STI 2018 Leiden

23rd International Conference on Science and Technology Indicators
"Science, Technology and Innovation Indicators in Transition"

STI 2018 Conference Proceedings

Proceedings of the 23rd International Conference on Science and Technology Indicators

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ISBN: 978-90-9031204-0

Openness and innovativeness across the value chain. Evidence on EU countries and industries[1]

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Open Innovation, Innovation and economic returns
The Open Innovation concept has pervaded the academic and policy debate, due to its potential to further stimulate the circulation of knowledge across business partners and institutions and, consequently, to increase their innovation potential. The contribution of this paper is to unveil the economic returns associated to such a model, to answer the main question whether the productivity growth slowdown observed in the EU in recent years could be overcome through a more open and dynamic innovation environment. An empirical analysis conducted on sectoral data for 16 EU countries is provided, exploiting three waves of the Community Innovation Survey. Results confirm the role of Open Innovation in stimulating – even at the aggregate level – innovation, and, to a limited extent, to economic returns. However, when testing for the association between Open Innovation and economic growth, no robust effect emerges.

1. Introduction

Following the "Open Innovation" (OI) literature (Chesbrough, 2003, 2006; Huggins et al., 2010) firms are increasingly opening in order to achieve and sustain their innovations: returns of internal R&D are decreasing while the capability to exploit knowledge coming from external sources allows capturing more opportunities that would "unlock their potential". Firms' organizational boundaries are getting "porous" and the interaction of firms with the external environment increases, such that the exploitation of a wide set of external actors and external sources becomes a strategic and deliberate choice of the firm.
When it comes to policies, open innovation often implies increased pressure on higher education institutes and public research organizations to obtain research funding from the private sector, accompanied by a reduction of institutional funding (Dankbaar and Vissers, 2010). However, as the Reflections of the EU's Research, Innovation and Science Policy Experts (RISE) High Level Group points out, longer-term, strategic vision is required to govern innovation activities in order to address the productivity growth slowdown observed in the EU in recent years, to which the creation of a more open and dynamic innovation environment is crucial (EC, 2017). This presents a double challenge that implies both the need to open up to external (including foreign) knowledge sources, as well as to strengthen absorptive capacity through investments in research and innovation. OI also implies that

[1] This work benefitted from Horizon2020 funding, under the INNOVA MEASURE III project (762135).

policy should focus on teams of innovators, rather than merely on innovative products, it nevertheless remains a challenge to identify the relevant teams and business partnerships. The same report also highlights the need for further investigations to understand whether and how the lack of openness hampers productivity growth.

Creating a coherent regulatory environment conducive for open innovation entails challenges. Insights from sector-level studies of innovation and growth suggest that innovation policies should take into consideration differences across industries in terms of maturity of technology, industrial organization, lengths of product development cycles, etc. However, innovators often see the lack of interoperability of the regulatory environments across sectors as barriers to co-operation and the development of open innovation based on multi-technology sourcing (EC, 2016). The literature on the effects of OI on innovative outcome is broad and rapidly expanding and it generally agrees on the positive net effect of OI on innovation outcomes. Still to be ascertained is whether OI affects innovation at a more aggregated level, i.e. the sectoral level of analysis, and with a broad EU coverage. This is the first contribution of the paper. Still under-investigated is the overall effect of OI on economic growth: unveiling such a relationship is the second contribution of the current paper.

The final contribution of the paper is of analysing the inter-sectoral relatedness and how this moderates the OI effects among clients and suppliers, based on input-output relatedness measures constructed from the World Input Output database (WIOD) (Timmer et al. 2015).

An empirical analysis is conducted on a panel dataset whose main source is the Community Innovation Survey aggregated at the sectoral level for 3 waves (2006-2008; 2008-2010; 2010-2012) for 16 EU countries, encompassing manufacturing and service activities. Eurostat and WIOD are ancillary sources of information.

Section 2 discusses the background literature of the paper and it outlines the main research questions. Section 3 describes the dataset construction and it assesses the empirical approach. Results are discussed into Section 4. The final section concludes and it draws the main implications.

2. Background literature and research hypothesis

The idea that firms may benefit from knowledge flows developed elsewhere is not at all new in the economics literature. The potential exploitation of positive knowledge externalities that would improve firm's innovativeness has been a core argument in explaining the emergence of clusters and industrial districts since the Marshall's seminal contribution (Marshall, 1890). Innovation is an interactive process, which not only is characterized by uncertainty, trials and errors, but it also involves multiple actors of the innovation systems, including suppliers, users and institutions, whose interaction shapes the ultimate success (or failure) of the innovation itself (e.g. Lundvall, 1992).

Drawing on this evidence, Cohen and Levinthal (1990) argue that the ability to recognize the value of external knowledge, assimilate this knowledge and applying it for commercial purposes is a key component of firm's innovative capability. Such ability, defined "absorptive capacity", is a function of the level of prior internal investments in related knowledge, which enables the firm to recognize the value of the external information and to extract it. In other terms, relying upon external flows of knowledge may be beneficial to firm's innovative outputs only if there exists enough "absorptive capacity" to gain from such flows. As "absorptive capacity" is intangible, what is its appropriate level of investment and when this is reached is not easy to define.

More recently, it has been theorized that such knowledge externalities might even be a deliberate, voluntary and strategic choice pursued by firms. Furthermore, it has been argued that firms are moving to a so called "open innovation" (OI) model in order to achieve and sustain their innovations, as the returns of internal R&D are decreasing while the capability to exploit knowledge coming from external sources allows capturing more opportunities that would "unlock their potential" (Chesbrough, 2003). Chesbrough (2003: XXIV) defines OI as a paradigm " that assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, as firms look to advance their technology".

In such a model firms organizational boundaries are "porous" and the interaction of firms with the external environment increases. Such OI model consists, in a nutshell, in exploiting a wide set of external actors and external sources. These can take multiple forms: "knowledge sourcing may involve learning to use new technology and equipment, especially that used by customers or suppliers, (…) drawing on new scientific research from universities to facilitate innovation, (…) using expert marketing advice or technical or business development expertise that is not available in-house" (Huggins et al., 2010 : 2). As for the actors, those can spam from suppliers of equipment, materials, service or software; clients; customers; commercial labs; private R&D institutes; consultants; competitors in the same industry; universities or higher education institutes; government or public research institutes; conferences, trade fairs, exhibitions; scientific journals and trade/technical publications; technical, industry or service standard (Huggins et al., 2010). Those can be located within the firm's own region, elsewhere in the same country or outside the countries' boundaries.

All in all, multiple factors are driving the shift towards an OI paradigm (Chesbrough, 2003): availability and mobility of skilled workforce; a venture capital market providing economic conditions; the emergence of new external options for their inventions; and the increased knowledge and capabilities of external suppliers.

In a later contribution, the concept of OI is extended by Chesbrough (2006) to include "the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively" (Chesbrough, 2003: 1).

In what follows a review of the main evidence on such an "OI" model is proposed (Section 2.1). In the subsequent section (Section 2.2) it is discussed how OI is related to growth.

2.1 Open Innovation – Innovation linkages

The literature on the effects of an open innovation mode on innovative outcome is broad and rapidly expanding. It encompasses empirical analyses (e.g. Laursen and Salter, 2006; Sofka and Grimpe, 2010) as well as theoretical contributions (e.g. Bogers et al., 2016; Dahlander and Gann, 2010; Reed, et al. 2012) and case studies (e.g. Ozkan, 2015; Sovacool et al., 2017). Broader analysis encompassing the broad set of manufacturing firms (e.g. Laursen and Salter, 2006) and service firms (Love et al. 2011) are combined with in depth analysis on specific sectors such as (to mention a few) high-tech firms (e.g. Wang et al. 2015), software firms (e.g. Colombo et al. 2014), bio-pharmaceuticals (Hu et al. 2015), power and energy sector (Greco et al. 2017) including a sub-focus on solar energy technologies (de Paulo and Porto, 2017) and oil industry (Radnejad et al. 2015). Such broad research effort does also include transition economies (Pilav-Velić and Marjanovic, 2016), as well as middle-income countries (Goedhuys and Veugelers, 2012; Wang et al., 2015).

The current section aims at summarizing the key findings of this literature with respect to the effects of an open mode on innovative performance.

One of the most cited contribution that empirically assessed the open innovation mode is Laursen and Salter (2006). The article empirically assesses how different strategies for using external knowledge sources (namely suppliers, users, and universities) affect the innovative performance on a cross sectional sample of U.K. firms drawn from the U.K. innovation survey. They differentiate between two main strategies: external search breadth and external search depth and they assess their effects on firm's innovation.

The first strategy is conceived in terms of the number of different search channels a firm draws upon in its innovative activities. Ex ante, managers do not know which of the possible sources would be effective and rewarding, given that such process of exploiting external knowledge channels faces uncertainty and its routinization undergoes a process of trials and errors. Consequently, external search breadth can improve innovative performance, but there is also the concrete risk of an unbalanced use of such a strategy that would ultimately lead to a negative innovative outcome.
Firms may also "over-search" for external sources, and this choice may be detrimental: firm can fail in handling a too wide set of new ideas and knowledge ('the absorptive capacity problem'), the time the new ideas come can be inappropriate ('the timing problem') and firms may dedicate little attention to the so many ideas ('the attention allocation problem'). Overall, the empirical paper does find a support on a direct and positive effect of external search breadth on firm's innovative outcome, but it does also depict a curvilinear effect pointing to the final result that external search is not costless, as it implies the risk of 'over-search' which might lead also to negative returns.
The second strategy refers to external search depth, and it involves drawing intensively on the external information sources. To be intensive such a search strategy, it is meant a deep and sustained over time pattern of interaction with external knowledge partners, such as lead users, suppliers or universities that would allow them to build a "shared understanding and common ways of working together" to achieve virtuous exchanges (Laursen and Salter, 2006: 136). Relying too deeply on such knowledge flows may be however detrimental as the maintenance of such links needs resources and attention. The paper finds indeed a curvilinear function between external search depth and innovative performance.
Sofka and Grimpe, (2010) find empirical support to the positive effect of firm's open search strategy on innovation, and that this positive gain is moderated by mainly two factors: firms' absorptive capacity, namely own investments in R&D, as well as the potential of the external environment in providing knowledge spillovers to exploit.
Roper, Vahter, and Love (2013) focus on the social benefits of the OI mode and on what they called "externalities of openness", suggesting that openness itself is capable of generating positive externalities that go beyond the organisations involved in the partnership. Their empirical analysis is based on the Irish innovation survey in the period 1994–2008 and it is grounded at the plant (rather than firm) level of analysis. They overall argue that an increase in the average degree of openness in a sector may result in positive externalities raising the innovation productivity of the sector itself. They do find support on the positive effect of the "externality of openness" to firms' innovation outcome.
Following an OI mode is not at all cost-less to the firm. First, it requires having adequate absorptive capacity to be able to capture and internalize the knowledge produced by external actors. Second, a business strategy that is too much oriented toward gaining from external information sources may indeed be detrimental to the firm, as firms also need to be focused on extracting the returns of the (open) innovations. The so called "paradox of openness" postulates that on the while the creation and invention phase benefits from openness, the commercialization (through which an invention becomes an innovation) would require protection rather than openness as, at the moment a cooperation is set up, certain knowledge would inevitably flow to the partners (Laursen and Salter, 2014). In other words, the appropriability strategy a firms selects to protect from imitation when it goes open, i.e. when it engages in collaborations with the external environment, does matter in explaining the rents it can capture from its innovation. The appropriability strategy is measured according to the formal or informal protection methods a firm exploits, namely: patents, registration of design, trade- marks, secrecy, lead time, and complexity. The empirical paper, on a sample of UK manufacturing firms, finds support that the exploitation of legal appropriability methods

affects the choice to select an OI mode, by giving managers the confidence to engage safely with external actors (Laursen and Salter, 2014).

A survey by Hagedoorn and Ridder (2012) does support the absence of contradiction between patenting and open innovations. In their sample, 90% of "open" firms declared patents to be a relevant tool to signal to the market their capabilities, pointing to the conclusion that "firms active in open innovation appear to prefer to systematically protect their innovative capabilities from their open innovation partners" (Hagedoorn and Ridder, 2012: 27).

Such a paradox has been revised in a recent contribution by Arora, Athreye and Huang (2016). The authors try to explain the apparently contradictory trend which sees on the one side an increase in patenting as an appropriability tool and, on the other side, an increase in openness in innovations. Arora, Athreye, and Huang (2016) build an empirical analysis on UK manufacturing firms to test for the "paradox of openness" and more precisely for the openness trade-off: firms will seek for external collaborations if their knowledge can be protected ("spillover prevention view" (Cassiman and Veugelers, 2002)) but firms that are too focused on patenting will be less effective in collaborations, weakening their attractive power as partners ("organizational openness view"). What the paper finds is that the decision whether to patent and/or opt for to external sourcing is contingent, jointly determined and depends on whether firms are leaders or followers in the market, the first being more vulnerable to knowledge spillovers than the latter. More precisely, "open" leaders patent more than "closed" leaders and more than "open" followers, whereas "closed" leaders and followers patent at similar degrees. The explanation provided to this result is that leading firms "are more vulnerable to unintended knowledge spillovers during collaboration as compared to followers, and consequently (…) the increase in patenting due to openness is higher for leaders than for followers. Followers, with incremental innovations that benefit less from patenting and with little proprietary technology and knowhow, may be less willing to patent because it makes them a less attractive open partner and perhaps also less able to derive value from collaboration" (Arora et al., 2016: 1360).

Additionally, Zobel et al. (2017) analysed how the degree of openness in innovation affects the choice on appropriation instruments between formal ones (Patents, trademarks, copyrights, and design rights) and informal ones (Secrecy, lead-time, and complexity) on a sample of Dutch firms. Whereas both external search breadth and depth are positively associated with the use of the second typology, i.e. informal appropriation mechanisms, only external search breadth is associated with the former, i.e. formal appropriation mechanisms.

In involving multiple internal and external technology sources and technology commercialization channels, firms are found to be able to become open in possibly two directions: inbound OI or outbound OI.

Inbound open innovation refers to a process of technology transfer from external sources inward, while outbound OI is related to outward technology transfer, whereby firms pursue a strategy of gaining monetary/strategic opportunities by commercializing a technology, e.g. through out-licensing (Lichtenthaler, 2009). In an outbound setting, firm must be able to capture value from their technology; consequently a strong patent protection system might affect firm's possibilities of profiting from outbound OI.

Dahlander and Gann, (2010) systematize the literature on the definition of OI through a bibliographic analysis, finding conceptualizations on two inbound processes, sourcing and acquiring external knowledge, and two outbound processes, revealing and selling. The two forms of OI are thus depending on the pecuniary vs non-pecuniary compensation of the knowledge flow. "Sourcing" is a type of inbound OI and it is related to the ways in which firms can exploit external information sources and their search towards those sources. "Acquiring" is related to the acquisition of sources and inputs to the innovation process in the market. "Revealing" refers to an outbound openness where firms reveal internal resources

without direct pecuniary compensation, whereas “Selling” refers to a commercialization of firms’ inventions or technologies by sells or licences.
Literature has been mostly focused on either inbound or outbound flows. Little evidence is provided on the interplay between those choices and their possible complementary. An exception to this is (Cassiman and Valentini, 2016), who empirically tested on Belgian manufacturing firms for the presence of a complementarity in the two strategies, namely that firms that combine the two strategies significantly out- perform those firms that choose only one of the two strategies more than by adding the second strategy in isolation to the first. This outperformance would be explained by a reduction in cognitive costs, transaction costs, and organizational costs that would be achieved when combining inbound and outbound strategies.

2.2 Open-Innovation – Growth linkages

Contrarily to the evidence on the linkages between OI and innovation outlined in the previous section, there is a lack of systematic evidence about the effect of external sourcing of knowledge on economic growth. Furthermore, all the available knowledge is at the firm level, as no studies – to the authors’ knowledge – are available at the aggregate level.
This section revises the sporadic available evidence.
Lichtenthaler (2009) analyses empirically how the external context affects the relationship between open innovation strategies and firm performance, measured in terms of return on sales (ROS), on a sample of medium and large industrial companies in Germany, Austria and Switzerland. The study finds a positive effect of outbound OI on firm performance. Furthermore, it unveils that the effect of outbound OI is moderated by the external context in which firms operate, mainly with respect to the technological turbulence and the competitive intensity in the technology market (Gambardella et al. 2007). Strong patent protection has instead not been found to moderate the effect of outbound OI on firm’s performance.
Goedhuys and Veugelers, (2012) empirically analyse the effects of the interplay between external technology sourcing (“technology buy”) and internal technology development (“technology make”) on both innovation and firms growth on a sample of Brazilian manufacturing firms in the period 2000-2002. In particular starting from firms’ strategies of developing technology versus the technology acquisition (which includes acquiring new technology embodied in new machinery, key personnel as well as licensing-in technology) they taxonomise 4 groups of firms depending on their innovation strategies. The first group consists of firms that only report in-house development of technology, the second consists of firms that only buy, the third consists of firms that report both own development activities and embodied technology acquisition and the last one groups firms with no make or buy strategy. Not only they support that both “technology buy” and “technology make” increase innovation, confirming the innovation effects of OI mode. Also, it is found that only those firms that combine successful product innovations with process innovations realize higher sales growth.
An assessment on the effects of both inbound and outbound OI on firm’s economic performance is provided also for a sample of 176 Taiwanese high-tech firms by (Hung and Chou, 2013). The main finding is that inbound vs outbound OI have differential effects on firm performance. In particular external technology acquisition positively affects firm performance, while external technology exploitation does not display significant effect on firms’ performance. This is against the main findings in Lichtenthaler, (2009).
Differential effects of inbound openness on firm’s performance have been also tested with respect to two main typologies of openness: namely horizontal versus vertical technological collaborations (Wang et al., 2015). The first corresponds to a cooperative and co-developed

way of sourcing for technology with multiple partners in which firms look for complementary resources to jointly develop new knowledge and technologies with the external partners selected. This first type applies to collaborations with competitors, suppliers and similar external partners. To the vertical typology belongs the set of collaborations established with customers and allows extracting not only new ideas and anticipating future demand needs, but also suggesting alternative ways to solve problems in the products/services the firm produces in a co-creative open production mode. On a sample of Taiwanese firms operating in the high-tech sector, it is found that the vertical technological collaborations pay more than horizontal ones (Wang et al., 2015).

The contribution by Segarra and Teruel (2014) aims at estimating the determinants of firms' growth in a sample of Spanish high-growth firms and it finds interesting evidence regarding the growth effect of openness. In assessing the impact of R&D investment on firm growth in sales and employees, the authors find that internal R&D has a significant positive impact for the upper quantiles in the growth distribution, while external R&D impacts up to the median point of the distribution. In other words, investment in internal R&D is an important driver for the fastest growing firms, while it has no effect on those that that grow at a slower rate. External R&D is instead effective for firms with a median growth rate, while it is ineffective for the group of fast growing firms. Furthermore, in assessing the probability for a firm to be "high-growth", only internal R&D has been found to display an effect, and only so for manufacturing firms.

In assessing OI determinants and economic effects on Spanish SMEs operating in the manufacturing sectors through structural equations models, Popa et al. (2017) find support that both inbound and outbound OI positively affect firm economic performance, being the latter measured as a self-reported value on a scale going from worse to better than firm's competitors.

The role of OI and in particular of the interactive search for knowledge in affecting firm's sales from new products is also confirmed by a study on a panel of UK firms (Roper, Love, and Bonner, 2017) on all sectors, and also when differentiating between manufacturing and service sector. This study also finds a confirmation on the curvilinear effect of interactive searches of knowledge on sales, suggesting that this relation suffers from diminishing return: as the number of collaborative partners increases, after a certain point so do the sales.

All in all, the empirical literature on the effect of OI on firm's economic performance, discussed so far, is rather scant. At the theoretical level, the same scarcity is encountered.

Reed et al. (2012) explored theoretically the changes in the drivers of competitive advantage and the consequent economic rents when firms adopt an OI mode. Some sources of economic rents for incumbents in an industry are expected to be reduced, such as rents extracted from property rights, from economies of scale and capital requirements. Instead those rents a firm extracts from experience-curve effects, differentiation, distribution, and switching costs as well as those for "difficult-to-imitate resources of networks and reputation" will remain. The ultimate conclusion of the authors is that for some firms the competitive advantage will not be eroded by an OI mode. For firms who instead gain a competitive advantage from barriers to entry, skills in innovation, the capability to anticipate customer's needs or from proprietary product design can be expected to loose from OI in the long run.

Hence, since the effect of OI on economic performance is expected to be rather unevenly distributed among the firms in the same industry (with the presence of both "winners" and "losers" in the same changing OI environment), one of the contributions of the present paper is to assess the net "aggregate" effect of different OI modes in different industries and countries, given also the lack of empirical studies that have analysed this nexus at meso or macro levels.

2.3 Research Hypothesis

Bogers et al., (2016) stress that extant research on OI predominantly has the firm as its unit of analysis, while other units of analysis should be considered. Coherently, the focus of the current study is the sector.

The choice of focusing on the sectoral level is supported by three main arguments: i) the growing recognition that other units of analysis than the firm "need to be considered [in order to] get a more detailed understanding of the antecedents, processes and outcomes of OI" (West et al. 2014); ii) the need to correct for the bias associated with the subjective nature of self-reported perceptions and responses typical in innovation survey data (Bogliacino and Pianta, 2016); and furthermore iii) to get a more integrated perspective on industrial dynamics.

Furthermore, a set of industry-level contingencies are relevant for explaining the effectiveness of OI across different sectoral settings. For instance, more R&D intensive sectors in which innovation is more uncertain than in others, might be well equipped for firms to share both knowledge and risks (Dyer et al. 2014).

Lastly, and more technically speaking, the use of aggregated industry analysis in innovation studies allows overcoming some sources of bias which are standard when exploiting survey data (Bogliacino and Pianta, 2016). It would allow correcting for the bias associated with the subjective nature of questions and responses, as the direction of the error is non-systematic for firms aggregated in the same sector, and it also allows capturing some sectoral features that the firm level would omit.

As for the sector coverage, it is well known that open innovation mainly started in the high-tech sector, but there this is influencing also the low-tech sector nowadays. According to Gassmann, Enkel, and Chesbrough (2010: 215) "Open innovation's management innovation has spread to different sectors, such as machinery, turbines, medical tools, fast moving consumer goods, food, architecture and logistics".

Coherently Love et al. (2011) extend the evidence on OI to the service sector, analysing in a sample of UK knowledge-based service firms finding support of the positive effects of the openness in searching for information or creating knowledge.

For these reasons, the empirical analysis will be conducted on both manufacturing and service sectors in Europe.

From the literature discussed in Section 2.1, we can draw our first research hypothesis:

H1: OI positively affects innovation adoption at the sectoral level, when considering both the breadth and the depth dimensions of the OI modes

And, following the discussion on the expected negative returns with the misuse of an OI mode also the second research hypothesis:

H2: Curvilinear effects are expected to characterize the linkage between OI modes and innovation outcomes.

From the literature discussed in Section 2.2 it is less straightforward to derive any clear research hypothesis concerning the nexus between OI modes and growth at the sectoral level. In fact, besides the ex-ante theoretical ambiguity on the sign of this relationship and the corresponding ex-post inconclusive evidence that is found at the firm level, doing predictions at a more aggregated level is even more difficult because of the complex relationships and trade-off dynamics that may emerge amongst the different actors in the same industry. Hence, the overall effect of OI on the economic growth in a given industry may be very different from the simple sum of the OI effects found for each member of that industry. Consequently,

no ex ante expectation can be formulated on the industry economic returns of an OI mode, which constitutes the third research line of the paper.
In the special issue on R&D Management (2010) on open innovation, Gassmann et al., (2010) outline the still open research direction, stressing that still weakly explored is the so called "supplier perspective", to assess the role of suppliers' early integration into the innovation process. Without, any ex ante expectation on this relationship, we draw on this suggestion and focus on the economic returns of this type OI mode by specifically focusing on suppliers-clients integration, and on how this shapes the OI effect on innovation and on economic growth. This would constitute the fourth research line of the paper.
Due to data availability, our hypothesis and research lines, and, consequently, our empirical analysis are only going to be focused on inbound OI, as we lack adequate information on the outbound forms of OI.

3. Empirical strategy

To test for the main research hypothesis and to investigate the main research lines we built a dataset on European sectoral data for 16 EU countries: BG, CY, CZ, DE, EE, ES, HR, HU, IT, LT, LV, NO, PT, RO, SI, and SK. This dataset allows a broader geographical coverage than previous studies, even if Southern and Eastern EU Member States are better represented.
A panel dataset is constructed based on the harmonized Community Innovation Survey micro data, which has been aggregated at the sectoral level for 3 waves (2006-2008; 2008-2010; 2010-2012), from which innovation and open innovation variables are extracted. The choice of the countries depends on the availability of the micro data for the 3 waves. Sectors covered are maximum 21 per country, classified according to NAVE Revision 2 classification to include both manufacturing and services, as reported in the Appendix.
Eurostat and WIOD (Timmer et al. 2015) are additional sources of information, used to draw information on value added, sectoral size and inter-sectoral relatedness (both upstream with suppliers and downstream with clients).
The empirical approach consists of two separate steps of analysis, which are so far treated as independent.
At first, an innovation production function is estimated, aimed at unveiling the drivers of innovation adoption, including OI. This would answer the first and the second research hypothesis (H1 and H2). The following pooled OLS model with robust standard errors is estimated:

$$Y_{i,t} = \alpha + \beta_1\, BREADTH_{i,t} + \beta_2\, DEPTH_{i,t} + \beta_3\, CONTROLS_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t} \qquad (1)$$

with i=1 → 298 (max 21 sectors in 16 EU countries); t=2008, 2010 or 2012.
Table 1 reports the main statistics for the variables, while Table 2 reports their pairwise correlations.

TABLE 1 and TABLE 2 here

The main dependent variable of the first step reflects the share of innovators (INNO) (both product and process) in the sector, and it is constructed from an aggregation of the micro data of the Community Innovation Survey (CIS) at the country and sectoral level. As a robustness test, all variables constructed from the CIS micro data have been built both with and without

using CIS sampling weights. Results are robust to this choice.2 To disentangle the heterogeneity across different typologies of innovation, we extended the analysis by additionally focusing on two alternative dependent variables: the share of product innovators in the sectors (INPD) and the share of process innovators in the sectors (INPS).
As for the explanatory variables, the main variable of interest, Open Innovation (OI), is constructed at the firm level using microdata following the breadth and depth concepts of OI (as in Laursen and Salter, 2006) and subsequently aggregated at the sectoral level. BREADTH thus captures, at the firm level the number of external information sources on which the firm rely to innovate, out of a list of 9 potential knowledge providers (suppliers; customers; competitors; consultants and private R&D institutes; universities; government or public research institutes; conferences, trade fairs, exhibitions; scientific journals and trade/technical publications; professional and industry associations). DEPTH captures the number of these external information sources to which firm attribute a high degree of importance among the listed options: not used, low, medium, high importance. BREADTH and DEPTH, constructed at the micro level, are later aggregated at the sectoral level by mean of their average value across sectors and countries.
The baseline model is then extended to include quadratic terms for both BREADTH and DEPTH, in order to test for the presence (if any) of curvilinear effects.
Standard controls are included to limit the risk of bias due to the omission of relevant variables. EXPORT controls for the share of exporting firms in the country-sector, and it is constructed from the self-reported information collected at the micro level from the CIS. Similarly, GROUP controls for the share of firms in the sector that belong to a group. R&D expenditures of the sectors, RD, are accounted for through the Eurostat statistic "Business R&D expenditure" expressed in billions PPS, in 2005, log transformed.
Lastly, country fixed effect δ_i and yearly fixed effects γ_t are included.
Results are reported in Table 3 and commented in the next section.
An extension of the model in equation (1) is to give deeper insights on the knowledge flows occurring among different actors along the value chain in a given industry-country combination. At first we created to separate variables, CLI_DEPTH and SUP_DEPTH, that would account for the relevance of the open innovation modes in the sector with, respectively, clients and suppliers. CLI_DEPTH is constructed at the firm level from CIS and it takes value 1 if the firm declared information sourcing from its client to be a highly important source of innovation for its innovative activities. It is then aggregated at the sectoral level so that it measures the share of firms in the sector to which open innovation with its clients is an important source of innovation. Similarly, SUP_DEPTH accounts for the share of firms in the sector to which suppliers constitute a highly relevant source of information for their innovations.
Then, we weighted these two variables, by the inter-relatedness of the sectors with their vertically inter-related sectors, both upstream and downstream. The aim is to weight open innovation measures by the real share of monetary flows occurring across sectors. This allows to account not only for the direct but also the indirect effect of OI, which is moderated by the degree of vertical integration of each sector with the other ones both at the national and international levels. By doing so, we explicitly recognize the importance of sectoral reciprocity in OI modes and we can test for the importance of the attitude towards OI of the main supplier and client sectors.
Such an indirect weighting matrix is constructed by multiplying the vectors of OI indicators from CIS (the vectors SUP_DEPTH and CLI_DEPTH) with the weighting matrix constructed from WIOD (Timmer et al. 2015). In particular, the weighting matrix W is constructed by

[2] Henceforth only tables with non weighted variables are reported. The others are available upon request.

keeping all the information on supply and use for countries and sectors covered in the CIS and by summing all the $W_{i,j}$ constructed as it follows:

$$W_{i,j} = \frac{S_{i,j}+U_{i,j}}{S_i+U_i} \quad (2)$$

with i,j=1→ 21 and $W_{i,j}$ = 0 if i = j. $S_{i,j}$ represents the supply flows between sector i and sector i, while $U_{i,j}$ the use flows between sector i and sector j. S_i represents the total flows of supplies by the i-th sector, while U_i is its total use. The diagonal values of W are set to 0, so as to count the flows within the same sector as a signal that the sector is not open to the externals, attributing them no value.

Finally, we constructed the variable OPEN_DEPTH_CLIENTS as the share of CLI_DEPTH in the sector weighted by the sectoral openness of the sector, by multiplying CLI_DEPTH for the weighting matrix:

$$\text{OPEN DEPTH CLIENTS} = [W] * [CLI\_DEPTH] \quad (3)$$

Similarly, we constructed the variable OPEN_DEPTH SUPPLIERS, as the share of SUP_DEPTH in the sector weighted by the sectoral openness as it follows:

$$\text{OPEN DEPTH SUPPLIERS} = [SUP\ DEPTH]' * [W] \quad (4)$$

Results are reported in, respectively, columns (3) and (4) of Table 3 when the dependent variable is INNO, in columns (7) and (8) when the dependent variable is INPD, and in columns (11) and (12) when the dependent variable is INPS.

This first step aims at shedding light on the determinants of sectoral innovation, by taking into account various forms of open innovation. We can now move to the second part of the analysis, aimed at unveiling the economic effects of OI mode.

The second step aims at assessing the economic returns associated to OI, once controlling for innovation. This would constitute the third research line of the paper, where no ex ante expectation was formulated on the role of OI. Country-sectoral value added is the core dependent variable, and it is estimated as a function of innovation, OI, capital and labour in an augmented Cobb Douglas production function framework.

The following baseline econometric log-linear augmented Cobb-Douglas model (Cobb and Douglas, 1928) is estimated through a pooled OLS:

$$\begin{aligned} logVA_{i,t} = \alpha + \beta_1\, BREADTH_{i,t} + \beta_2\, DEPTH_{i,t} + \beta_3\, logL_{i,t} + \beta_4\, logK_{i,t} + \\ + \beta_5\, logTEC_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t} \end{aligned} \quad (5)$$

with i=1 → 342 (max 21 sectors in 16 EU countries); t=2008, 2010 or 2012. The economic output is the dependent variable and it is approximated by the natural logarithm of country-sector value added (source: Eurostat). Capital input K is approximated by the natural logarithm of net investments in tangible capital (L_INVESTMENT) (Eurostat: structural business statistics)[3]. Labour input is approximated by the natural logarithm of the number of employees in the country-sector (L_SIZE). The Technological input TECH is approximated by the logarithm of RD expenditures (RD). Lastly, country fixed effect δ_i and yearly fixed effects γ_t are included. The baseline model is then extended, as it was for the previous step of

[3] An alternative would have been to measure Capital through a Capital Formation variable, but too many missing values conditioned our choice.

analysis, to include quadratic terms for both BREADTH and DEPTH, in order to test for the presence (if any) of curvilinear effects.
Results are reported into Table 4. As a further robustness alternative time lags of the dependent variable have been considered, in particular a one year lead having VA in t+1 as dependent variable, and a two years lead having VA in t+2 as dependent variable. Additionally, we test whether OI acts as a moderation factor in enhancing the effect technology displays on the economic output. The model is thus augmented by an interaction term between OI and R&D, through, respectively, RD*BREADTH and RD*DEPTH, kept separate to limit double counting and collinearity. This would allow assessing whether the sector absorptive capacity affects its economic output.
Then the analysis moves from a static analysis on the economic returns of OI, to a more dynamic analysis aimed at assessing whether OI entails any effect on the economic growth, namely on the growth in value added. We thus modified the framework proposed in equation (5) by considering all the variables not in levels, rather in growth rates with respect to the year before. As for the dependent variable, the growth rates are either measured with respect to a 1 year (VA_GR_t1) or a two years lag (VA_GR_t2) with respect to the regressors. Results of this analysis are reported in Table 5. Finally, we account for OPEN_DEPTH_CLIENTS and OPEN_DEPTH_SUPPLIERS, in the same way they have been constructed and exploited in the first part of the analysis. Results of this inclusion are reported in Table 6.

4. Results and discussion

As for the first and second hypothesis we find a confirmation that OI affects innovation – even at the aggregate level, and that curvilinear effect emerge.

TABLE 3 here

Results of the first part of the analysis, focused on the sectoral drivers of innovation, confirm some of the curvilinear effects of the different OI modes on the innovation outcomes, as found in Laursen and Salter (2006) at the firm level, can also be extended at a broader industry level with further important differences and qualifications. When distinguishing between product and process innovation outcomes, we find that widening OI modes (BREADTH) have a larger effect with a stronger statistical significance than deepening OI modes (DEPTH) when predicting innovation outcomes, with DEPTH being not significant for the single typologies of product and process innovation. Hence, if we consider the industry-country unit of observations as "systems of actors", then increasing the number of connections and collaborations amongst the "nodes" within each system increases the likelihood of introducing more innovations at the aggregate level, since the more knowledge is shared among a wider variety of actors the more innovation tends to be distributed. The curvilinear effect of BREADTH is confirmed, and it can be explained again in the framework of innovation network theory, by assuming that, as the number of connections becomes larger, the redundancy of information shared among the nodes also increases. Hence, since the marginal value (in term of originality of information shared) of adding one more connection into the system tend to decrease (when the number of connections are to large) then we may observe a decreasing aggregate level of innovation when there are too many links, since the units tend to become more "homogeneous" when they share the same type of knowledge (Granovetter, 1973; Burt, 1992). In addition, the curvilinear effects of deepening OI modes is almost negligible for product and process innovation, meaning that the returns in terms of innovation outcomes are decreasing more steeply when considering widening rather than deepening OI modes. These results suggest that, on the one hand, having a wide set of sources is a key asset that is likely to generate a wider variety of new ideas for general, product and process innovations. On the other hand, engaging in deep the linkages with some of these external sources, does not affect product nor process innovation, probably due to the enhanced risk of information leakages and hold-up situations stemming out from too close and exclusive relationships with external partners. As for the main control, internal R&D remains an important determinant, thus confirming the key role that investments in innovation have in enhancing both the innovative and absorptive capacity of the firms (Cohen and Levinthal, 1990).

Instead, no significant effect is found when we measure the sectoral inter-relatedness and their OI attitudes, as both OPEN_DEPTH_CLIENTS and OPEN_DEPTH_SUPPLIERS, fail to reach a statistically significant effect.

When considering economic performance as dependent variable (in term of value added, Table 4), only OI widening modes (BREADTH) are statistically significant (again, with an inverted U-shaped effect), whereas deepening OI modes (DEPTH) do not show any significant effect. This inverted U relationship may be explained, again, in the light of the increased transaction and coordination costs and information leakage risks that managing too many relationships may entail without a proper level of coordination and control.

TABLE 4 here

The last columns of Table 4 show that the estimated effects of OI on performance are strictly dependent on the level of R&D, since both BREADTH and DEPTH lose statistical significance when adding R&D investments as additional regressor. Most interestingly, when adding also the interaction terms in our models, we find that R&D positively moderates both OI modes. Hence, we find some evidence of complementarity between OI modes and the “absorptive capacity” (proxied by R&D) when explaining the performance of an industry, a result that is different form the “substitution effect” between internal R&D and openness at the firm level found by Laursen and Salter (2006).

When adding to this picture the role of inter-sectoral relatedness, no significant additional result emerges (Table 5).

TABLE 5 here

Finally, when we consider the model estimated in first differences (Table 6) we find in general no robust effect of OI on the economic growth.

TABLE 6 here

In particular, it seems from our results that only OI deepening modes (DEPTH) are displaying some statistically significant effect for explaining growth rates in value added with two years after the reference period of the regressors (t+2). These results can be explained by assuming a direct positive relationship between the radicalness of the innovation developed and the economic returns generated from its commercialization. In fact, while exploiting a wide set of information sources may be beneficial to introduce clusters of incremental innovations in a given industry, developing a radical (and economically breakthrough) innovation (that usually require some time to become profitable) is more likely to rely on the access to exclusive and specialized knowledge which can be effectively exploited only by establishing closed and repeated relationships with a restricted number of key external partners. These preliminary results suggest for the presence of a double effect of the OI mode, which does contribute on both innovative and economic outcomes. However, only deep and persistent relationships with partners generate significant economic outcomes and strategic advantages after some years since its development. Policy implications are derived from this finding.

5. Conclusive Remarks

The paper aimed at studying the innovative and economic returns of having an open innovative strategy at the aggregate sectoral level for 16 EU countries. Overall the analysis supports for the presence of positive returns of OI on innovative outcomes, both on overall innovation and, more specifically, on product and process innovations. A positive return is also found between a deep knowledge sourcing and value added levels. However, OI suffers of possible diminishing returns: relying too much on external knowledge can be detrimental for sectors innovativeness. An OI mode seems from our analysis not to be associated to any economic growth pattern. Additionally, not even innovation manages to be found significant in explaining growth.

For policy makers, the evidence on the importance of an open mode for successful innovation, and especially of having a broader range of partners firms can draw upon when searching for information, implies that it is important to create and maintain conditions for knowledge and innovation networks to flourish. Furthermore, the results not only confirm the importance of absorptive capacity in general for (open) innovation, but more specifically of being actively involved in pursuing R&D. Thus, it further confirms that policies promoting R&D investments throughout the innovation system are pointing in the right direction.

There are certain limitations the study could not solve, which should be acknowledged. Although largely discussed to be a useful source of information, Community Innovation Survey contains self-reported information at the firm level, which are thus subjective to a systematic response bias. We aggregated values at the sectoral level, such that in principle, if the direction of the error is random, this should largely mitigate this problem, however we cannot be sure about the absence of any bias with this respect. Secondly, data on OI were only available for the 3 selected consecutive waves, as the next edition of the CIS (2012-2014) has removed the section on external information sourced. This limited the sample of the analysis and forced us to limit to the minimum – reasonable – the number of explanatory variables.

Table 1 Main variables descriptive statistics

Variable	Description	Source	N	Mean	sd	Min	Max
VA	Value added of the sector (then log transformed)	Eurostat	298	13166	27007	14.30	191436
INNO	Share of innovators	CIS	298	0.341	0.173	0.0411	0.844
INPD	Share of product innovators	CIS	298	0.245	0.155	0	0.781
INPS	Share of process innovators	CIS	298	0.262	0.141	0	0.676
BREADTH	Breadth of the open innovation	CIS	298	5.623	0.977	3.125	9
DEPTH	Depth of the open innovation	CIS	298	1.254	0.571	0	5
BREADTH2	Squared breadth	CIS	298	32.56	11.23	9.766	81
DEPTH2	Squared depth	CIS	298	1.896	2.166	0	25
EXPORT	Share of exporting firms in the sector	CIS	298	0.523	0.230	0.0550	0.984
GROUP	Share of firms being part of the group	CIS	298	0.360	0.224	0.0415	1
RD	RD expenditures of the sector (billions, PPS, 2005)	Eurostat	298	0.167	0.607	0	7.394
INVESTMENT	Sectoral investment in tangible capital (then log transformed)	Eurostat	298	1435	2629	0.300	20325
SIZE	Average number of employees in the firms of the sector (then log transformed)	CIS	298	17.94	17.33	2.118	131.8
SUP DEPTH	Share of firms highly relying on the depth of information sources from suppliers in the sector	CIS	298	0.273	0.149	0	1
CLI DEPTH	Share of firms highly relying on the depth of information sources from clients in the sector	CIS	298	0.798	0.130	0.400	1
OPEN_DEPTH_CLI	CLI DEPTH weighted by Input Output relatedness	WIOD	298	0.252	0.0793	0.0185	0.746
OPEN_DEPTH_SUP	SUP DEPTH weighted by Input Output relatedness	WIOD	298	0.279	0.103	0.0515	0.590
EMPL	Employees of the sector (then log transformed)	Eurostat	298	189.3	318.3	0.670	2151

Table 2 Main variables correlation matrix

		1	2	3	4	5	6	7	8	9	10
1	VA	1.00									
2	INNO	0.13	1.00								
3	INPD	0.10	0.93	1.00							
4	INPS	0.12	0.93	0.79	1.00						
5	BREADTH	-0.18	0.27	0.37	0.17	1.00					
6	DEPTH	-0.22	0.01	0.08	0.01	0.55	1.00				
7	BREADTH2	-0.16	0.25	0.34	0.14	0.99	0.56	1.00			
8	DEPTH2	-0.18	-0.03	0.02	-0.01	0.43	0.93	0.45	1.00		
9	EXPORT	-0.26	0.33	0.30	0.30	0.17	-0.01	0.14	-0.07	1.00	
10	EMPL	0.79	0.14	0.09	0.14	-0.13	-0.20	-0.13	-0.18	-0.19	1.00
11	GROUP	0.05	0.31	0.33	0.20	0.47	0.11	0.51	0.07	0.14	-0.09
12	RD	0.50	0.35	0.37	0.28	0.15	-0.01	0.14	-0.04	0.08	0.50
13	INVESTMENT	0.82	0.15	0.09	0.17	-0.19	-0.24	-0.17	-0.20	-0.26	0.76
14	SIZE	-0.18	0.22	0.24	0.18	0.08	-0.05	0.07	-0.06	0.30	-0.17
15	SUP BREADTH	-0.24	0.18	0.19	0.21	0.54	0.42	0.54	0.39	0.07	-0.26
16	SUP DEPTH	-0.24	-0.07	-0.10	0.03	0.21	0.63	0.22	0.60	-0.07	-0.27
17	CLI BREADTH	-0.31	0.20	0.27	0.15	0.71	0.54	0.69	0.42	0.24	-0.27
18	CLI DEPTH	-0.18	0.14	0.22	0.05	0.58	0.74	0.59	0.64	0.12	-0.17
19	OPEN_DEPTH_CLI	-0.01	-0.08	-0.08	-0.08	-0.17	0.02	-0.18	-0.01	0.10	-0.02
20	OPEN_DEPTH_SUP	-0.01	-0.11	-0.08	-0.14	-0.04	0.09	-0.04	0.07	-0.10	-0.07

		11	12	13	14	15	16	17	18	19	20
11	GROUP	1.00									
12	RD	0.11	1.00								
13	INVESTMENT	0.06	0.43	1.00							
14	SIZE	0.30	0.12	-0.11	1.00						
15	SUP BREADTH	0.28	-0.09	-0.20	0.19	1.00					
16	SUP DEPTH	0.14	-0.19	-0.19	0.12	0.48	1.00				
17	CLI BREADTH	0.20	0.07	-0.34	0.09	0.56	0.30	1.00			
18	CLI DEPTH	0.26	0.10	-0.20	0.04	0.38	0.41	0.68	1.00		
19	OPEN_DEPTH_CLI	-0.20	0.00	-0.03	0.05	-0.08	-0.05	-0.06	0.02	1.00	
20	OPEN_DEPTH_SUP	-0.02	0.03	-0.09	-0.07	-0.05	-0.03	-0.05	0.01	0.09	1.00

Table 3 First equations estimating drivers of innovation, product innovation and process innovation

	(1) INNO	(2) INNO	(3) INNO	(4) INPD	(5) INPD	(6) INPD	(7) INPS	(8) INPS	(9) INPS
DEPTH	0.074** (0.037)			0.054 (0.038)			0.049 (0.030)		
BREADTH	0.181*** (0.068)			0.138** (0.064)			0.151*** (0.048)		
DEPTH2	-0.012 (0.008)			-0.007 (0.007)			-0.0099 (0.0066)		
BREADTH2	-0.014** (0.006)			-0.010* (0.0061)			-0.011** (0.004)		
EXPORT	0.147*** (0.033)	0.175*** (0.038)	0.183*** (0.037)	0.123*** (0.034)	0.128*** (0.038)	0.139*** (0.036)	0.105*** (0.025)	0.153*** (0.030)	0.150*** (0.029)
GROUP	0.257*** (0.045)	0.309*** (0.053)	0.313*** (0.051)	0.186*** (0.062)	0.237*** (0.064)	0.259*** (0.063)	0.237*** (0.039)	0.274*** (0.041)	0.264*** (0.039)
RD	0.027*** (0.004)	0.033*** (0.004)	0.036*** (0.005)	0.030*** (0.005)	0.035*** (0.005)	0.037*** (0.004)	0.016*** (0.004)	0.023*** (0.004)	0.025*** (0.004)
CLI_DEPTH		0.143** (0.070)			0.157 (0.098)			0.039 (0.052)	
OPEN_DEPTH _CLIENTS		-0.056 (0.095)			0.021 (0.092)			-0.105 (0.077)	
SUP_DEPTH			0.054 (0.077)			-0.043 (0.094)			0.087 (0.059)
OPEN_DEPTH _SUPPLIERS			-0.014 (0.056)			0.000 (0.055)			-0.045 (0.048)
_CONS	-0.448** (0.195)	0.108 (0.077)	0.137* (0.083)	-0.470** (0.187)	-0.009 (0.073)	0.105 (0.079)	-0.316** (0.132)	0.218*** (0.065)	0.170** (0.071)
N	298	225	225	298	225	225	298	225	225
R^2	0.739	0.748	0.741	0.648	0.654	0.644	0.763	0.766	0.767
ADJ. R^2	0.716	0.720	0.713	0.617	0.617	0.605	0.742	0.740	0.741

Notes: Standard errors in parentheses. Country dummies and time dummies are also included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 Cobb Douglas on Value Added

	(1) L_VA	(2) L_VAt+1	(3) L_VAt+2	(4) L_VA	(5) L_VAt+1	(6) L_VAt+2	(7) L_VA	(8) L_VA
L_EMP	0.429***	0.430***	0.4169***	0.431***	0.432***	0.409***	0.433***	0.441**
	(0.029)	(0.032)	(0.032)	(0.029)	(0.031)	(0.031)	(0.029)	(0.029)
L_INVESTMENT	0.418***	0.428***	0.429***	0.396***	0.403***	0.404***	0.399***	0.394***
	(0.023)	(0.025)	(0.025)	(0.022)	(0.024)	(0.024)	(0.022)	(0.022)
BREADTH	0.579**	0.504**	0.525**	0.340	0.274	0.347	-0.070	-0.007
	(0.233)	(0.252)	(0.256)	(0.232)	(0.247)	(0.248)	(0.050)	(0.043)
DEPTH	0.044	0.022	-0.009	-0.011	-0.070	-0.111	-0.005	-0.118
	(0.141)	(0.153)	(0.156)	(0.139)	(0.148)	(0.149)	(0.072)	(0.084)
BREADTH2	-0.046**	-0.038*	-0.036	-0.032	-0.024	-0.029		
	(0.021)	(0.023)	(0.023)	(0.021)	(0.022)	(0.022)		
DEPTH2	-0.004	-0.001	-0.005	0.008	0.017	0.018		
	(0.035)	(0.037)	(0.038)	(0.034)	(0.036)	(0.036)		
RD				0.077***	0.086***	0.096***	-0.093	-0.003
				(0.017)	(0.018)	(0.018)	(0.084)	(0.040)
c.RD#c.wide							0.029**	
							(0.014)	
c.RD#c.deep								0.064**
								(0.029)
_CONS	1.003	0.919	0.846	1.925***	1.863**	1.722**	3.680***	3.442***
	(0.697)	(0.755)	(0.768)	(0.710)	(0.758)	(0.759)	(0.275)	(0.244)
N	298	298	298	298	298	298	298	298
R^2	0.965	0.959	0.957	0.967	0.962	0.961	0.967	0.967
adj. R^2	0.9621	0.9558	0.9531	0.9641	0.9592	0.9578	0.9645	0.9637

Notes: Standard errors in parentheses. Country dummies and time dummies are also included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 Cobb Douglas adding input output relation on VA

	(1) L_VA	(2) L_VA	(3) L_VA	(4) L_VA
L_EMP	0.432*** (0.029)	0.419*** (0.03)	0.414*** (0.033)	0.423*** (0.034)
L_INVESTMENT	0.387*** (0.023)	0.402*** (0.028)	0.380*** (0.027)	0.382*** (0.028)
RD	0.084*** (0.015)	0.0710*** (0.017)	0.0908*** (0.018)	0.088*** (0.018)
CLI_DEPTH	-0.304 (0.197)		-0.435* (0.246)	-0.440* (0.255)
SUP_DEPTH	-0.116 (0.226)	0.103 (0.266)		0.218 (0.276)
OPEN_DEPTH_SUPPLIERS		0.480* (0.256)		0.433* (0.257)
OPEN_DEPTH_CLIENTS			-0.039 (0.344)	-0.038 (0.346)
_CONS	2.975*** (0.282)	2.896*** (0.271)	3.424*** (0.265)	3.157*** (0.313)
N	298	225	225	225
R^2	0.967	0.965	0.965	0.965
ADJ. R^2	0.964	0.961	0.961	0.961

Notes: Standard errors in parentheses. Country dummies and time dummies are also included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 Cobb Douglas on growth in value added

	(1) VA_GRt+1	(2) VA_GRt+1	(3) VA_GRt+1	(4) VA_GRt+2	(5) VA_GR t+1	(6) VA_GR t+1	(7) VA_GRt+2
GROWTH_EMP	0.181^{**}	0.1107^{*}	0.0693	0.1163	0.1341^{*}	0.1223	0.187
	(0.084)	(0.0665)	(0.0684)	(0.0935)	(0.0731)	(0.0743)	(0.115)
GROWTH_INVESTMENT	-0.012	0.039^{*}	0.041^{*}	0.040	-0.009	-0.010	-0.031
	(0.020)	(0.021)	(0.021)	(0.028)	(0.016)	(0.015)	(0.022)
GROWTH_RDIMP		0.001	0.0005	-0.003			
		(0.004)	(0.004)	(0.005)			
GROWTH_DEPTH			-0.039	-0.017		0.023^{*}	0.087^{***}
			(0.034)	(0.035)		(0.013)	(0.033)
GROWTH_BREADTH			-0.069	-0.098		-0.145	-0.225
			(0.105)	(0.126)		(0.096)	(0.134)
GROWTH_INNO					0.060^{**}	0.067^{**}	0.103^{*}
					(0.030)	(0.030)	(0.052)
_CONS	0.988^{***}	0.920^{***}	0.913^{***}	0.901^{***}	0.920^{***}	0.912^{***}	0.903^{***}
	(0.009)	(0.039)	(0.042)	(0.106)	(0.025)	(0.025)	(0.070)
N	135	108	108	108	135	134	134
R^2	0.080	0.276	0.300	0.311	0.264	0.290	0.314
ADJ. R^2	0.066	0.140	0.148	0.162	0.157	0.171	0.200

	(8) VA_GRt+1	(9) VA_GRt+1	(10) VA_GRt+2	(11) VA_GRt+1	(12) VA_GRt+1	(12) VA_GRt+1
GROWTH_EMP	0.127^{*}	0.118	0.195^{*}	0.173^{**}	0.162^{**}	0.255^{*}
	(0.073)	(0.0735)	(0.1131)	(0.0794)	(0.082)	(0.119)
GROWTH_INVESTMENT	-0.009	-0.010	-0.032	-0.013	-0.013	-0.037
	(0.016)	(0.015)	(0.021)	(0.015)	(0.015)	(0.023)
GROWTH_DEPTH		0.0320^{**}	0.0985^{***}		0.0211	0.086^{**}
		(0.0132)	(0.0302)		(0.0148)	(0.037)
GROWTH_BREADTH		-0.148	-0.236		-0.136	-0.208
		(0.096)	(0.144)		(0.097)	(0.141)
GROWTH_INNO						
GROWTH_INPS	0.056^{**}	0.060^{**}	0.075^{*}			
	(0.024)	(0.024)	(0.039)			
GROWTH_INPD				0.024	0.024	0.029
				(0.020)	(0.022)	(0.045)
_CONS	0.920^{***}	0.912^{***}	0.969^{***}	0.925^{***}	0.910^{***}	0.968^{***}
	(0.024)	(0.046)	(0.043)	(0.028)	(0.048)	(0.046)
N	134	133	133	134	134	134
R^2	0.267	0.292	0.305	0.248	0.260	0.279
ADJ. R^2	0.160	0.173	0.188	0.138	0.137	0.159

Notes: Standard errors in parentheses. Country dummies and time dummies are also included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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Appendix. Covered sectors

Nace2	Sector description	count
10-12	Manufacture of food, beverages and tobacco products	24
13-15	Manufacture of textile, wearing apparel and leather and related products	40
19-23	Manufacture of coke and refined petroleum products, chemicals and chemical products, of basic pharmaceutical products and pharmaceutical preparations, rubber and plastic products, and of other non-metallic mineral products	6
24-25	Manufacture of basic metals, of fabricated metal products, except machinery and equipment	41
28	Manufacture of machinery and equipment n.e.c.	20
33	Other Manufacturing	25
41-43	Construction	20
49	Land transport and transport via pipelines	11
50	Water transport	7
51	Air transport	4
52-53	Warehousing and support activities for transportation, Postal and courier activities	14
55-56	Accommodation and food service activities	7
58	Publishing activities	15
59-60	Motion picture, video and television programme production, sound recording and music publishing activities; Programming and broadcasting activities	1
61	Telecommunications	17
68	Real estate activities	7
69-75	Legal, accounting, management, architecture, engineering, technical testing and analysis activities, Scientific research and development, other professional, scientific and technical activities	39
	TOTAL	298