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Abstract.

The aim of this paper is to explore the impact of intra- and inter-industry spillover components on productivity of large International firms. We use data from all EU R&D investment scoreboards editions issued every year until 2011 by the JRC-IPTS (scoreboards). The analysis is based upon a new dataset composed of 879 worldwide R&D-intensive manufacturing firms whose information has been collected for the period 2002-2010. Given the panel data structure of the sample, ad hoc econometric techniques that deal with both firm's unobserved heterogeneity and weak exogeneity of the right hand-side variables are implemented. The main contribution to the literature is that of further investigating the industry spillovers at firm level within the Triad for a period of time that considers also the economic crisis. In order to measure the distribution of the firm's research interests through the different technological areas, we use the patent distribution over technological sectors according to the International Patent Classification (IPC). The patent distribution relies on the whole number of patent applications filed to the European Patent Office until 2011. The empirical results suggest a significant impact of R&D spillover effects on firms' productivity but the results are quite differentiated according to the spillover stock type and this may represent a relevant source of policy implications.

Keywords: Panel Data Models, R&D Spillovers, Total Factor Productivity growth

JEL codes: C23, O33, O47

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1. Introduction

The aim of this paper is to analyse the role of R&D spillovers on firms' productivity performance. The framework implemented relies on the assumption that knowledge externalities are realised in two steps: first, knowledge flows take place whenever ideas generated by a firm are learned by another firm and then in the second step such learning process creates a pool of accessible external knowledge, which may affect the productivity. The pool of external knowledge is usually measured as the amount of R&D conducted elsewhere weighted by some measure of proximity in the technological space. These weights are assumed to be representative of the intensity of knowledge flows between the source and the recipient of R&D spillovers.

As in Capron and Cincera (1998), Aldieri and Cincera (2009), the pool of knowledge spillovers are computed following the Jaffe' s procedure (1986): the closer two firms are in the technological space, the more the research activity of one firm is supposed to be affected by the technological spillovers generated by the research activities of the second firm. Hence, it is assumed that each firm faces a potential 'stock' of spillovers, which is a weighted sum of the technological activities undertaken by all other firms. In order to measure the technological closeness between firm *i* and *j*, Jaffe uses the 'angular separation' between them, *i.e.* he computes the uncentered correlation between their respective vectors of technological position. This measure of closeness takes values between one and zero according to the common degree of research interest of both firms. In order to measure the distribution of the firm's research interests through the different technological areas, we use the patent distribution over technological sectors according to the International Patent Classification (IPC). The patent distribution relies on the whole number of patent applications filed to the European Patent Office until 2011. We divide the potential stock of spillovers into two distinct components: intra-industry stock which corresponds to the sum of R&D stocks of firms belonging to a same cluster of technological activities and an inter-industry stock which is computed from the other firms. Thanks to the international dimension of our sample, distinguishing, besides the intra and inter-industry stocks, national stocks from international ones, extends Jaffe's methodology. In this way, we will be able to appreciate to what extent geographical and cultural contiguity matters. Furthermore, in order to consider the technological as well as the geographical closeness, the potential stock of spillovers is dissociated into four components: the intra-industry national stock, the intra-industry international stock, the inter-industry national stock and finally the inter-industry international one.

The remainder of the paper is organized as follows. The next section briefly reviews the literature on R&D spillovers at the firm level. Section 3 outlines the theoretical framework. The data and empirical methods are described in section 4 and the empirical results in section 5. Finally, section 6 offers some concluding comments as well as some points deserving further research.

2. Literature review

Knowledge accumulation and its progress have been for a long time recognized as one of the central tenets of economic growth (Jones, 2002). Also Rogers (2003) shows that countries that are good at acquiring and diffusing new knowledge actually achieve faster economic growth. For Romer (1990), the non-rival and partially non-excludable feature of the knowledge good does not allow inventors to fully prevent other firms from using their inventions. More generally, knowledge spillovers may be driven by a variety of channels such as the mobility of workers, the exchange of information at technical conferences, or knowledge available in the scientific and technological literature including patent documents. These knowledge externalities or R&D spillovers can benefit to competitors' R&D by lowering the costs of their own R&D activities and in turn may contribute to their productivity performance. However, new products and processes can also render existing ones obsolete or less competitive and firms that encounter difficulties to stay in the R&D race may suffer from rivals' R&D. In this case, R&D externalities are associated with competitive pressures, which will translate into negative effects on firms' performance (Kafouros and Buckley, 2008). The specific type of knowledge flows that economists have most been interested in concerns pure knowledge spillovers. There are studies relative to knowledge spillovers in product and process innovation (Ornaghi, 2006), while other economists often investigate the patterns of these knowledge flows from a geographic or a technological perspective, i.e. in terms of geographic proximity or technological linkages between the unit generating these flows and the recipients. Over the last decade, several studies in the literature that examines the spatial dimension of innovative activities find that knowledge spillovers tend to be locally concentrated (Jaffe, 1989; Jaffe et al., 1993) or they raise in firms organized in 'networks' (Meagher and Rogers, 2004). At the same time, other studies show evidence of a positive relationship between the R&D of 'technological neighbours' and the firm's R&D productivity (Griffith, Harrison and Van Reenen, 2006). In terms of productivity performance, the effects of R&D spillovers also appear to be mainly technologically localised (Jaffe 1986, 1988). While very important for economic growth, the two types of geography and technology based R&D externalities have rarely been investigated together (Orlando 2004). Also

Aldieri and Cincera (2009) implement an empirical investigation to gauge the extent to which R&D spillover effects are intensified by both geographic and technological proximities between spillover generating and receiving firms, but they also control for the firm's ability to identify, assimilate and absorb the external knowledge stock (absorptive capacity) in a unified framework. Following this line of research, Lychagin, Pinkse, Slade and Van Reenen (2010) assess the contributions to productivity of three sources of research and development spillovers: geographic, technology and product–market proximity. To do this, they construct a new measure of geographic proximity that is based on the distribution of a firm's inventor locations rather than its headquarters, and they report both parametric and semiparametric estimates of their geographic–distance functions. In particular, they find that: i) Geographic space matters even after conditioning on horizontal and technological spillovers; ii) Technological proximity matters; iii) Product–market proximity is less important; iv) Locations of researchers are more important than headquarters but both have explanatory power; and v) Geographic markets are very local. In order to analyse the relationship between R&D spillovers and productivity, O'Mahoni and Vecchi (2009) consider a different instrument of technological proximity. Indeed, they implement a cluster analysis and they summary the industry data in two different taxonomies: factor and skill intensive groups, which account for differences in the knowledge intensity and innovative activities within sectors. The results provide evidence of higher productivity in R&D and skill intensive industries and this can be interpreted as evidence in favour of the presence of spillover effects. There are also studies which examine to what extent the total factor productivity by local firms can be affected by the presence of affiliates of foreign multinationals (Bernard and Jensen, 2004; Muûls and Pisu, 2008). In particular, they investigate how local spillovers from foreign affiliate and local firm internationalization through import and export activities interact in affecting the productivity levels of local firms. In this context, we may distinguish the effects of horizontal (intra-industry) spillovers within the sector as well as vertical (inter-industry) spillovers across industries through local client and supplier relations with affiliates of foreign multinationals. As far as the horizontal spillovers are concerned, Caves (1974) and Globerman (1975) find positive externalities in Australia and Canada, respectively. More recently, Driffield (2001) and Dimelis and Louri (2002) confirm the existence of intra-industry spillovers using data from UK and Greece respectively. Haskel et al. (2002) find that the foreign-affiliate presence in an industry is correlated with the domestic firms' total factor productivity in that industry, but other studies report non-significant or negative effects on productivity (Girma and Wakelin, 2001; Barrios and Strobl, 2002). As far as vertical or inter-industry spillovers are concerned, Javorcik (2004) and Kugler (2006) do not find any evidence of forward spillover effects, but report significant backward spillovers to local firms. Their results are not robust across all different specifications of the models. This phenomenon may occur because foreign multinationals have strong incentives to protect their technology by patenting mechanism (Veugelers and Cassiman, 2004).

The contribution of our paper to the existing literature is twofold: first, we use an international sample in such a way that we may compare the empirical results among different economic markets; second, we assess the importance of technological activity of firms on productivity, by exploring different components of potential stock of spillovers also after the beginning of world economic crisis. In particular, we extend Jaffe's methodology to distinguish, besides the intra and inter-industry components, national and international stocks. In this way, we will be able to appreciate to what extent geographical and cultural contiguity matters. Furthermore, in order to consider the technological as well as the geographical closeness, the potential stock of spillovers is dissociated into four components: the intra-industry national stock, the intra-industry international stock, the inter-industry national and inter-industry international one.

3. A basic model with search and random matching in the labour market

Following an interesting strand of economic literature based on Acemoglu (1996) we consider a simple Non-Overlapping Generation Model in which each generation is assumed to consist of workers and entrepreneurs a continuum of normalized to unity. All agents, assumed to be risk neutral and with an intertemporal preference rate equal to zero live for two periods. In the first workers choose their desired labor intensity, and firms must select the optimal levels of *R&D* and physical capital. The entrepreneurs' choice will depend on the impact of technological *R&D* spillovers on firms productivity growth besides traditional inputs and the firms' own *R&D* stock. In the second one production takes place in the form of a partnership of one worker and one entrepreneur. Consumption takes place at the end of this second period and then agents die leaving no bequests. Workers are assumed to choose the amount of labor input before they know the entrepreneurs they will match, as a consequence their private decisions depend on what types of physical capital and *R&D* they will expect to use. On the other hand the reverse is obviously true in the sense that entrepreneurs decisions concerning physical and *R&D* capital levels depend on the workforce human capital In this economy there is a homogeneous final good with the following extended Cobb-Douglas production function:

$$Y_{i,j,t} = AL_{i,t}^{\beta_1} C_{j,t}^{\beta_2} K_{j,t}^{\beta_3} X_{j,t}^{\gamma} \quad \text{with: } 0 < \beta_1, \beta_2, \beta_3, \gamma < 1 \quad (1)$$

where $Y_{i,j,t}$ is the firm's output at time *t*, $L_{i,t}$ the labor input of the *i-th* worker, $C_{j,t}$ and $K_{j,t}$ stand for physical and *R&D* capital levels, and finally $X_{j,t}$ is a vector of spillover components. Since we know that $X_{j,t} = X\left(\int_0^1 K_j dj\right)$ we assume $X_{j,t} = \left(\int_0^1 K_j dj\right)^{\alpha}$ where $\alpha > 0$ ($\alpha < 0$) in case of positive (negative) impact of the *R&D* stock on $X_{j,t}$. The positive parameter *A* captures all the exogenous components (such as technology of the economy) that affect productivity. In what follows we will focus on the case of an economic system where the labor market is characterized by no unemployment and a costly search activity and a matching technology function assumed random and constant returns to scale in its arguments: job vacancies and unemployed workers give rise to the fact that entrepreneurs and workers have the same probability to meet each other, and once a match has been created to break it up is a very costly activity in order to search new partnership for each agents. Following the standard search literature it will be assumed a bargaining process, and the consequent distribution rule according to which the total output has to be shared in constant proportions *b* and *(1-b)* between workers and firms that captures their respective bargaining strength. Further, as well emphasized in Acemoglu (1996) the randomness of the matching technology function implies anonymity of contracts in the sense that each worker (entrepreneur) does not know the entrepreneur (worker) she/he is going to meet and consequently her/his expected wage bill (firm' s return) will depend on the total distribution of *R&D* and physical (human) capital across all the entrepreneurs (workers).

The *i-th* worker expected wage bill, and the *j-th* entrepreneur expected income will respectively be:

$$W_{i,t}^{e} = bAL_{i,t}^{\beta^1}\left[\int C_{j,t}^{\beta_2}\,dj\right]\left[\int K_{j,t}^{\beta_3}\,dj\right]\left[\int K_{j,t}^{\alpha\gamma}\,dj\right] \quad (2)$$

$$R_{j,t}^{e} = (1-b)AC_{j,t}^{\beta_2}K_{j,t}^{\beta_3}\left[\int L_{i,t}^{\beta^1}\,di\right]\left[\int K_{j,t}^{\alpha\gamma}\,dj\right] \quad (3)$$

Each worker will choose her/his optimal labor input by maximizing the following utility function:

$$U_{i,t} = c_{i,t}^{e} - \frac{\theta_i L_{i,t}^{(1+\eta)}}{(1+\eta)} \quad (4),$$

where $c_{i,t}^{e}$ stands for the worker expected consumption, θ_i is a taste positive parameter from disliking working. The distribution of θ_i across workers is taken as common knowledge. The above utility function (eq. (4)) has to be maximized subject to the following budget constraint:

$$c_{i,t}^{e} \leq W_{i,t}^{e} \quad (5)$$

The f.o.c. of the worker maximization process of eq (4) subject to eq (5) we may easily derive:

$$L_{i,t} = \left\{ \frac{bA \int C_{j,t}{}^{\beta_2} dj \int K_{j,t}{}^{\beta_3} dj \int K_{j,t}{}^{\alpha\gamma} dj}{\theta} \right\}^{\frac{1}{\eta+1-\beta_1}} \quad (6)$$

Entrepreneurs will invest in physical capital and in capital from *R&D* in order to maximize the following expected profits[1]:

$$\prod_{j,t}^{e} = R_{j,t}^{e} - r_1 C_{j,t} - r_2 K_{j,t} \quad (7).$$

Being evident the assumption of production price equal to unity, and with r_1 and r_2 standing respectively for the per unit cost of physical and R&D capital, the *f.o.c.*, after simple algebraic manipulations, we may easily derive:

$$C_{j,t} = \left\{ \frac{(1-b)AK_j{}^{(\beta_3+\alpha\gamma)} \left[\int L_i{}^{\beta_1} di \right]}{r_1} \right\}^{\frac{1}{(1-\beta_2)}} \quad (8)$$

$$K_{j,t} = \left\{ \frac{(1-b)AC_j{}^{\beta_2} \left[\int L_i{}^{\beta_1} di \right]}{r_2} \right\}^{\frac{1}{(1-\beta_3-\alpha\gamma)}} \quad (9)$$

From the above results we may derive:

Proposition *Assuming: $\theta_i = \theta$, the randomness of the matching technology function, the nature of the spillover components and the above distribution rule, from the analysis of the interaction between labor, physical and R&D capital we may state what follows:*

- *There exists a unique equilibrium in the decentralized search economy.*
- *The above equilibrium is inefficient in the sense of Pareto.*

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[1] We remind that the expected value for profits depends on the assumption of the randomness of the matching technology function resulting in the lack of knowledge of the workers' quality they are going to match.

- *The equilibrium exhibits social increasing returns in the labor input an in the physical capital accumulation in the sense that small increases in entrepreneurs' (workers ') in physical capital (real labor) investments will push workers (firms) to work hardly (to invest in physical capital).*
- *The equilibrium exhibits social increasing returns in labor and in R&D capital accumulation if* $\alpha \geq 0$ *and if* $\alpha > -\frac{\beta_3}{\gamma}$ *in case of* $\alpha \leq 0$. *In all other cases we will have social decreasing returns*

The above proposition (proved in *Appendix B*) states that with the incompleteness of contracts and a costly search activity in the labor market social increasing returns *a la Acemoglu* (1996) in labor and in both *R&D* and physical capital accumulation operate when $\alpha \geq 0$and if $\alpha > -\frac{\beta_3}{\gamma}$ for $\alpha \leq 0$. The uncertainty of the results obviously depends on the impact of *R&D* spillover effects on firms' productivity. Since this result comes from the *R&D* stock type, and this may be a very relevant source for economic policies, in the following section we will proceed with empirical analysis.

4. Data and empirical framework

4.1 Data sources and matching procedure

The dataset is constructed with the view of setting up a representative sample of the largest firms at the international level that reported R&D expenditures. The information on company profiles and financial statements comes from all EU R&D investment scoreboards editions issued every year until 2011 by the JRC-IPTS (scoreboards). R&D data from the scoreboards represent all R&D financed by the companies, regardless of the geographical localization of R&D activities. Scoreboard data are collected from audited financial accounts and reports[2]. Combining the most recent scoreboard to avoid multiple counting of the same observation, we obtain an unbalanced panel of 22697observations for 3430 firms, for the period 2000-2010. For each firm, information is available for net sales (S), the number of employees (L), the annual capital expenditures (Cexp), annual R&D expenditures (RD) and main industry sectors according to the Industrial Classification Benchmark (ICB) at the two digits level. OECD, REGPAT database, January 2012[3,4] is the second source of information used in this study. This database covers firms' patent applications to the European Patent Office (EPO) including patents published up to December

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[2] See Moncada Paternò Castello et al. (2009) for more details.

[3] See Maraut S., H. Dernis, C. Webb, V. Spieazia and D. Guellec (2008) for the methodology used for the construction of REGPAT.

[4] Please contact Helene.DERNIS@oecd.org to download REGPAT database.

2011. The dataset covers regional information for most OECD and EU27 countries, plus BRICS countries.

The matching between the firms in the R&D scoreboard and their counterpart in OECD, REGPAT database, January 2012 is not straightforward and involves a manual matching procedure considering two difficulties. First, patents are assigned to firms on the basis of their names which can vary from one data source to the other, e. g. 'Co' instead of 'Company', 'LTD' instead of 'Limited', 'Inc' instead of 'Incorporated' and other such changes or abbreviations. Second, many large firms have several R&D performing subsidiaries in several countries and it is not obvious to link the patents applied by these subsidiaries to the parent company. We should have a 'mapping' of the main firms company to their subsidiaries and affiliates. Unfortunately, it is not easy to construct an accurate mapping, since it changes over time through the process of merger and acquisition.

Following our criteria, the matching procedure consists of two steps. In a first step, patents are assigned to firms on the basis of their generic name. For instance, when searching for the firm 'INTEL' we retrieve 3177 patent documents. Examining more in detail the firm's full names reported in these documents, it appears that 3166 patents are assigned to 'Intel Corporation' (located in USA), 2 patents to 'Intel Network Systems, Inc.' (also located in USA), 4 patents to 'Intel China Ltd.' (located in China), 1 patent to 'Intel DSPC' (located in Israel), 2 patents to 'Intel GASGARDS PRIVATE LIMITED' (located in India) and 2 patents to 'Intel Mobile Communications Technology GmbH' (located in Germany). These last companies are clearly foreign subsidiaries of the American firm. Thus, the patents of which these firms are applicants are consolidated with the ones of 'INTEL'. In a second step, this procedure is repeated for each firm of the sample. For about 22% of the sample, there is only one first name in the retrieved documents. For the rest, firm names that could be identified without any doubts as subsidiaries are matched with generic names.

4.2 Construction of the variables

Each monetary observation is converted into constant currency (in EUR) and prices[5]. It should be noted that data in the R&D scoreboards are already expressed in Euros and that a single scoreboard uses a fixed exchange rate for each currency to convert data into Euros for every periods that it covers. Thus, first we convert the data into original currencies by using the exchange rates specific to each scoreboard. Second, data in original currencies are converted into

[5] Reference year is 2007. Sources for exchange rates and deflators are EUROSTAT.

Euros using a fixed exchange rate[6]. Data are transformed into constant prices[7] using national GDP price deflators with 2007 as the reference year. The R&D and physical capital stocks (K and C, respectively) are constructed by using a perpetual inventory method (Griliches, 1979), by considering a depreciation rate of 0.15 for R&D capital stock and 0.08 for physical capital stock, which are usually assumed in the literature. The growth rates that are used for the initial values in this study are the sample average growth rates of R&D and physical capital expenditures in each two-digit Industry Classification Benchmark (ICB) industry.

Once the firms with missing values for some variable of our sample are removed, we get 909 firms over the period 2002-2010. Furthermore, in order to trim the dataset from outliers, the following procedure is implemented. All observations for which the R&D intensity (defined as the R&D investments divided by the firm's net sales) is below 0.1% or above 100% are deleted. This removes 5 firms for the first threshold (mainly firms from the retail and travel and leisure industry sectors) and 25 firms for the second criteria (firms mainly in the pharmaceuticals sector[8]). This leads to an unbalanced panel of 879 firms.

Table 1 gives a view of the geographical and sectorial composition of the sample. In particular, we assign ICB sectors into High-, Medium- and Low-tech sectors according to R&D intensity. Low-tech firms have a R&D intensity below 2%, Medium-tech firms have a R&D intensity below 5% and High-tech firms have a R&D intensity above 10%. With more than 30% of firms, USA and European area are well represented in the sample. Also Japan is quite represented with 26% of firms. The R&D intensity of industries goes from below 1% in the Oil & Gas, Basic Resources and Banks industries to above 10% in the Health care and Technology industries. If we look at the sectorial distribution of firms, we observe that the weight of American firms is particularly important in High-tech taxonomy (Health care and Technology sectors), while European and Japanese have the highest number of firms in Medium-tech taxonomy (Industrial goods and services sector). This explains why the American firms included in the sample are more R&D intensive than European and Japanese ones.

[6] We use the exchange rates in Eurostat for year 2007.
[7] Eurostat GDP deflators.
[8] These firms are research specialized laboratories whose unique activity is R&D. Sales are very limited and this explains a very high R&D intensity, i. e. above 100%.

Table 1. Sectorial and Geographical characteristics of Variables

(Average over the period 2002-2010)

Sectors	Number of firms RW[a]	EU[b]	JP	US	S[c]	L	C	K	RD	TS	R&D intensity
Low-tech											
Oil & Gas	5	7	4	8	5273	8908	1607	110	24	54157	0.9
Basic Resources	3	11	10	3	1939	7577	655	82	14	44189	0.8
Construction & materials	0	12	9	4	975	4486	265	62	11	50797	1.4
Food & Beverage	0	11	12	6	2087	8788	721	151	30	76492	1.7
Telecommunications	2	9	2	1	3146	10410	5269	257	46	57913	1.9
Utilities	1	6	9	1	1994	5292	3209	204	20	85770	1.1
Banks	0	4	0	0	6777	41823	2874	210	72	110734	0.9
Medium-tech											
Automobiles & parts	0	27	22	13	2818	10191	1515	668	116	72162	4.1
Industrial goods & services	5	93	53	44	766	4360	247	146	27	62671	4.7
Chemicals	1	26	34	20	766	2725	318	180	30	65250	3.6
Personal & household goods	0	21	24	18	1313	6923	428	331	62	79193	4.4
Media	0	4	2	3	1081	3973	554	132	22	70621	4.1
Retail	0	2	1	4	1199	3137	238	55	13	53202	4.6
Travel & leisure	1	0	1	1	108	405	23	19	5	31517	4.3
High-tech											
Health care	8	42	29	59	749	2904	404	407	103	84864	16.8
Technology	15	41	20	105	638	3289	234	360	68	78181	15.5
Average					1744	7765	1164	227	45	69955	4.4
Rest of the World	41				1705	8464	881	254	56	90807	3.3
Europe		316			1452	5880	777	297	55	64834	3.8
Japan			232		993	4079	497	199	40	89654	4
United-States of America				290	1090	4244	436	333	69	60746	6.3

a: Australia, Canada, China, Croatia, Hong Kong, India, Israel, Norway, Russia, South Africa, South Korea, Taiwan

b: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Spain, Sweden, Switzerland, The Netherlands and the United Kingdom

c: S=net sales, L=number of employees, C=physical capital stock, K=R&D capital stock, RD=R&D expenditures, TS=Total stock of spillovers, R&D intensity=R&D expenditures/net sales (in %)

A key issue in the empirical analysis on knowledge spillovers is the measurement of the pool of external knowledge. This stock is usually built as the amount of R&D conducted elsewhere weighted by some proximity measure, which reflects the intensity of knowledge flows between the source and the recipient of spillovers[9]. In this paper, we follow the methodology developed by Jaffe (1986) to compute the technological proximity. This procedure rests in the construction of a technological vector for each firm based on the distribution of its patents across technology classes[10]. These vectors allow one to locate firms into a multi-dimensional technological space where technological proximities between firms are performed as the uncentered correlation coefficient between the corresponding technology vectors:

$$P_{ij} = \frac{\sum_{k=1}^{K} T_{ik} T_{jk}}{\sqrt{\sum_{k=1}^{K} T_{ik}^2 \sum_{k=1}^{K} T_{jk}^2}} \qquad (10)$$

where T_i is the technological vector of the firm i and P_{ij} is the technological proximity between firm i and j.

According to this procedure, the total weighted stock of R&D spillovers is computed as follows:

$$Ts_i = \sum_{i \neq j} P_{ij} K_j \qquad (11)$$

where K_j is the R&D capital stock of firm j.

Table 2 illustrates some technological proximity measures for different firms in the dataset. We observe that 'BASF' and 'BAYER' are closer to each other than 'SAMSUNG' or 'SONY'. This is quite normal given the nature of the research activities of these firms.

[9] See Griliches (1992), Mohnen (1996) or Cincera and Van Pottelsberghe (2001) for a review of different proximity measures used in the literature.

[10] 118 technological classes compose the International Patent Classification (IPC) at the two-digit level. In order to ease the calculations, these 118 classes are grouped into broader classes. On this basis, a table of contingency, i. e. a table reporting the distribution of the firms' patents across the 50 IPC classes, is constructed, as in Cincera (1998). This table is used to compute the index of technological closeness and then the stocks of spillovers.

Table 2. Example of technological proximity between firms

Firm	NPA[a]	BASF	BAYER	SAMSUNG	SONY
BASF	25651	1			
BAYER	23666	0.933	1		
SAMSUNG	9498	0.258	0.202	1	
SONY	16780	0.142	0.109	0.954	1

a: # of patent applications field to the European Patent Office during the period 2002-2010

As emphasised by Jaffe (1986), this technological distance index, which takes only positive values, relies on the strong assumption that the appropriability conditions of knowledge are the same for all firms. The more outcomes of R&D activities are appropriable, the less there is knowledge flows between R&D performers and the potential users of this knowledge. Since these variables are not observable at the firm level, their direct assessment is hard to pick up. However, in a context of panel data, we may assume that these firm specific unobserved effects are constant over the period considered.

4.3 Econometric framework

Following Griliches (1979), the impact of technological R&D spillovers on firms' productivity growth besides traditional inputs and the firms' own R&D stock, is estimated by means of an extended Cobb-Douglas production function:

$$Y = AL^{\beta 1}C^{\beta 2}K^{\beta 3}X^{\gamma} \qquad (12)$$

Taking the logarithms and introducing a set of time dummies leads to:

$$lnY_{it} = \alpha_i + \lambda_t + \beta_1 lnL_{it} + \beta_2 lnC_{it} + \beta_3 lnK_{it} + \gamma X_{it} + \varepsilon_{it} \quad (13)$$

Where ln is the natural logarithm; *i* indices the firm; *t* indices time; Y_{it} is the net sales; L_{it} is the number of employees; C_{it} is the physical capital stock; K_{it} is the R&D capital stock; α_i is the firm's fixed effect; λ_t is a set of time dummies; X_{it} is a vector of spillover components; β and γ are vectors of parameters and ε_{it} is the disturbance term.

Six alternative specifications of X_{it} are considered:

- Specification I: Impact of the total stock of spillovers

$$\gamma lnX_{it} = \gamma_T TS_{it} \quad (14)$$

where TS is the total stock of spillovers;

- Specification II: Differentiated impact of the national and international spillovers stocks

$$\gamma lnX_{it} = \gamma_N NS_{it} + \gamma_I IS_{it} \quad (15)$$

where NS and IS are the national and international stocks of spillovers respectively;

- Specification III: Differentiated impact of the intra-industry and inter-industry spillovers stocks, according to ICB at the two-digit level (16 technological sectors, as in table 1)

$$\gamma lnX_{it} = \gamma_{IntraS} IntraS_{it} + \gamma_{InterS} InterS_{it} \quad (16)$$

where $IntraS$ and $InterS$ are the intra-industry and inter-industry stocks of spillovers respectively;

- Specification IV: Totally differentiated impact of spillover stocks, according to ICB at the two-digit level (16 technological sectors, as in table 1)

$$\gamma lnX_{it} = \gamma_{IntraNS} IntraNS_{it} + \gamma_{InterNS} InterNS_{it} + \gamma_{IntraIS} IntraIS_{it} + \gamma_{InterIS} InterIS_{it} \quad (17)$$

where $IntraNS$, $InterNS$, $IntraIS$ and $InterIS$ are the intra-industry national, inter-industry national, intra-industry international and inter-industry international spillover stocks respectively;

- Specification V: Differentiated impact of the intra-industry and inter-industry spillovers stocks, according to High-, Medium- and Low-tech taxonomy

$$\gamma lnX_{it} = \gamma_{IntraS} IntraS2_{it} + \gamma_{InterS} InterS2_{it} \quad (18)$$

where $IntraS2$ and $InterS2$ are the intra-industry and inter-industry stocks of spillovers respectively;

- Specification VI: Totally differentiated impact of spillover stocks, according to High-, Medium- and Low-tech taxonomy

$$\gamma lnX_{it} = \gamma_{IntraNS} IntraNS2_{it} + \gamma_{InterNS} InterNS2_{it} + \gamma_{IntraIS} IntraIS2_{it} + \gamma_{InterIS} InterIS2_{it} \quad (19)$$

where $IntraNS2$, $InterNS2$, $IntraIS2$ and $InterIS2$ are the intra-industry national, inter-industry national, intra-industry international and inter-industry international spillover stocks respectively.

To estimate equation (13), we use standard panel data estimation procedures that allow one to take into account firms unobserved over time fixed effects. These effects take into account permanent differences among firms (such as the ability of engineers to discover new inventions). Neglecting these effects, as it is the case in cross-section estimates may lead to some omitted variables biases. In the context of panel data, it is possible to get around this issue by appropriate transformations of data in order to remove fixed effects.

The fixed effects can be deleted through the so-called within transformation which can be estimated by OLS provided that α_i are fixed over time and the regressors are strictly exogenous. Another way to eliminate the unobserved fixed effects consists of first-differencing the productivity equation (13). An advantage of this transformation is that it does not longer require the strict exogeneity of regressors. However, because of possible measurement in all the variables, this procedure leads generally to estimates which are more biased towards zero than does the within correction. For this reason, we implement the system Generalized Method of Moments (GMM) [11] estimator, which combines the standard set of equations in first difference with suitably lagged levels as instruments (GMM in First Differences), with an additional set of equations in levels with suitably lagged first differences as instruments. The validity of these additional instruments, which consist of first difference lagged values of the regressors, can be tested through difference Sargan over-identification tests. The system GMM (GMM SYS) estimator can lead to considerable improvements in terms of efficiency as compared to the GMM in First Differences (GMM FD). Furthermore, GMM-SYS takes into account the possible endogeneity or simultaneity issue of the explanatory variables with the error term.

[11] See Arellano and Bover (1995), Blundell and Bond (1998).

In the following section, we present the empirical estimates for two estimators: Within-Group[12] estimator and GMM-SYS[13] one.

5. Empirical findings

Estimates of the productivity equation are given in Table 3. We may observe that the two estimation methods lead to different results, particularly for the spillover variables. Given the reasons discussed in the previous section, our favourite estimates are given by the GMM-SYS model. The Sargan test of overidentifying restrictions as well as tests for first order (AR(1)) and second order (AR(2)) serial correlation tests of the first-differenced residuals are reported. While the latter are consistent with the assumption of no serial correlation in the residuals in levels[14], the Sargan test rejects the null hypothesis of valid instruments, indicating that some of the instruments in our sample are correlated with the error term. As in O'Mahoni and Vecchi (2009), given the plausibility of the results, we rely on existing evidence on the tendency of the Sargan test to over-reject the null hypothesis in equations specified in first-differences (Blundell and Bond, 1998). The coefficients obtained for the employment and the physical capital are significant. The estimated elasticities associated with the labour variable is 0.56-0.57, while for the physical variable the coefficients are 0.24-0.26. The results of own R&D capital on productivity performance are not significant for the possible multicollinearity issue with the spillover components, while there is a strong link between technologically based R&D spillovers and firms' productivity performance. The estimated elasticity associated with the total stock of spillovers (TS) is 0.86. By considering the classification of industries according to ICB at the two-digit level (16 sectors) or according to High-, Medium-, Low-tech taxonomy, the distinction between intra- and inter-industries components exhibits a higher elasticity of output with respect to the inter-industry stock. This observation seems to indicate that the inter-industry spillover effects are relatively more important than the intra-industry ones, as far as we consider that there is a close relationship between industries and technological classes, as in Capron and Cincera (1998). The distinction between national and international R&D components puts forward the importance of foreign R&D activities, while national stock is not significant. This result is

[12] Hausman's test is also implemented to test fixed effect versus random effect model, providing that the null hypothesis may be rejected at the value of 5%, and then fixed effect model is the best. Results from this analysis are available from the authors upon request.

[13] See Capron and Cincera (1998), Aldieri and Cincera (2009) for other applications of GMM-SYS estimator to R&D technological spillovers.

[14] The assumption of no serial correlation in the residuals in levels is very relevant to obtain consistent GMM estimates. This assumption holds if there is evidence of significant and negative first-order serial correlation and no evidence of second-order serial correlation in the first-differenced residuals (Arellano and Bond, 1998).

confirmed when the spillover stock is completely disaggregated. Indeed, the intra-national and inter-national components are not significant.

Table 3. Productivity Estimates

Dependent variable: ln S			sample: 879 firms x 9 years		
WITHIN Level			GMM-SYS		
	Est.	S. E[a].		Est.	S. E.
lnL	0.66***	(0.041)	ΔlnL	0.57***	(0.037)
lnC	0.23***	(0.073)	ΔlnC	0.24***	(0.066)
lnK	0.15**	(0.065)	ΔlnK	0.01	(0.001)
lnTS	0.99***	(0.237)	ΔlnTS	0.86***	(0.129)
			AR(1)[c] test	p=-8.91	p>z=0.000
			AR(2) test	p=-0.72	p>z=0.471
R^2		0.65	Sargan[b]: χ^2 (80)=405.11		[0.000]
lnL	0.66***	(0.041)	ΔlnL	0.57***	(0.038)
lnC	0.21***	(0.076)	ΔlnC	0.24***	(0.068)
lnK	0.17**	(0.068)	ΔlnK	0.01*	(0.001)
lnintraS	0.19***	(0.062)	ΔlnintraS	0.07*	(0.039)
lninterS	0.39***	(0.112)	ΔlninterS	0.23**	(0.109)
			AR(1) test	p=-8.90	p>z=0.000
			AR(2) test	p=-1.00	p>z=0.317
R^2		0.64	Sargan χ:^{2}(100)=482.89		[0.000]
lnL	0.67***	(0.042)	ΔlnL	0.57***	(0.038)
lnC	0.22***	(0.074)	ΔlnC	0.24***	(0.066)
lnK	0.16**	(0.066)	ΔlnK	0.01	(0.001)
lnNS	0.11*	(0.063)	ΔlnNS	0.03	(0.062)
lnIS	0.75***	(0.199)	ΔlnIS	0.67***	(0.086)
			AR(1) test	p=-8.57	p>z=0.000
			AR(2) test	p=-0.50	p>z=0.619
R^2		0.65	Sargan χ:^{2}(100)=497.17		[0.000]
lnL	0.65***	(0.041)	ΔlnL	0.57***	(0.037)
lnC	0.21***	(0.077)	ΔlnC	0.26***	(0.062)
lnK	0.17**	(0.069)	ΔlnK	0.01	(0.001)
lnintraNS	0.03	(0.019)	ΔlnintraNS	-0.02	(0.011)
lnintraIS	0.11**	(0.051)	ΔlnintraIS	0.10***	(0.026)
lninterNS	-0.06	(0.053)	ΔlninterNS	-0.06	(0.047)
lninterIS	0.41***	(0.103)	ΔlninterIS	0.31***	(0.083)

			AR(1) test	p=-9.54	p>z=0.000
			AR(2) test	p=-1.12	p>z=0.262
R^2		0.64	Sargan: $\chi^2(140)=504.38$		[0.000]
lnL	0.66***	(0.041)	ΔlnL	0.56***	(0.037)
lnC	0.23***	(0.076)	ΔlnC	0.24***	(0.067)
lnK	0.16**	(0.066)	ΔlnK	0.01***	(0.001)
lnintraS2	0.54***	(0.193)	ΔlnintraS2	0.28***	(0.085)
lninterS2	0.27**	(0.127)	ΔlninterS2	0.45***	(0.069)
			AR(1) test	p=-8.95	p>z=0.000
			AR(2) test	p=-0.77	p>z=0.442
R^2		0.64	Sargan: $\chi^2(100)=459.48$		[0.000]
lnL	0.66***	(0.041)	ΔlnL	0.57***	(0.038)
lnC	0.22***	(0.076)	ΔlnC	0.25***	(0.067)
lnK	0.16**	(0.067)	ΔlnK	0.01**	(0.001)
lnintraNS2	0.04	(0.048)	ΔlnintraNS2	-0.08	(0.051)
lnintraIS2	0.39***	(0.149)	ΔlnintraIS2	0.31***	(0.057)
lninterNS2	0.01	(0.047)	ΔlninterNS2	0.04	(0.031)
lninterIS2	0.14	(0.093)	ΔlninterIS2	0.32***	(0.055)
			AR(1) test	p=-8.76	p>z=0.000
			AR(2) test	p=-0.81	p>z=0.418
R^2		0.64	Sargan: $\chi^2(140)=554.30$		[0.000]

a: heteroskedastic-consistent standard errors. b: Sargan is the Sargan-test of over identifying restrictions, the p-value is in squared brackets. c: AR(1) and AR(2) are tests for first and second order serial correlation. ***,**, * Coefficient significant at the 1%, 5%, 10%. Time dummies are included.

In Table 4, we present the productivity estimates by geographical area. Also in this case, the Sargan test of overidentifying restrictions as well as tests for first order (AR(1)) and second order (AR(2)) serial correlation tests of the first-differenced residuals are reported. The latter confirm the assumption of no serial correlation in the residuals in levels and this time the Sargan test does not reject the null hypothesis of valid instruments at the 1% (US case) and 5% (JP and EU cases).

Table 4. Productivity Estimates by Geographical Area

WITHIN LEVEL			GMM-SYS		
	Sample: 290 US firms x 9 years				
	Est.	S. E[a].		Est.	S. E.
lnL	0.69***	(0.084)	ΔlnL	0.57***	(0.054)
lnC	0.30**	(0.123)	ΔlnC	0.31***	(0.091)
lnK	0.16	(0.149)	ΔlnK	0.01	(0.001)
lnNS	0.68**	(0.302)	ΔlnNS	0.89***	(0.234)
lnIS	1.04***	(0.306)	ΔlnIS	0.59***	(0.154)
			AR(1)[c] test	p=-7.13	p>z=0.000
			AR(2) test	p=-0.36	p>z=0.715
R^2		0.68	Sargan[b]: $\chi^2(100)$=134.91		[0.011]
	Sample: 232 JP firms x 9 years				
lnL	0.61***	(0.085)	ΔlnL	0.54***	(0.100)
lnC	0.12*	(0.063)	ΔlnC	0.07	(0.148)
lnK	0.12**	(0.061)	ΔlnK	0.01	(0.001)
lnNS	0.71***	(0.256)	ΔlnNS	-0.28**	(0.115)
lnIS	-0.22	(0.197)	ΔlnIS	1.07***	(0.174)
			AR(1) test	p=-2.43	p>z=0.015
			AR(2) test	p=-0.51	p>z=0.612
R^2		0.58	Sargan: $\chi^2(100)$=102.78		[0.404]
	Sample: 316 EU firms x 9 years				
lnL	0.67***	(0.053)	ΔlnL	0.57***	(0.064)
lnC	0.08*	(0.048)	ΔlnC	0.18**	(0.086)
lnK	0.11**	(0.052)	ΔlnK	0.01	(0.001)
lnNS	0.46***	(0.120)	ΔlnNS	0.28***	(0.088)
lnIS	-0.18	(0.212)	ΔlnIS	0.58***	(0.198)
			AR(1) test	p=-5.34	p>z=0.000
			AR(2) test	p=-0.94	p>z=0.347
R^2		0.69	Sargan: $\chi^2(100)$=121.86		[0.068]

a: heteroskedastic-consistent standard errors. b: Sargan is the Sargan-test of over identifying restrictions, the p-value is in squared brackets. c: AR(1) and AR(2) are tests for first and second order serial correlation. ***,**, * Coefficient significant at the 1%, 5%, 10%. Time dummies are included.

In the United-States, the national stock affects significantly and positively the output and its magnitude is higher than international stock. An opposite observation emerges for Japan and European area that appear to benefit from the international stock. So, Japan and European countries seem to depend, to a large extent, on technologies developed outside while American firms are mainly turned to their domestic technologies. These empirical observations are in accordance with the positioning often emphasized for the three geographical areas. As a technological leader, the United-States is principally concerned by its own technological development.

6. Discussion and conclusions

The purpose of this paper is that to analyze the relationship between R&D activity, spillovers and productivity at the firm level. Particular attention is put on the formalization of technological spillovers. The analysis is based upon a new dataset composed of 879 worldwide R&D-intensive manufacturing firms whose information has been collected for the period 2002-2010. Given the panel data structure of the sample, ad hoc econometric techniques that deal with both firm's unobserved heterogeneity and weak exogeneity of the right hand-side variables are implemented. We use data from all EU R&D investment scoreboards editions issued every year until 2011 by the JRC-IPTS (scoreboards). In order to measure the distribution of the firm's research interests through the different technological areas, we use the patent distribution over technological sectors according to the International Patent Classification (IPC). The patent distribution relies on the whole number of patent applications filed to the European Patent Office until 2011.

The contribution of our paper to the existing literature is twofold: first, we use an international sample in such a way that we may compare the empirical results among different economic markets; second, we assess the importance of technological activity of firms on productivity, by exploring different components of potential stock of spillovers also after the beginning of world economic crisis. In particular, we extend Jaffe's methodology to distinguish, besides the intra and inter-industry components, national and international stocks. In this way, we will be able to appreciate to what extent geographical and cultural contiguity matters. Furthermore, in order to consider the technological as well as the geographical closeness, the potential stock of spillovers is dissociated into four components: the intra-industry national stock, the intra-industry international stock, the inter-industry national and inter-industry international one. The estimates obtained are performed by using ad hoc panel data estimation methods, the system GMM (GMM-SYS), which control for specific hypothesis typically associated with this kind of data, namely, correlated firms' unobserved fixed effects with regressors and weakly exogenous explanatory variables. From the empirical results, we observe that the coefficients obtained for the employment and the physical capital are significant. The estimated elasticities associated with the labour variable is 0.56-0.57, while for the physical variable the coefficients are 0.24-0.26. The results of own R&D capital on productivity performance are not significant for the possible multicollinearity issue with the spillover components, while there is a strong link between technologically based R&D spillovers and firms' productivity performance. The estimated elasticity associated with the total stock of spillovers (TS) is 0.86. By considering the classification of industries according to ICB at the two-digit level (16 sectors) or according to High-, Medium-, Low-tech taxonomy, the distinction between intra- and inter-industries components exhibits a higher elasticity of output with respect to the inter-industry stock. This observation seems to indicate that the inter-industry spillover effects are relatively more important than the intra-industry ones, as far as we consider that there is a close relationship between industries and technological classes, as in Capron and Cincera (1998). The distinction between national and international R&D components puts forward the importance of foreign R&D activities, while national stock is not significant. This result is confirmed when the spillover stock is completely disaggregated. Indeed, the intra-national and inter-national components are not significant.

As far as the analysis by geographical area is concerned, the results show that United-States are mainly sensitive to their national spillover's stock while Japan and European countries appear to mainly draw from the international stock, by evidencing the role of technological leader of United-States.

In order to further explore these questions, further analyses are needed. First, we could consider the distribution of patents' inventors rather than patents' application to compare the robustness of our results. Furthermore, since every Patent Office has some weaknesses, we could construct the technological proximity between the firms, taking into account both their patents in European Patent Office (EPO) and US Patents and Trademarks Office (USPTO), as in Aldieri (2013). Finally, we could use information on patent citations to construct a more direct measure for R&D spillovers.

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Appendix A.

Correlation between technological spillover components

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
TS (1)	1														
NS (2)	0.47	1													
IS (3)	0.93	0.17	1												
IntraS (4)	0.43	0.27	0.35	1											
InterS (5)	0.76	0.34	0.75	-0.14	1										
IntraNS (6)	0.34	0.59	0.14	0.83	-0.13	1									
InterNS (7)	0.36	0.83	0.15	-0.11	0.55	0.17	1								
IntraIS (8)	0.44	0.17	0.41	0.97	-0.10	0.71	-0.14	1							
InterIS (9)	0.77	0.16	0.83	-0.10	0.96	-0.16	0.33	-0.05	1						
IntraS2 (10)	0.59	0.34	0.51	0.80	0.11	0.67	0.02	0.77	0.15	1					
InterS2 (11)	0.17	0.02	0.21	-0.47	0.53	-0.42	0.34	-0.42	0.48	-0.61	1				
IntraNS2 (12)	0.47	0.70	0.26	0.69	0.07	0.82	0.36	0.60	0.01	0.85	-0.55	1			
InterNS2 (13)	0.08	0.55	-0.06	-0.34	0.37	-0.06	0.77	-0.36	0.18	-0.46	0.74	-0.13	1		
IntraIS2 (14)	0.61	0.24	0.58	0.78	0.15	0.59	-0.04	0.78	0.22	0.99	-0.57	0.76	-0.49	1	
InterIS2 (15)	0.21	-0.09	0.31	-0.45	0.55	-0.46	0.22	-0.38	0.56	-0.58	0.98	-0.59	0.61	-0.52	1

Appendix B

Proof of Proposition: The combinations of eqs.(6), (8) and (9) give the following equilibrium values:

$$K^* = \left\{(1-b)^{(\eta+1-\beta_1)} A^{(1+\eta)} \left[\frac{b}{\theta}\right]^{\beta_1} r_1^{-\beta_2(2+\eta-\beta_1)} r_2^{(1+\eta)[\beta_2(\beta_3+\alpha\gamma]+1}\right\}^{\sigma} \quad \text{(B1)}$$

$$C^* = \left\{(1-b)^{(\eta+1-\beta_1)} A^{(1+\eta)} \left[\frac{b}{\theta}\right]^{\beta_1} r_1^{-(1+\eta)[\beta_1(1-\beta_3-\beta_2+\alpha\gamma]-\beta_1^2-\beta_2(1-\beta_1)} r_2^{(1+\eta)[(1-\beta_3+\alpha\gamma]-\eta+\beta_1}\right\}^{\sigma} \quad \text{(B2)}$$

$$L^* = \left\{\left(\frac{b}{\theta}\right)^{(1-\beta_2-\beta_3-\alpha\gamma)} A^{\frac{1}{(\eta+1-\beta_1)}} (1-b)^{(\beta_3+\beta_2+\alpha\gamma)} r_2^{\beta_2(\beta_3+\alpha\gamma)} r_1^{\frac{-\beta_1\beta_2[(1+\eta)(1-\beta_2-\beta_3-\alpha\gamma)-\beta_1]-\beta_2(\eta+2-\beta_1)(\beta_2+\beta_3+\alpha\gamma}{(1+\eta-\beta_1)}}\right\}^{\sigma}$$

(B3)

with $\sigma = \dfrac{1}{(\eta+1)[(1-\beta_3-\beta_2-\alpha\gamma)-\beta_1]}$.

In order to demonstrate Pareto-inefficiency we may write firms' returns as: $\prod = (1-b)AL^{*\beta_1}K^{*(\beta_3+\alpha\gamma)}C^{*\beta_2} - r_1C^* - r_2K^*$ and consider the effects of small changes in the equilibrium values: L^*, C^*, K^*. As a result it will be:

$$d\prod = \left[(1-b)\beta_1 AC^{*\beta_2}K^{*(\beta_3+\alpha\gamma)}L^{*\beta_1-1}\right]dL^* + \left[(1-b)(\beta_3+\alpha\gamma)AL^{*\beta_1}C^{*\beta_2}K^{*(\beta_3+\alpha\gamma-1)} - r_2\right]dK^* +$$
$$+\left[(1-b)\beta_2 AC^{*(\beta_2-1)}K^{*(\beta_3+\alpha\gamma)}L^{*\beta_1} - r_1\right]dC^*$$

from inspection of which since the terms multiplied by dC^* and dK^* are zero by the f.o.c. it will be: $d\prod > 0$. Similar reasoning may be applied to workers' welfare:

$$dU = \left[b\beta_1 AC^{*\beta_2}K^{*(\beta_3+\alpha\gamma)}L^{*\beta_1-1} - \theta L^{*\eta}\right]dL^* + \left[b(\beta_3+\alpha\gamma)AL^{*\beta_1}C^{*\beta_2}K^{*(\beta_3+\alpha\gamma-1)}{}_2\right]dK^* +$$
$$+\left[(1-b)\beta_2 AC^{*(\beta_2-1)}K^{*(\beta_3+\alpha\gamma)}L^{*\beta_1} - r_1\right]dC^*$$

from which it is clear that the term multiplied by dL^* is = by the foc, while the one multiplied by multiplied by dC^* is positive and that multiplied by multiplied by $dK^*$is $\gtrless 0$ if $(\beta_3+\alpha\gamma) \gtrless 0$. Further it is very interesting to consider that if   it may be possible that $dU = 0$ only if $\dfrac{dC^*}{C^*}\dfrac{K^*}{dK^*} = \dfrac{-(\beta_3+\alpha\gamma)}{\beta_2}$ since it will be that: $\left[(1-b)\beta_2 AC^{*(\beta_2-1)}K^{*(\beta_3+\alpha\gamma)}L^{*\beta_1} - r_1\right]dC^*$ = $-\left[b(\beta_3+\alpha\gamma)AL^{*\beta_1}C^{*\beta_2}K^{*(\beta_3+\alpha\gamma-1)}{}_2\right]dK^*$.

The last points of the above proposition derive from inspection of eqs. (6,8 and 9).