
N	4521	4521	3609	3609
pseudo R^2	0.183	0.184	0.172	0.174

Note. Probit estimation of equation (7). Marginal effects calculated at the mean for continuous variables; discrete change from 0 to 1 for dummy variables. Robust standard error in parenthesis. Coefficient on EMP omitted. Sector dummies included.
[a] $p < 0.01$, [b] $p < 0.05$, [c] $p < 0.10$

impact on firms' export propensity, in line with the results of Becker and Egger (2013). However, differently from them, we find that also process innovation in isolation has an effect, even if the effect is lower than the one obtained from product innovation alone, in agreement with the findings of Caldera (2010). The more relevant difference with respect to the regression using Micro.3 is in the wage coefficient, which is here not significant. Columns (2) and (4) show that both innovations new for the market and innovations new only for the firms are important in determining selection into export markets. Moreover, based on Wald test, we do find that the coefficient on $BOTH\_MKT$ is significantly greater than the coefficient on $BOTH\_FIRM$: in the case of firms that introduced both product and process innovation, having a product new also for the market raises the probability to enter export markets.

Results from Tables 12 show a negative and significant coefficient on wage for CIS3, which becomes non significant for CIS4: another hint that cost competition might have become less important over time (see section 4.3). Introducing a new product or intro-

Table 12: Levels of exports, CIS3 and CIS4

	CIS3		CIS4	
	(1)	(2)	(3)	(4)
WAGE	-0.629^b	-0.628^b	0.255	0.255
	(0.266)	(0.266)	(0.258)	(0.259)
PROD	1.297^a	1.297^a	1.053^a	1.053^a
	(0.146)	(0.146)	(0.137)	(0.137)
INPDT	0.458^a		0.270^b	
	(0.096)		(0.126)	
INPCS	-0.020	-0.020	0.072	0.073
	(0.116)	(0.116)	(0.111)	(0.111)
BOTH	0.292^a		0.341^a	
	(0.083)		(0.095)	
INPDT_FIRM		0.544^a		0.264
		(0.149)		(0.213)
INPDT_MKT		0.436^a		0.274^b
		(0.107)		(0.139)
BOTH_FIRM		0.118		0.322^b
		(0.169)		(0.145)
BOTH_MKT		0.325^a		0.350^a
		(0.085)		(0.104)
N	3699	3699	3014	3014
R^2	0.413	0.413	0.418	0.418

Note. OLS estimation of equation (8). Robust standard error in parenthesis. Coefficient on EMP omitted. Sector dummies included. ^{a} $p < 0.01$, ^{b} $p < 0.05$, ^{c} $p < 0.10$

ducing both a new product and a new process has an impact on levels of exports; on the other hand, we do not find any effect for process innovation in isolation. From Column (2) and (4), it is apparent that introducing a product new only for the firm may not have a significant effect on competitiveness, whereas introducing a product new also for the market is always significantly associated to higher levels of exports.

In the analyses carried out in Section 4 it was possible to exploit the panel nature of Micro.3 to assess the robustness of the findings to unobserved heterogeneity and endogenity of both innovation and costs. The same solution cannot be implemented with the CIS data we have access to, as they provide only two observations over time and a very small set of firms being surveyed in both waves.[12] In order to circumvent this data limitation we resort to an emerging stream of empirical literature studying the differential response of firms' exports to an exogeneous shock. In particular, the emphasis is on indentifying those characteristics which enable the firm to suffer less from a negative shock, such as a

[12]Also notice, that firms being sampled twice do not provide a representative sample as bigger firms are over-represented.

real exchange rate appreciation (see among the others, Berman et al., 2012; Chatterjee et al., 2013). In this respect, we take advantage of the finer level of disaggregation that is available for exports over the latest years (Section 3) and we disaggregate total firm's exports in a given year, in the sum of exports to each product-country destination served by the firm in that year. In turn, firm's exports to a given product-country destination can be decomposed in the product of the quantity sold times the unit value.[13] This of course results in a larger number of observations which we employ to study the sensitivity of innovating and non-innovating firms to annual exchange rate movements by considering export value, quantity and unit value. The regression framework that we consider is

$$\Delta\ln X_{fpct} = c + \alpha D_{ft}^{\mathrm{BOTH}} + \beta\Delta\ln RER_{ct} + \gamma\Delta\ln RER_{ct} * D_{ft}^{BOTH} + d_j + \varepsilon_{fpct} \qquad (9)$$

where $\Delta\ln X_{fpct}$ is the change (log difference) in firm-level product-country export value, quantity or unit value, D_{ft}^{BOTH} is a dummy for firms that introduced product and process innovations in CIS3 and CIS4,[14] $\Delta\ln RER_{ct}$ is the change in the log of the real bilateral exchange rate of the Italian currency, $\Delta\ln RER_{ct} * D_{ft}^{BOTH}$ is their interaction, and d_j a set of of fixed effects. Results in Table 13 show that while the volume of exports to a given product-country destination (Col. 1 and 2) decrease for all firms following a currency appreciation, such reduction is almost cut by half (Col. 2) for innovating firms, as accounted by the interaction term. Also note that the smaller response of firms' export is almost entirely driven by a smaller reduction in the quantity sold (Col. 3 and 4). No apparent effect is found on prices as proxied by unit values.

Overall, the evidence from Table 13 contributes to lend support to the robustness of our findings on the role of innovation and, more in detail, the results also provide evidence in favor of models of trade based on "quality sorting" more than "efficiency sorting" (Crozet et al., 2012; Manova and Zhang, 2012).

6. Conclusions

The paper contributes to the analysis of the the determinants of international competitiveness offering a discussion of the macro and sectoral evidence and contributing new one at the micro level on the relative importance of cost and technological competition. It vindicates also at a micro level the broad conjecture stemming from *technology gap* theories of international trade according to which the primary drivers of international competitiveness are lags and leads in sector-specific process and product innovation compared to other countries, rather than inter-sectoral patterns of allocation of resources

[13]For a detailed description of the trasaction level trade data and the product classification employed refer to Bernard et al. (forthcoming).

[14]Similar results are found when considering different definition of innovating firms.

Table 13: Exchange rates and firms exports to product-country destinations, by different type of firms

	Annual Differences					
	$\ln X_{fcpt}$ (1)	$\ln X_{fcpt}$ (2)	$\ln Quantity_{fcpt}$ (3)	$\ln Quantity_{fcpt}$ (4)	$\ln UnitValue_{fcpt}$ (5)	$\ln UnitValue_{fcpt}$ (6)
D_{ft}^{BOTH}	0.005		0.007		-0.002	
	(0.009)		(0.009)		(0.005)	
$\Delta \ln RER_{ct}$	-0.327^{a}	-0.360^{a}	-0.308^{a}	-0.344^{a}	-0.018	-0.015
	(0.104)	(0.112)	(0.115)	(0.122)	(0.021)	(0.020)
$\Delta \ln RER_{ct} * D_{ft}^{BOTH}$	0.117^{b}	0.149^{b}	0.115^{c}	0.155^{b}	0.002	-0.005
	(0.053)	(0.062)	(0.064)	(0.075)	(0.029)	(0.030)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	No	Yes	No	Yes	No
Firm-Product FE	No	Yes	No	Yes	No	Yes
N	329697	329697	329697	329697	329697	329697
adj. R^2	0.005	0.007	0.002	0.003	0.000	0.030

Note. Table reports results of regressions at the firm product country level, using data on exports, quantity and unit value between 2000 and 2007. The dependent and independent variables are defined as annual differences. BOTH is a dummy for firms that introduced both product and process innovations in CIS3 and CIS4. Robust standard errors clustered at country-year level in parenthesis. Year dummies included. ^{a} $p < 0.01$, ^{b} $p < 0.05$, ^{c} $p < 0.10$

within each country.

The analysis at the micro level provides a joint account of the role of costs and innovation. The micro evidence has been decomposed in two different processes: the selection of firms into export markets and the perfomance of exporting firms. In both cases, technology is found to have a major role. How much a firm invests and whether a firm patents or not appears to be correlated both to the probability of being an exporter and to the capacity to acquire and sustain trade volumes. On the other hand, there is no widespread evidence that lower costs of labor boosts exports. When distinguishing between short and long run effects, they turn out to be mostly long-run one.

We further refine our analysis studying the role of product and process innovation using CIS data, as it is usually done in the literature addressing the role of innovation in firms export behaviour. Results from CIS survey confirm the foregoing findings. In particular, they show that product innovation is a more relevant dimension than process innovation in determining firms export success.

This evidence, of course, adds microfoundations also to the proposition, so far provided basically on macro and sectoral evidence, that technological absolute advantages do matter a lot in the interpretations of trade flows as suggested by technology gap theories (as in Posner, 1961; Hirsch, 1965; Fagerberg, 1988; Dosi et al., 1990). At the micro level, the evidence speaks in favor of models of trade based on "quality sorting" more than "efficiency sorting", along the conclusions drawn at the product level in Manova and Zhang (2012), but the implications go well beyond, urging the abandonment of interpretations of trade patterns which rely too quickly upon incentive-driven allocations of fungible resources as compared to activity-specific, persistently different, asymmetric firm-level technological capabilities.

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Table A.14: Industry aggregation

Sectors	NACE Rev. 1.1
Food, beverages, tobacco	15-16
Textiles, wearing, leather	17-19
Wood	20
Paper & printing	21-22
Coke & petroleum	23
Chemicals	24
Rubber and plastics	25
Non-metallic (mineral products)	26
Basic metals	27
Fabricated metal (products)	28
Machinery	29
Computing & electrical (machinery)	30-33
Transport equipment	34-35
Other Manufacturing	36-37

Note: The table lists the sectoral aggregation that will be used in the analysis. NACE codes perfectly matches to the ISIC rev. 3 classification of OECD STAN at this level of aggregation.

Appendix A. The macro evidence

In this Appendix, we offer a reassessment of the relative importance of technology *vs.* cost-related factors driving international competitiveness using a sectoral dataset on 15 OECD countries over the years 1989-2006.

Data

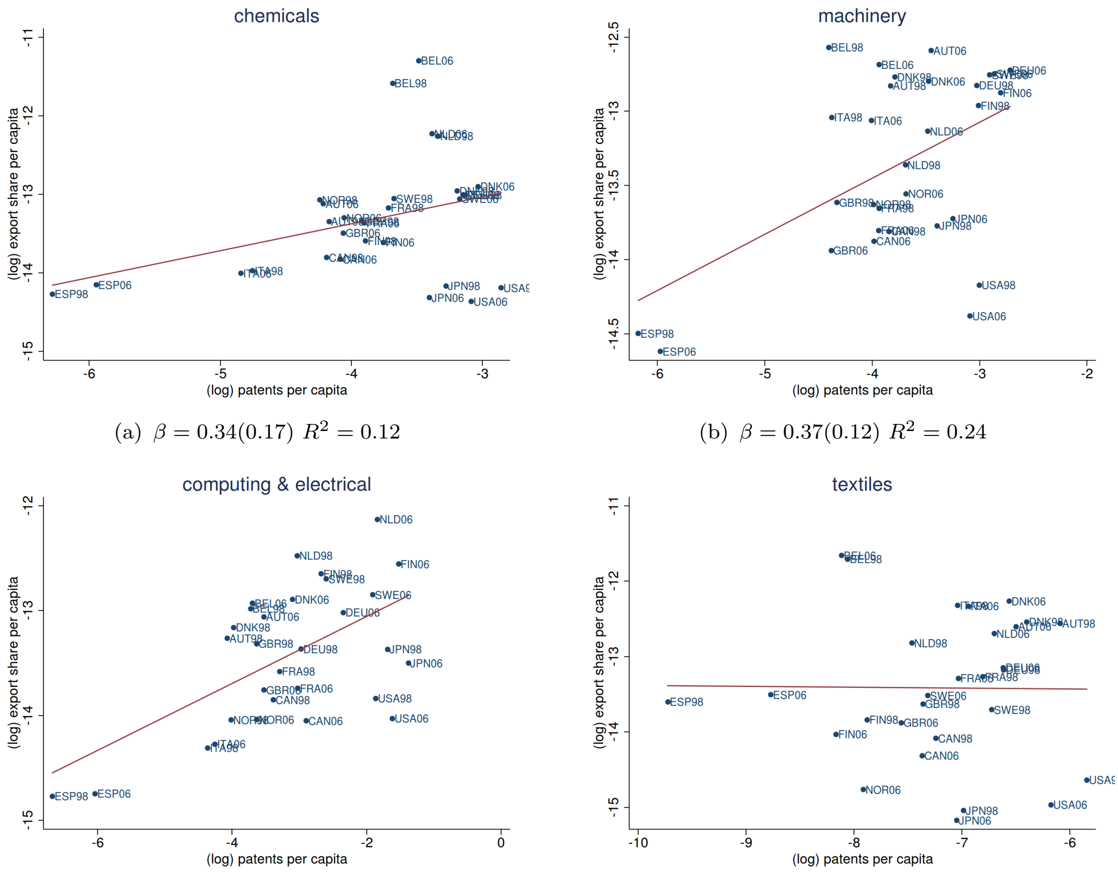
We use data for 15 OECD countries from STAN database: Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, UK and USA[15]. They account on average for 86% of total dollar exports of all OECD countries.

The STAN database comprise all manufacturing sectors at different levels of aggregation. Our selection, for comparability purposes, contains 11 manufacturing sectors, reported in table A.14, in order to have a nearly complete time series for each sector and each country in the sample.

Estimation

Let us start with an overview of the evidence on the relation between international competitiveness and innovation, as proxied by patents, at the country-sector level. A first snapshot is offered in Figure A.1, displaying simple scatter plots for the relationship between (log) export shares per capita and (log) patents per capita, across countries and within four selected industries in 1998 and 2006.

[15]Data on gross fixed capital formation for Japan come from EU KLEMS database.



(a) $\beta = 0.34(0.17)$ $R^2 = 0.12$

(b) $\beta = 0.37(0.12)$ $R^2 = 0.24$

(c) $\beta = 0.31(0.08)$ $R^2 = 0.32$

(d) $\beta = -0.01(0.22)$ $R^2 = 0.00$

Figure A.1: Patents and export shares, per capita terms, in 1998 and 2006.

A strong correlation between the two variables emerges sharply in many (even if not all) sectors: see in figure A.1 three of the four sectors (chemicals, machinery, and computing), as shown both by the R^2 reported below each plot and by the β's (standard error in parenthesis).

The graphical analysis of the bivariate relationship between patents and international market shares leaves no doubt that technology strongly correlates with the pattern of international competitiveness among countries. This basic evidence about sectoral absolute advantages at the country level largely holds also at finer sectoral disaggregation.

Building upon the theoretical and empirical framework of Fagerberg (1988) and Dosi et al. (1990), let us study the simple relationship between an absolute measure of competitiveness (i.e. independent of the competitiveness of other sectors within the same country), and a set of costs and technology related variables. The dependent variable, our measure of (absolute) competitiveness, is represented by export market shares. The latter are calculated for a given country i in industry j (XMS_{ij}), by taking each country's exports in the industry (in current dollars) over the total industry's export from the 15 countries of the OECD-STAN database.

Among the regressors, the cost variable is represented by the (current dollar) labour cost per employee ($WAGE$). The industry labour productivity ($PROD$) is proxied by value added at constant prices divided by total employment (including the self-employed).[16] The figure thus obtained is however an imperfect and possibly biased proxy for physical output if "absolute prices", even after the exchange rate corrections, are different across countries. In order to partly deal with such possible biases, sectoral productivities are converted, as often done, to a common currency by using PPP exchange rate of 2000 (i.e., the reference year of the national measure of real output in STAN database).[17]

Technology variables include a measure of investment intensity and patenting activity intensity, respectively INV and $PATSH$. INV is calculated as the ratio between industry expenditures on gross fixed capital formation and value added, both at current prices. $PATSH$ is the share of national industry patents granted (both USPTO and EPO) over the sum of the industry's patents granted to the 15 countries.

The following regression is run for each of the 14 industries, and results are reported in Table A.15:

$$\begin{aligned} XMS_{ijt} =& \beta_{1j} WAGE_{ijt} + \beta_{2j} PROD_{ijt} + \beta_{3j} INV_{ijt} \\ &+ \beta_{4j} PATSH_{ijt} + \beta_{5j} POP_{it} + \epsilon_{ijt} \end{aligned} \tag{A.1}$$

where each variable is taken in log, i indexes countries, j industries and t time. POP stands for the total population and is included to control for the sheer size effect that influences the dependent variable.

The first noteworthy result is the strong significance of the patent variable across the vast majority of sectors. As expected, patented innovations appear to be important for competitiveness in sectors in which patents as a mean to appropriate returns from innovation play an important role (for the sectoral evidence see Levin et al., 1987 and the discussion in Dosi and Nelson, 2010). This is the case of the chemical sector and of the electrical and non-electrical machinery sectors, part of the "science-based" and the "specialised suppliers" categories according to Pavitt taxonomy (Pavitt, 1984). These three industries account for around 80% of total patents across countries in our sample.[18] Patenting activity, on the contrary, is a poor proxy for product innovation in sectors where they are indeed less relevant mechanisms of appropriation. This is the case, for example,

[16]STAN database contains figures both on the number of employees and on the total employment. The first number is used to get the $WAGE$ variable, since labour costs refer only to employees. The second is used to get the $PROD$ variable.

[17]It is worth noting that measures of PPP based on national GDP pose some problems on their own - including the lack of adjustments for production prices, different VAT regimes - when used to revaluate industry output. At the very least we undertook the consistency check suggested by Sørensen (2001), i.e., using different base years for making the conversions. Results were largely unchanged.

[18]These three industries also report the highest patent intensity (number of patents over value added) as computed for USA industries in 2000 in OECD STAN dataset.

Table A.15: Industry regressions

Dependent variable: export market share						
	WAGE	PROD	INV	PATSH	Obs.	R^2
All manufacturing	0.155^b	0.347^a	0.698^a	0.270^a	3161	0.68
	(0.075)	(0.046)	(0.031)	(0.015)		
Food, beverages, tobacco	0.445	0.833^b	0.924^a	0.208^b	249	0.36
	(0.501)	(0.362)	(0.246)	(0.088)		
Textiles, wearing, leather	−0.326	1.517^a	1.288^a	0.016	227	0.77
	(0.316)	(0.377)	(0.120)	(0.063)		
Wood	0.284	2.217^a	1.172^a	0.426^a	221	0.67
	(0.283)	(0.210)	(0.121)	(0.050)		
Paper & printing	-1.649^a	1.415^a	−0.068	0.290^a	226	0.78
	(0.213)	(0.164)	(0.085)	(0.025)		
Coke & petroleum	0.062	−0.095	0.369^a	0.384^a	200	0.49
	(0.206)	(0.095)	(0.104)	(0.052)		
Chemicals	1.594^a	0.078	0.069	0.130^b	223	0.78
	(0.252)	(0.171)	(0.133)	(0.060)		
Rubber & plastics	−0.323	0.459	0.702^a	0.238^a	223	0.78
	(0.323)	(0.323)	(0.136)	(0.067)		
Other non-metallic	-0.534^b	0.469^c	0.893^a	0.021	251	0.79
	(0.257)	(0.244)	(0.115)	(0.048)		
Basic metals	0.795^a	0.834^a	0.241^b	0.163^a	190	0.76
	(0.270)	(0.134)	(0.097)	(0.048)		
Fabricated metal	−0.341	−0.307	0.732^a	0.314^a	190	0.87
	(0.224)	(0.266)	(0.097)	(0.041)		
Machinery	−0.346	0.317	0.427^a	0.341^a	240	0.88
	(0.212)	(0.213)	(0.072)	(0.046)		
Computing & electrical	−0.190	0.006	0.258^a	0.424^a	240	0.92
	(0.179)	(0.077)	(0.073)	(0.029)		
Transport equipment	0.578^a	1.326^a	0.453^a	−0.046	251	0.91
	(0.213)	(0.122)	(0.069)	(0.041)		
Other manufacturing	−0.129	0.510^b	0.875^a	0.045	230	0.76
	(0.273)	(0.212)	(0.122)	(0.072)		

Note. Pooled OLS estimation with standard errors in parentheses. Coefficient of POP omitted. Sector-year dummies (in the aggregate regression) and year dummies (in the sectoral regressions) included. ^{a} $p < 0.01$, ^{b} $p < 0.05$, ^{c} $p < 0.10$.

of labour-intensive sectors such as textile or in industries that are intensive in the use of natural resources, such as non-metallic mineral products.

The INV variable, a proxy for capital-embodied, process innovation, is positive and significant in almost all sectors but two (paper and chemicals).

Interestingly, the coefficient for $WAGE$ is significant and negative only in two sectors (paper and non-metallic minerals sectors). Only there the lower costs of labor per employee appear to be relevant in sustaining country's exports. On the contrary, chemicals, basic metals and transport industries report a positive and significant coefficient on $WAGE$.

The results are broadly supportive of the evidence reviewed in Section 2.1. In particular, they support the hypothesis that technology advantages dominate over cost-related factors in shaping international competitiveness.