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THE TRANSATLANTIC PRODUCTIVITY GAP: IS R&D THE MAIN CULPRIT?

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ABSTRACT

The literature has pointed to different causes to explain the productivity gap between Europe and United States in the last decades. This paper tests the hypothesis that the lower European productivity performance in comparison with the US can be explained not only by a lower level of corporate R&D investment, but also by a lower capacity to translate R&D investment into productivity gains.

The proposed microeconometric estimates are based on a unique longitudinal database covering the period 1990-2008 and comprising 1,809 US and European companies for a total of 16,079 observations.

Consistent with previous literature, we find robust evidence of a significant impact of R&D on productivity; however – using different estimation techniques - the R&D coefficients for the US firms always turn out to be significantly higher.

To see to what extent these transatlantic differences may be related to the different sectoral structures in the US and the EU, we differentiated the analysis by sectors. The result is that both in manufacturing, services and high-tech sectors US firms are more efficient in translating their R&D investments into productivity increases.

Keywords: R&D, productivity, embodied technological change, US, EU.

JEL Classification: O33

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1. Introduction: aggregate trends and motivation.

The literature has pointed different causes as the main explanations of the productivity gap between US and Europe in the last decades. Among others, the quality of human capital (Gu *et al.*, 2002), the rigidity of the European labour markets (Gordon and Dew-Becker, 2005; Gomez-Salvador *et al.,* 2006), the role and diffusion of ICTs (Wilson, 2009), the importance of new managerial practices and organizational investments (Gu and Wang, 2004; Bloom *et al.,* 2005; Crespi *et al.,* 2007) and the endowment of capital appeared to be the most relevant ones.

However, most of these explanations can be related to a revealed technological disadvantage of the EU, ultimately constraining the demand for human capital, ICT diffusion, innovative organizational and management practices and the diffusion of innovation through embodied technology in new capital formation. Both at the aggregate and the microeconomic level, R&D expenditures are a good proxy of technological investment.

Therefore, the gap in corporate R&D investment can be seen as one of the main culprits of the European delay in terms of productivity growth in comparison with the US (see O'Mahony and van Ark, 2003; Blanchard, 2004). In this context, it is not surprising that for the last decade the increase of R&D investment has been the main target of European policy, as was obvious in the "Lisbon Agenda", the ambitious targets of which were recently confirmed and widened in the "Europe 2020 – Innovation Union Initiative" strategies (see European Commission, 2002, 2008, 2010).

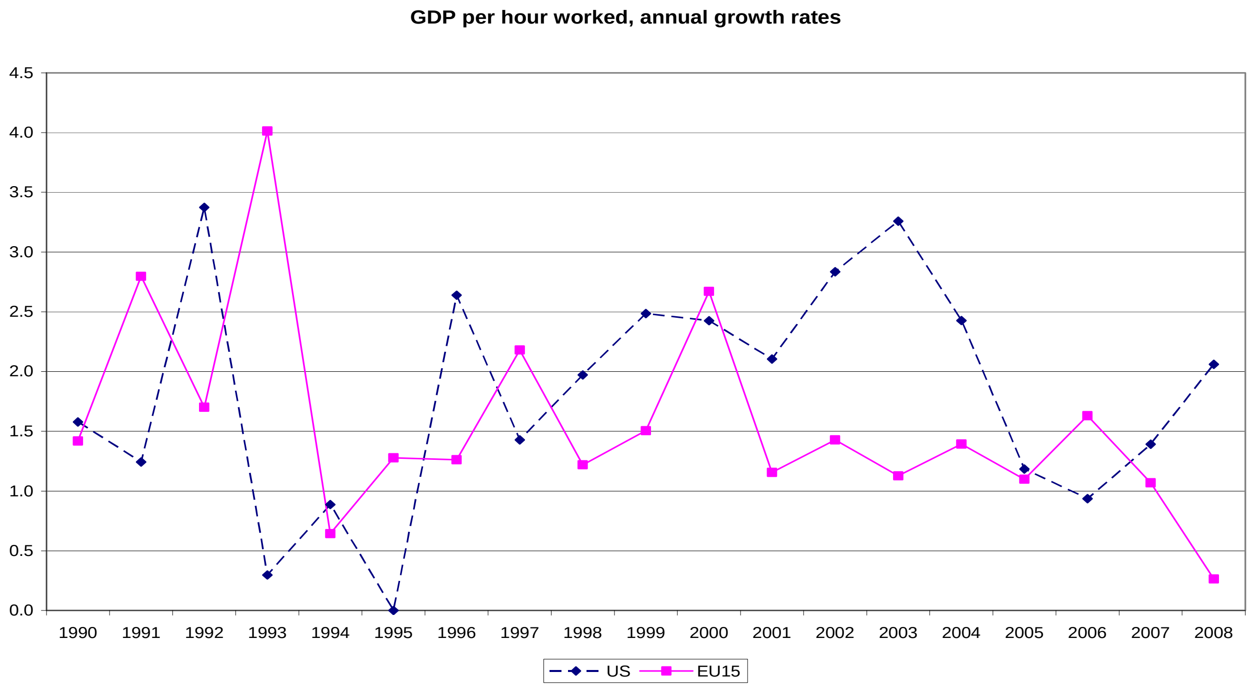
However, the hypothesis that will be tested in this paper is that the lower European productivity performance in comparison with the US can be explained not only by a lower level of corporate R&D investment, but also by a lower capacity to translate R&D investment into productivity gains.

As can be seen in Fig. 1, average annual labour productivity growth (measured as GDP per hour worked), in the US accelerated from 1.2% in the 1973-95 period to 2.3% in the 1996-06 period (see van Ark *et al.*, 2008); conversely, in the EU15 labour productivity growth declined from 2.4% in the former period to 1.5% in the latter one (resulting in the trends shown in Fig. 1). Hence, the labour productivity slowdown in EU15 since the '90s has reversed what was once thought as a long-term pattern of convergence.

While, during the '80s and the first half of the '90s, most studies found little or no evidence of a significant contribution of ICTs on productivity growth (e.g. and Griliches, 1992; Oliner and Sichel, 1994; Siegel Berndt and Morrison, 1995), more recently most scholars agree that the spread of ICT technologies has been positively associated with conventional measures of productivity and that - to explain the transatlantic productivity gap - one has to primarily take into account the R&D

and innovation divide which has emerged between the two sides of the Atlantic in the last fifteen years (see Oliner and Sichel, 2000; Daveri, 2002; Timmer and van Ark., 2005; Crespi and Pianta, 2008). Moreover, the dynamics in the industries have influenced the productivity levels: in the second half of the ‘90s there was a burst of higher productivity in ICT producer industries (Jorgenson *et al*., 2008), while in the ’00 there was also a productivity surge in user industries, including market services such as large-scale retailing and the financial and business services (see Triplett and Bosworth, 2004; Bosworth and Triplett, 2007; Jorgenson *et al*., 2003, 2005, 2008). Indeed, these trends linked to the spread of new technologies were more marked and accelerated in the US than in the EU (see Jorgenson *et al*., 2005, Timmer *et al*., 2010) resulting into a widening gap in the Total Factor Productivity (TFP) trends (see Fig. 2; see also Corrado *et al.,* 2007; van Ark *et al.*, 2008; McMorrow *et al.*, 2009; Timmer *et al.,* 2010).

<u>Fig. 1: Labour productivity growth in the US and the EU15: 1990-2008</u>

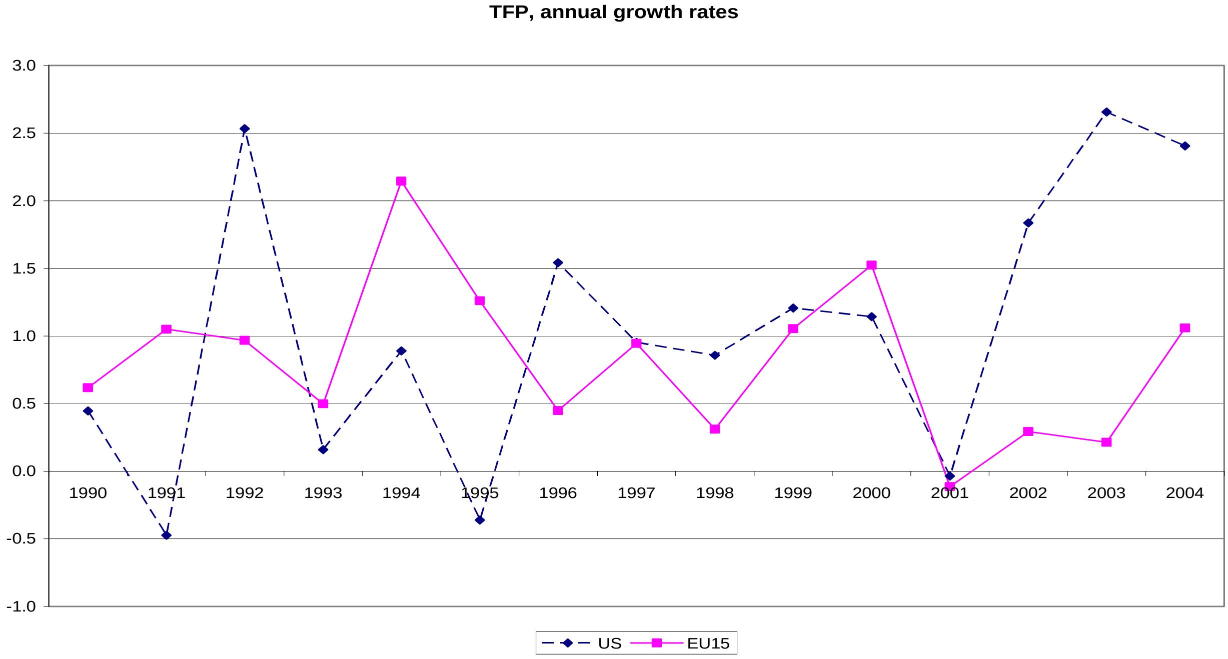


Source: OECD (OECD Statistical Extracts: *http://stats.oecd.org*)

In turn, R&D expenditures are the core investments originating ICT diffusion and innovation in general and - not surprisingly - have been demonstrated to play an important role in explaining the productivity differentials within the industrialised countries in the last decades (see Oliner and Sichel, 1994, 2000; Jorgenson and Stiroh, 2000; Gordon, 2000; Stiroh, 2002; Turner and Boulhol, 2008; Wilson, 2009). Indeed, - as can be seen in Fig. 3 (GERD = Gross Domestic

Expenditure on R&D[1]) - the EU has persistently invested around the 70% of the US economy all over the last two decades as far as the total private and public expenditures in R&D are concerned.

Fig. 2: TFP growth in the US and the EU15: 1990-2004



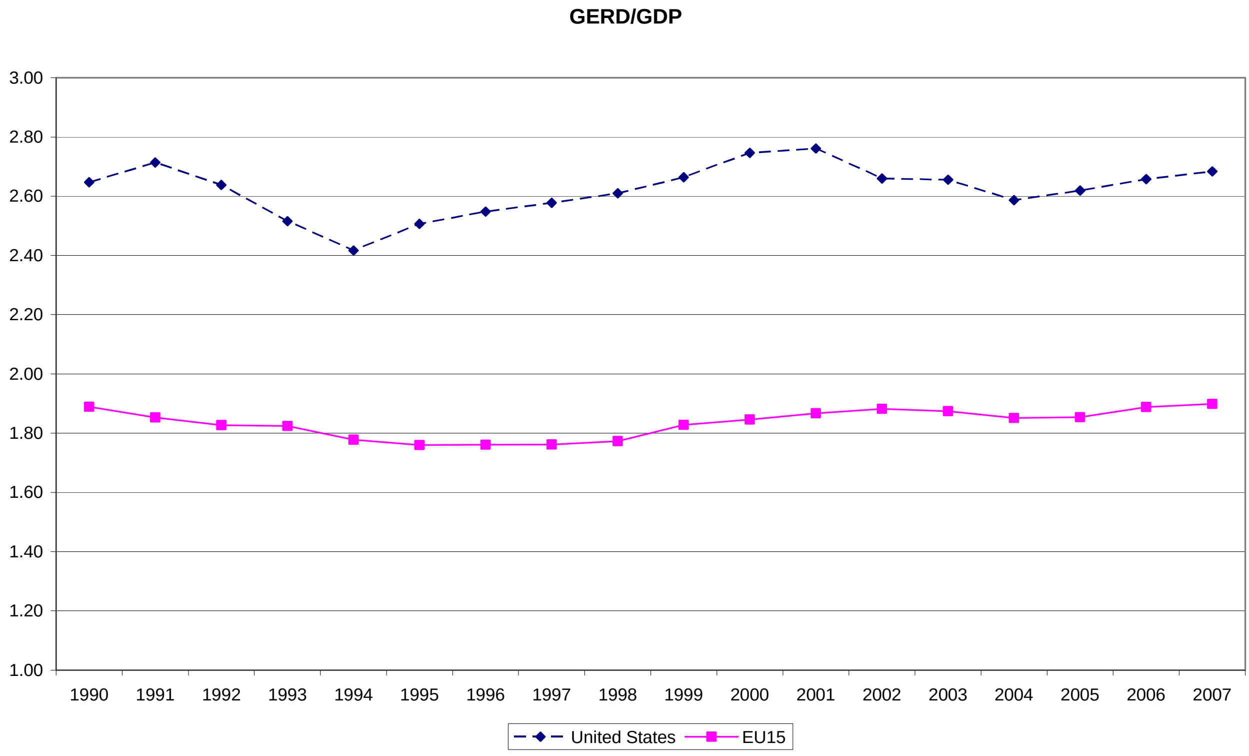
Source: Timmer, M.P. *et al*., 2003, Appendix Tables; here updated to June 2005

In particular, the role of private R&D investment by corporate firms (Business Enterprise Expenditure on R&D: BERD) has been recognised as a fundamental driver for productivity growth both at the macro and microeconomic level (see Baumol, 2002; Jones, 2002). In this respect, the EU15 has lagged considerably and persistently behind the US, even more strikingly than in terms of total R&D (see Fig. 4).

Therefore, the EU underinvestment in total R&D and particularly in BERD might be considered one of the main determinants of the productivity transatlantic gap. As briefly mentioned above, increasing R&D investment was the rationale behind the "Lisbon agenda 2000" to make Europe the most dynamic knowledge economy in the world by 2010 and of the more specific "Barcelona target" which - two years later - committed the EU to reach the objective of an R&D/GDP level of 3%, two thirds of which accounted for BERD (European Council, 2002; European Commission, 2002). Consistently, the recent "Innovation Union" document advocates for a boost in R&D to increase the competitiveness of the European private sector (European Commission, 2010).

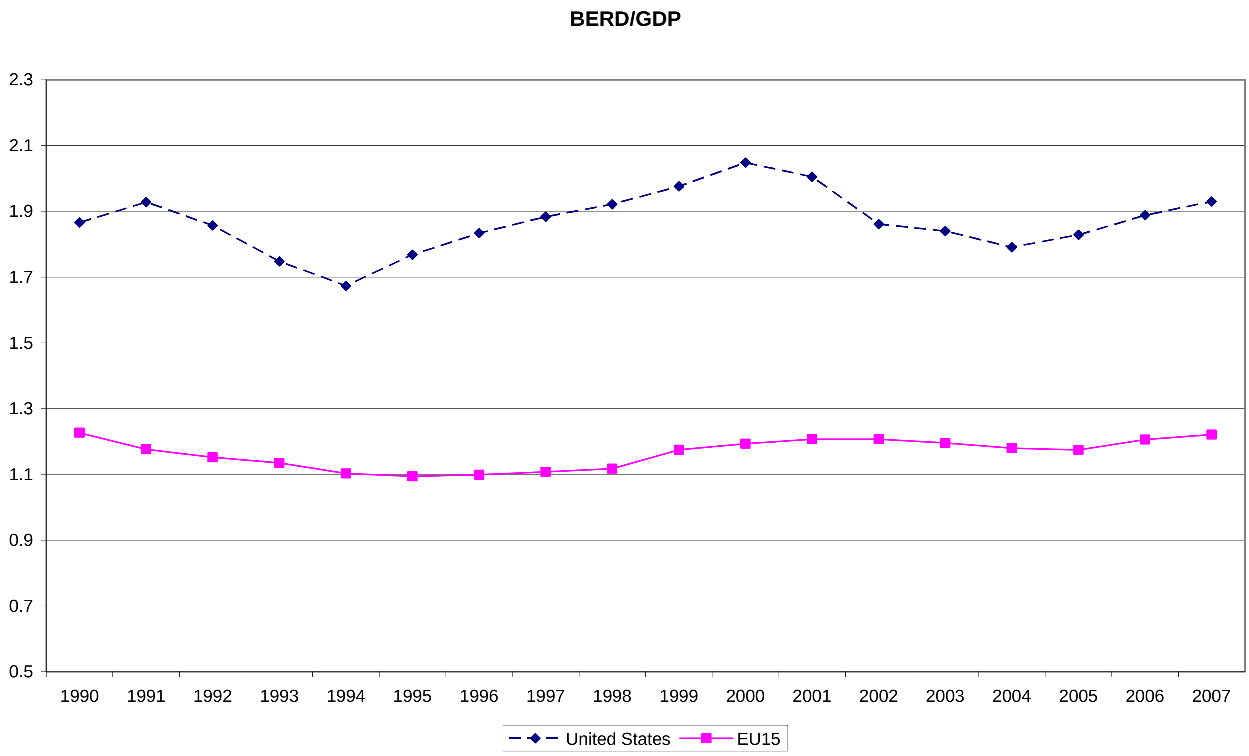
[1] GERD = BERD (Business Enterprise Expenditure on R&D) + HERD (Higher Education Expenditure on R&D) + GOVERD (Government Expenditure on R&D) + PNPRD (Private Non-profit Expenditure on R&D).

Fig. 3: GERD/GDP in the US and in the EU15: 1990-2007



Source: OECD - Main Science and Technology Indicators (2009 edition)

Fig. 4: Private R&D (BERD)/GDP in the US and in the EU15: 1990-2007



Source: OECD – Main Science and Technology Indicators (2009 edition)

However - turning our attention to the microeconomic foundations of the aggregate trends discussed so far – it may be that the overall European productivity delay can be explained not only by a lower level of total and private R&D investment, but also by a lower capacity to translate R&D investment into productivity gains. With regard to the latter explanation, the European economies may be still affected by a sort of Solow's (1987) paradox, *i.e.* by a difficulty to translate their own investments in technology into increases in productivity.

This will be the major hypothesis investigated in this microeconometric study; in fact, it might be well the case that European economies not only invest *less R&D,* but also *get less* from their R&D investment because of a lower R&D-productivity elasticity in the EU compared with the US.

Previous literature has shown that the R&D-productivity link is positive and significant at the microeconomic level, but also that this relationship is stronger in the high-tech sectors. Thus, it might be the case that the EU industrial structure (disproportionally characterised by traditional, middle and low-tech sectors) implies a lower capacity to translate R&D efforts in productivity gains (*structural effect;* see Mathieu and van Pottelsberghe de la Potterie, 2008). Moreover, previous studies disaggregated by sectors suggest that this European structural disadvantage also embraces ICT-intensive services such as the wholesale and retail trade and financial sectors (O'Mahony and van Ark, 2003; Gordon, 2004)[2].

However - in contrast with an explanation only pointing to the differences in the sectoral structure of the two economies - it might be also the case that (even within the same sectors and including both high-tech manufacturing and services) European firms would reveal a lower capacity of translating R&D investments into productivity gains. If this is the case in terms of the following empirical results, there will be support for the so-called *intrinsic effect* (see Erken and van Es, 2007), that is a structural difficulty of European firms in achieving productivity gains, independently from the sectors considered.

2. Previous microeconometric evidence

With respect to the microeconomic evidence on the subject, Zvi Griliches (1979) started a flourishing literature devoted to investigate the relationship between R&D and productivity at the firm and sectoral level. On the whole, this microeconometric literature has found robust evidence of a positive and significant impact of R&D on productivity at the firm level. In previous studies, the

[2] As Jorgenson *et al*. (2005) note, the enormous heterogeneity of productivity growth across industries means that analysts should focus on industry-level detail in order to understand the origins of US growth resurgence compared with the EU slowdown.

estimated overall elasticity of productivity in respect to R&D turned out positive, statistically significant and with a magnitude - depending on the data and the adopted econometric methodology - ranging from 0.05 to 0.25 (for comprehensive surveys, see Mairesse and Sassenou, 1991; Griliches 1995 and 2000; Mairesse and Mohnen, 2001).

It is interesting to note that the consensus about the existence of a positive and significant impact of R&D on productivity stands on different studies using different proxies for productivity according to the data available: labour productivity measured as the ratio between value added and employment; labour productivity as the ratio between value added and hours worked; total factor productivity; Solow's residual; etc. (see, for instance, Hall and Mairesse 1995; Klette and Kortum, 2004; Janz *et al*., 2004; Lööf and Heshmati, 2006; Rogers, 2006; Heshmati and Kim, 2011). Hence, the legacy of the previous microeconometric literature is clear in indicating the role of R&D in enhancing productivity at the firm level.

However, the intensity of the R&D-productivity relationship may widely vary across the different economic sectors; since technological opportunities and appropriability conditions are so different across sectors (see Freeman, 1982; Pavitt, 1984; Winter, 1984; Aghion and Howitt, 1996; Dosi, 1997; Greenhalgh *et al*., 2001; Malerba, 2004), they may involve substantial differences in the specific sectoral R&D-productivity links. Indeed, previous sectoral studies clearly suggest a greater impact of R&D investment on productivity in the high-tech sectors rather than in the low-tech ones.

Examples are Griliches and Mairesse (1982) and Cuneo and Mairesse (1983), who performed two companion studies - using French and US microdata - finding that the impact of R&D on productivity for scientific firms (elasticity equal to 0.20) was significantly greater than for other firms (0.10).

By the same token, Verspagen (1995) carried out a multi-country study, testing the impact of R&D expenditures and singling out three macro sectors: high-tech, medium-tech and low-tech, according to the OECD classification (Hatzichronoglou, 1997). The major finding of his study was that the impact of R&D was significant and positive only in high-tech sectors, while for medium and low-tech sectors no significant effects could be found.

Using the methodology set up by Hall and Mairesse (1995), Harhoff (1998) studied the R&D/productivity link in German manufacturing firms and found a significant impact ranging from 0.125 and 0.176 for the high-tech firms, while for the remaining firms the R&D elasticity resulted either not being significant or being significantly lower (ranging from 0.090 to 0.096).

Rincon and Vecchi (2003) also used a Cobb–Douglas framework in dealing with micro-data extracted from the Compustat database over the time period 1991–2001. They found that R&D-reporting firms were more productive than their non-R&D reporting counterparts throughout the entire time period. However, the positive impact of R&D expenditures turned out to be statistically significant both in manufacturing and services in the US, but only in manufacturing in the main three European countries (Germany, France and the UK). Their estimated significant elasticities ranged from 0.15 to 0.20.

Dealing with Taiwanese data, Tsai and Wang (2004) found that R&D investment had a significant and positive impact on the growth of a firm's productivity (with an average elasticity equal to 0.18). However, this impact was much greater for high-tech firms (0.3) than for other firms (0.07).

Consistent with previous studies, Ortega-Argilés *et al.* (2010) looked at the top 577 EU R&D investors and found that the R&D-productivity coefficient increased monotonically moving from the low-tech to the medium-high and high-tech sectors, ranging from a minimum of 0.03/0.05 to a maximum of 0.14/0.17.

Finally, Bogliacino and Pianta (2011) – using sectoral data obtained from the innovation surveys CIS2, CIS3 and CIS4 conducted in eight major European countries – found out a significant impact of in-house R&D expenditures on labour productivity growth in the high-tech sectors (the *Science-Based* and *Specialised Suppliers* categories, according to the Pavitt taxonomy, see Pavitt, 1984), but not in the *Scale Intensive* and *Suppliers Dominated* categories.

On the whole, previous microeconometric studies – using different datasets across different countries - seem to suggest a greater impact of R&D investments on firm productivity in the high-tech sectors rather than in the low-tech ones.

However, R&D is not the sole investment determinant in explaining firm productivity gains: while the R&D input is capturing that portion of technological change which is related to the disembodied new knowledge, gross investment is an alternative innovative input capturing the new knowledge embodied in physical capital, mainly machinery.

This second input represents the so-called *embodied technological change,* with its great potential to positively affect productivity growth. The embodied nature of technological progress and the effects related to its spread in the economy were originally discussed by Salter (1960) who underlined that technological progress might be incorporated in new vintages of capital introduced either through additional investment or simply by scrapping[3]. More recently, the role of capital accumulation in fostering productivity growth and economic development has been recognised by

[3] On the theoretical side, the embodied nature of technological change was at the core of the controversy between Robert Solow (1960) and Dale Jorgenson (1966) with Solow arguing that embodied technological change was dominant, hence investment was the key mechanism of economic growth, while Jorgenson arguing that – from the data available then – one could not provide a clear answer. Recent empirical macroeconomic estimates actually conclude that embodied technological change is the main transmission mechanism of new technologies into economic growth (see Greenwood *et al.*, 1997).

growth theorists (see Hulten, 1992; Greenwood *et al.*, 1997; Hercowitz, 1998; Abowd *et al.,* 2007; Wilson, 2009).

Turning our attention to the microeconomic analysis, previous literature suggests that more complex and radical product innovation generally relies on formal R&D, while process innovation (which is often incremental rather than radical) is much more related to embodied technical change achieved by investment in new machinery and equipment (see Parisi *et al.*, 2006). If such is the case, in traditional low-tech sectors – which are focusing on process innovation – productivity gains might be much more related to capital accumulation rather than to R&D expenditures. This was also one of the main messages of the well-known Pavitt taxonomy (Pavitt, 1984), where firms in traditional sectors (*Supplier Dominated*) innovate mainly through embodied technological change acquired from firms in the *Specialised Suppliers* sector.

Indeed, previous literature supports the hypothesis that firms in traditional sectors (most of them SMEs) face a different technological and economic environment (see Acs and Audretsch, 1988 and 1990; Acs *et al.*, 1994). In particular, in the low and medium-tech sectors, R&D does not represent the sole input through which firms can achieve innovative outcomes and productivity gains; for these firms it seems much easier to rely on the market and choose "to buy" embodied technical change rather than "to make" their own technology (see Acs and Audretsch, 1990; Santarelli and Sterlacchini, 1994; Santamaría *et al.*, 2009).

Unfortunately, previous literature dealing with the R&D-productivity relationship has generally neglected the investigation of the possible different impacts of embodied technological change across sectors. One exception is the already quoted contribution by Ortega-Argilés *et al.* (2010), where the authors found that the R&D-productivity coefficient was higher and more significant in the high-tech sectors rather than in the middle and low-tech ones. Interestingly enough, they found that for capital formation the results were the opposite: in fact, its productivity impact was stronger in the low-tech sectors, lower but still significant in the medium-tech sectors, while it turned out to be not significant in the high-tech sectors. Consistently with what discussed in this section, this evidence seems to suggest that embodied technological change is crucial in the low-tech sectors, while in the high-tech sectors technological progress is mainly introduced through in-house R&D investments.

3. Data and methodology

3.1 The data

The microdata used in this study were provided by the JRC–IPTS (Joint Research Centre-Institute for Prospective Technological Studies) of the European Commission; the information provided only concerns publicly-traded companies and is extracted from a variety of sources, including companies' annual reports, Securities and Exchange Commission (SEC) 10-K and 10-Q reports, daily news services and direct company contacts, using standardized data definitions and collection procedures to assure consistent presentation of data[4].

Available data includes:

- Company identification, name and address, industry sector (Global Industry Classification Standard (GICS) that can be translated in the standard SIC classification);
- Fundamental financial data including income statements, cash flows, taxes, dividends and earnings, pension funds, property assets, ownership data, etc.
- Fundamental economic data, including the crucial information for this study, namely: sales, cost of goods (the difference between the former and the latter allows us to obtain value added), capital formation, R&D expenditures, and employment.

Given the crucial role assumed by the R&D variable in this study, it is worthwhile to discuss in detail what is intended by R&D in our database. This item represents all costs incurred during the year that relate to the development of new products and services. It is important to notice that this amount is only the company's contribution and excludes amortization and depreciation of previous investments, so being a genuine flow of current in-house R&D expenditures[5]. On the whole, the adopted definition of R&D is quite restrictive and refers to the genuine flow of current additional resources coming from internal sources and devoted to the launch and development of entirely new products[6].

The period covered is 1990-2008; however, the number of years available for each company depends upon the company's history; therefore, the data source is unbalanced in nature and comprises 1,809 companies (1,170 American firms and 639 European firms) for a total of 16,079 observations.

Once we acquired the rough original data from IPTS, we proceeded in the construction of a longitudinal database that would be adequate to run panel estimations for testing the hypotheses discussed in the previous section. In the Appendix, we describe in detail the procedure we adopted to construct the dataset.

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[4] The original data source being the Compustat Global dataset provided by Standard&Poor's.

[5] In particular, the figure excludes: customer or government-sponsored R&D expenditures; engineering expenses such as routinised ongoing engineering efforts to define, enrich or improve the qualities and characteristics of the existing products; inventory royalties; market research and testing.

[6] When using R&D expenditures, the risk of "double counting" might bias the estimates. As Hall and Mairesse (1995) point out, the researchers' wages are included in the R&D expenditures, as well as researchers are counted in the employment figures, therefore the relationship between R&D and employment might be biased because of these inclusions. We cannot get rid of this "double counting" effect as far as we do not have separate figures for researchers, but we assume that, if thisi is the case, the "bias effect" might be equally distributed among US and European countries (especially because we are dealing with large multinational companies).

3.2 The econometric specification and descriptive statistics

Consistent with previous literature discussed in Section 2, we will test the following augmented production function, obtainable from a standard Cobb-Douglas function in three inputs: physical capital, labour and knowledge capital (see Hall and Mairesse, 1995, formulas 1-2-3, pp. 268-69)[7].

(1) $$\ln(VA/E) = \alpha + \beta \ln(K/E) + \gamma \ln(C/E) + \lambda \ln(E) + \varepsilon$$

Our proxy for productivity is labour productivity (Value Added, VA, over total employment, E), while our pivotal impact variables are the R&D stock (K) per employee and the physical capital stock (C) per employee.

As is common in this type of literature (see Hulten, 1990; Jorgenson, 1990; Hall and Mairesse, 1995; Parisi *et al*., 2006), stock indicators rather than flows were considered as impact variables; indeed, productivity is affected by the accumulated stocks of capital and R&D expenditures and not only by current or lagged flows.

Moreover, dealing with R&D stocks - rather than flows - has two additional advantages: on the one hand, since stocks incorporate the accumulated R&D investments in the past, the risks of endogeneity are minimised; on the other hand, there is no need to deal with the complex (and often arbitrary) choice of the appropriate lag structure for the R&D regressor. R&D and physical capital stocks were computed using the *perpetual inventory method,* according to the formulas (A.1) and (A.2) reported in the Appendix (fifth step).

Finally, taking per capita values permits both standardisation of our data and elimination of possible size effects (see, for example, Crépon *et al*., 1998, p.123). In this framework, total employment (E) is a control variable: if λ turns out to be greater than zero, it indicates increasing returns. All the variables are taken in natural logarithms.

While *K/E* (R&D stock per employee) captures that portion of technological change which is related to the accumulated R&D investment, *C/E* (physical capital stock per employee) is the result of the accumulated investment, implementing different vintages of technologies. So, this variable encompasses the so-called *embodied technological change*, possibly affecting productivity growth (see Section 2).

Table 1 reports the correlation matrix of the variables included in eq. 1. As can be seen, a preliminary evidence of the expected positive impacts of both K/E and C/E upon VA/E emerges.

[7] As clearly stated and demonstrated in Hall and Mairesse (1995), the direct production function approach to measure returns to R&D capital is preferred on other possible alternative specifications.

Moreover, no evidence of possible serious collinearity problems is detectable, since the three correlation coefficients between the regressors turn out to be less than 0.285 in absolute values.

Tab. 1: Correlation table: correlation coefficients

	Log(Value added per employee)	Log(R&D stock per employee)	Log(Physical stock per employee)	Log(Employment)
Log(Value added per employee)	1			
Log(R&D stock per employee)	0.451	1		
Log(Physical stock per employee)	0.278	0.252	1	
Log(Employment)	-0.040	-0.284	0.209	1

Note: all correlation coefficients are 1% significant.

Specification (1) was estimated through different estimation techniques. Firstly, pooled ordinary least squared (POLS) regressions were run to provide a preliminary evidence. Although very basic, these POLS regressions were controlled for heteroskedasticity (we used the Eicker/Huber/White sandwich estimator to compute robust standard errors) and for a complete set of three batteries of dummies, namely country (19 countries), time (19 years) and sector (52 two-digit SIC-sectors) dummies.

Secondly, fixed effect (FE) regressions were performed in order to take into account firm specific unobservable characteristics such as managerial capabilities. The advantage of the FE estimates is that different firms are not pooled together but taken into account individually. The disadvantage is that country and sector dummies are dropped for computational reasons, since they are encompassed by the individual dummies.

Thirdly, random effect (RE) regressions were run to provide more complete results, where both individual (randomized) effects are taken into account together with the possibility to retain all the entire batteries of dummies. Tables 2, 3, 4 and 5 report the means and standard deviations of the four relevant variables in specification (1)[8]. We will refer to them – when appropriate – in the following Section 4 that is devoted to discuss the econometric results.

[8] When referring to the EU, the following tables are based on the observations relative to the 18 countries listed in table A1 in the Appendix.

Tab. 2: VA/E (Value Added/Employees) in PPP-2000 US dollars

	Mean	**Standard deviation**
Whole sample (16,079)	102.781	91.008
US (12,605)	108.793	96.475
EU (3,474)	80.965	62.912
Manufacturing (12,876)	99.565	92.914
High-tech manufacturing sectors (7,693)	112.038	108.275
Other manufacturing sectors (5,183)	81.050	58.938
Services (3,203)	115.709	81.648
US Manufacturing (10,214)	104.18	98.355
EU Manufacturing (2,662)	81.324	65.678
US High-tech manufacturing (6,462)	116.125	112.525
EU High-tech manufacturing (1,231)	90.583	79.089
US Other manufacturing sectors (3,752)	83.983	61.733
EU Other manufacturing sectors (1,431)	73.359	50.093
US Services (2,391)	127.907	86.000
EU Services (812)	79.789	52.858

Note: the number of observations is reported in brackets

Tab. 3: K/E (R&D Stock/Employees) in PPP-2000 US dollars

	Mean	**Standard deviation**
Whole sample (16,079)	86.076	105.899
US (12,605)	93.467	110.310
EU (3,474)	59.267	82.701
Manufacturing (12,876)	82.470	106.904
High-tech manufacturing sectors (7,693)	110.748	119.007
Other manufacturing sectors (5,183)	40.497	66.507
Services (3,203)	100.574	100.478
US Manufacturing (10,214)	88.593	110.932
EU Manufacturing (2,662)	58.974	85.842
US High-tech manufacturing (6,462)	114.977	121.210
EU High-tech manufacturing (1,231)	88.545	103.958
US Other manufacturing sectors (3,752)	70.251	43.153
EU Other manufacturing sectors (1,431)	33.536	54.921
US Services (2,391)	114.286	105.119
EU Services (812)	60.199	71.483

Note: the number of observations is reported in brackets

Tab. 4: C/E (Physical capital Stock/Employees) in PPP-2000 US dollars

	Mean	Standard deviation
Whole sample (16,079)	81.026	80.542
US (12,605)	81.567	79.633
EU (3,474)	79.065	83.742
Manufacturing (12,876)	84.886	81.585
High-tech manufacturing sectors (7,693)	78.142	76.709
Other manufacturing sectors (5,183)	94.895	87.380
Services (3,203)	65.512	74.222
US Manufacturing (10,214)	84.785	81.171
EU Manufacturing (2,662)	85.272	83.167
US High-tech manufacturing (6,462)	79.272	77.609
EU High-tech manufacturing (1,231)	72.208	71.535
US Other manufacturing sectors (3,752)	94.279	86.153
EU Other manufacturing sectors (1,431)	96.510	90.532
US Services (2,391)	67.819	71.089
EU Services (812)	58.718	82.433

Note: the number of observations is reported in brackets

Tab. 5: E (Employees)

	Mean	Standard deviation
Whole sample (16,079)	11,204	35,302
US (12,605)	9,124	31,064
EU (3,474)	18,752	46,846
Manufacturing (12,876)	11,951	35,250
High-tech manufacturing sectors (7,693)	8,179	23,264
Other manufacturing sectors (5,183)	17,551	47,237
Services (3,203)	8,199	35,356
US Manufacturing (10,214)	9,714	31,116
EU Manufacturing (2,662)	20,535	46,937
US High-tech manufacturing (6,462)	7,298	21,294
EU High-tech manufacturing (1,231)	12,803	31,259
US Other manufacturing sectors (3,752)	13,876	42,752
EU Other manufacturing sectors (1,431)	27,187	56,244
US Services (2,391)	6,600	30,718
EU Services (812)	12,908	46,096

Note: the number of observations is reported in brackets

4. Econometric analysis

From Table 2 we get a further confirmation of the US/EU productivity gap that was discussed from a macroeconomic point of view in Section 1. As can be seen, the US advantage in labour productivity homogeneously emerges both in aggregate and within the different sectoral groups: 109 *vs.* 81 in the whole sample; 104 *vs.* 81 in manufacturing; 116 *vs.* 90 in the high-tech manufacturing sectors; 84 *vs.* 73 in the other manufacturing sector; 128 *vs.* 80 in the service sectors. In this section, we will try to provide some explanations of these differentials.

Table 6 provides the overall results concerning the whole sample of 1,809 firms (16,079 observations). As can be seen, we found robust evidence of a positive and significant impact of R&D on productivity with an elasticity ranging from 0.089 to 0.205, according to the different adopted estimation techniques. As discussed in Section 2, in the reference literature the estimated overall elasticity of productivity in respect to R&D is positive, statistically significant and with a magnitude - depending on the data and the adopted econometric methodology - ranging from 0.05 to 0.25; hence, the obtained estimates are within the bounds set by previous empirical studies.

As far as physical capital is concerned, here again we have no surprise in assessing a positive and significant impact ranging from 0.093 to 0.115; together with the intangible R&D investment, capital formation – embodying vintages of new technologies – emerges as a still important driver of productivity growth.

The whole sample estimates will be the reference for all the following analyses and the correspondent results will be reported in the left panel of all the following tables.

Tab. 6: Whole sample, US and EU

	Whole sample			US			EU		
	POLS	**FE**	**RE**	**POLS**	**FE**	**RE**	**POLS**	**FE**	**RE**
Log(R&D stock per employee)	0.205*** (0.006)	0.089*** (0.007)	0.107*** (0.007)	0.228*** (0.007)	0.098*** (0.008)	0.119*** (0.008)	0.144*** (0.013)	0.058*** (0.011)	0.074*** (0.010)
Log(Physical stock per employee)	0.115*** (0.006)	0.093*** (0.006)	0.099*** (0.006)	0.106*** (0.007)	0.100*** (0.007)	0.102*** (0.007)	0.125*** (0.012)	0.053*** (0.011)	0.078*** (0.009)
Log(Employees)	0.031*** (0.003)	-0.049*** (0.007)	-0.012** (0.007)	0.035*** (0.004)	-0.034*** (0.008)	-0.006 (0.006)	0.015** (0.007)	-0.162*** (0.017)	-0.059*** (0.011)
Constant	0.860* (0.493)	3.529*** (0.038)	1.115 (0.984)	3.906*** (0.103)	3.523*** (0.036)	1.124 (0.697)	2.330*** (0.135)	3.744*** (0.079)	2.256** (1.016)
Wald time-dummies [p-value]	4.5*** [0.000]	11.4*** [0.000]	165.4*** [0.000]	5.4*** [0.000]	9.6*** [0.000]	199.2*** [0.000]	1.9*** [0.009]	2.4*** [0.001]	19.3 [0.313]
Wald country-dummies [p-value]	52.5*** [0.000]	-	67.2*** [0.000]	-	-	-	18.6*** [0.000]	-	25.8* [0.078]
Wald sectoral-dummies [p-value]	174.2*** [0.000]	-	233.1*** [0.000]	86.4*** [0.000]	-	154.0*** [0.000]	99.8*** [0.000]	-	83.0*** [0.000]
R^2 (overall)	0.32	0.18	0.29	0.34	0.21	0.31	0.27	0.01	0.17
Obs.	16,079			12,605			3,474		
N. of firms	1,809			1,170			639		

Notes: - (Robust in POLS) standard-errors in parentheses; * significance at 10%, ** 5%, *** 1%.

- For Time-dummies, Country-dummies and Sectoral-dummies Wald tests of joint significance are reported (p-values in square parentheses).

The hypothesis of this study is that the lower European economic performance in comparison with the US can be explained not only by a lower level of corporate R&D investment, but also by a lower capacity to translate R&D investment into productivity gains. This hypothesis can be tested running specification 1 separately for the US and the EU firms (1,170 *vs.* 639 companies).

As can be seen in the second and third panel of Table 6, the results seem to fully confirm the proposed hypothesis. Although uniformly positive and statistically significant at the 99% level of confidence, the R&D coefficients for the US firms turn out to be consistently larger than the corresponding coefficients for the European firms. Indeed, the three estimation techniques consistently provide European elasticities equal to about 60% of their US counterparts. We interpret these unambiguous results as a clear evidence of the better ability of US firms in translating R&D investments in productivity gains and as a signal of a gap of efficiency that European firms and European policy have to deal with.

As far as the productivity impact of the physical capital, POLS and FE/RE estimates tell us different stories in terms of the US-EU comparison. However, if we rely on the more reliable methodologies controlling for the idiosyncratic effects, it appears that the US reveals an advantage similar to the one that emerged for the intangible R&D investments. Therefore, US firms resulted in being more efficient in getting productivity gains both from the R&D and the physical capital investments[9].

However, previous literature - discussed in Section 2 – came to the conclusion that a greater impact of R&D investment on productivity is expected in the high-tech sectors rather than in the low-tech ones. Therefore, it may well be the case that the US advantage in terms of R&D efficiency is totally due to a sectoral composition effects (*structural effect*), since high-tech sectors are over-represented in the US economy in comparison with the European one. In contrast, if an *intrinsic effect* is present, the US advantage should be detectable across all sectors of the economy[10].

Table 7 displays the US/EU comparison with regard to the manufacturing sectors only. As is obvious, the aggregate European gap in terms of efficiency is fully confirmed: as it was the case for the whole economy, in the manufacturing sectors the four relevant US coefficients are uniformly larger that their European counterparts.

[9] In order to check if differences among the coefficients for US and EU are significant, we computed t-tests on the more reliable RE estimates. Results for R&D stock, Physical stock and Employment are, respectively, 3.68***, 1.95** and 3.92***, all significant at 1% supporting the hypothesis that US and EU behave differently.

[10] Splitting the sample in sub-periods would allow to better understand the dynamics of the “structural” and “intrinsic” effects. Unfortunately the unbalanced nature of the dataset and the paucity of the observations do not allow to run these additional estimates.

Moreover, Table 8 focusing on the service sectors tells us exactly the same story, confirming the US advantage across all the coefficients[11].

[11] Interestingly enough, US service sectors appear to be characterized by increasing returns (the coefficients of the log-employment turning out to be positive and highly significant in the FE and POLS estimates), while in all the other regressions (focusing our attention on the most reliable FE and RE models) we always find decreasing returns. Hence, US service sectors emerge as the only ones still positively affected by scale economies (a kind of "Wal-Mart" big box effect, see Van Ark *et al.*, 2008, p. 41).

Tab. 7: US versus EU: Manufacturing

	Whole sample			US			EU		
	POLS	**FE**	**RE**	**POLS**	**FE**	**RE**	**POLS**	**FE**	**RE**
Log(R&D stock per employee)	0.205*** (0.006)	0.089*** (0.007)	0.107*** (0.007)	0.228*** (0.008)	0.078*** (0.009)	0.103*** (0.009)	0.147*** (0.014)	0.052*** (0.013)	0.070*** (0.012)
Log(Physical stock per employee)	0.115*** (0.006)	0.093*** (0.006)	0.099*** (0.006)	0.099*** (0.008)	0.089*** (0.008)	0.093*** (0.008)	0.135*** (0.014)	0.059*** (0.013)	0.086*** (0.012)
Log(Employees)	0.031*** (0.003)	-0.049*** (0.007)	-0.012** (0.007)	0.027*** (0.004)	-0.069*** (0.010)	-0.029*** (0.008)	0.023*** (0.008)	-0.166*** (0.022)	-0.045*** (0.014)
Constant	0.860* (0.493)	3.529*** (0.038)	1.115 (0.984)	2.155*** (0.468)	3.560*** (0.040)	2.309* (1.158)	2.607*** (0.146)	3.769*** (0.093)	3.016*** (0.921)
Wald time-dummies [p-value]	4.5*** [0.000]	11.4*** [0.000]	165.4*** [0.000]	4.9*** [0.000]	13.2*** [0.000]	204.4*** [0.000]	1.7** [0.029]	2.1*** [0.004]	16.1 [0.514]
Wald country-dummies [p-value]	52.5*** [0.000]	-	67.2*** [0.000]	-	-	-	26.8*** [0.000]	-	20.6 [0.244]
Wald sectoral-dummies [p-value]	174.2*** [0.000]	-	233.1*** [0.000]	73.7*** [0.000]	-	128.3*** [0.000]	14.4*** [0.000]	-	33.8 [0.139]
R^2 (overall)	0.32	0.18	0.29	0.32	0.15	0.28	0.28	0.01	0.17
Obs.	16,079			10,214			2,662		
N. of firms	1,809			914			469		

Notes: - (Robust in POLS) standard-errors in parentheses; * significance at 10%, ** 5%, *** 1%.

- For Time-dummies, Country-dummies and Sectoral-dummies Wald tests of joint significance are reported (p-values in square parentheses).

Tab. 8: US versus EU: Services

	Whole sample			US			EU		
	POLS	**FE**	**RE**	**POLS**	**FE**	**RE**	**POLS**	**FE**	**RE**
Log(R&D stock per employee)	0.205*** (0.006)	0.089*** (0.007)	0.107*** (0.007)	0.215*** (0.017)	0.125*** (0.017)	0.150*** (0.014)	0.126*** (0.023)	0.086*** (0.024)	0.097*** (0.018)
Log(Physical stock per employee)	0.115*** (0.006)	0.093*** (0.006)	0.099*** (0.006)	0.149*** (0.017)	0.140*** (0.016)	0.143*** (0.015)	0.108*** (0.024)	0.045** (0.022)	0.070*** (0.020)
Log(Employees)	0.031*** (0.003)	-0.049*** (0.007)	-0.012** (0.007)	0.086*** (0.010)	0.051*** (0.016)	0.058*** (0.013)	0.017 (0.015)	-0.141*** (0.030)	-0.076*** (0.021)
Constant	0.860* (0.493)	3.529*** (0.038)	1.115 (0.984)	3.268*** (0.195)	3.755*** (0.093)	3.242*** (0.520)	-0.457 (0.301)	3.623*** (0.185)	3.138*** (0.854)
Wald time-dummies [p-value]	4.5*** [0.000]	11.4*** [0.000]	165.4*** [0.000]	3.4*** [0.000]	4.9*** [0.000]	92.6*** [0.000]	1.1 [0.348]	0.6*** [0.000]	13.1 [0.728]
Wald country-dummies [p-value]	52.5*** [0.000]	-	67.2*** [0.000]	-	-	-	4.1*** [0.000]	-	15.5 [0.213]
Wald sectoral-dummies [p-value]	174.2*** [0.000]	-	233.1*** [0.000]	84.7*** [0.000]	-	70.4*** [0.000]	73.5*** [0.000]	-	64.8*** [0.000]
R^2 (overall)	0.32	0.18	0.29	0.40	0.30	0.39	0.31	0.03	0.27
Obs.	16,079			2,391			812		
N. of firms	1,809			256			170		

Notes: - (Robust in POLS) standard-errors in parentheses; * significance at 10%, ** 5%, *** 1%.

- For Time-dummies, Country-dummies and Sectoral-dummies Wald tests of joint significance are reported (p-values in square parentheses).

Hence, at this stage, we can conclude that both US manufacturing and US service firms are more efficient in translating their investments (both in R&D and in physical capital) into productivity increases. Hence, the transatlantic productivity divide can be explained not only by a lower level of corporate R&D investment[12], but also by a lower capacity to translate R&D and capital investment into productivity gains, and this seems to be obvious both within manufacturing and within services.

Tables 9 and 10 display the results concerning only manufacturing firms split across the high-tech sectors *vs.* other sectors. These results can be commented on along two dimensions: between areas and within areas. Let us start from the between areas comparison.

As far as the high-tech sectors are concerned, American firms are revealed to be more efficient in translating both the R&D and the capital expenditures into productivity increases. As usual, all the coefficients are positive, fully significant and within the expected magnitude ranges; however, looking at the more sophisticated FE and RE estimates, all the four US coefficients are larger than the corresponding European ones. Hence, at least in the high-tech manufacturing sectors, US firms are more able to transfer their own investments into productivity gains.

With regard to the rest of the manufacturing sectors, US firms are still more efficient with regard to the R&D stock, while embodied technological change seems to play a more relevant role in the European firms. On the whole, US firms are leading in terms of R&D efficiency regardless of the sectors, while embodied technological change appears the most effective in the US high-tech sectors and in the EU non-high-tech manufacturing sectors.

Turning our attention to the within area comparisons, the following pictures emerge.

Within the US, high-tech sectors display larger productivity elasticities both with regard to the R&D and the capital investment (all the six coefficients in the high-tech estimates are larger than their correspondent figures in the other sectors). Hence, the US manufacturing high-tech sectors appear to be characterized by a higher efficiency in translating investments into productivity advantages.

In contrast, European firms in the high-tech sectors show higher coefficients concerning the productivity elasticity of the R&D stock (all the three coefficients), while the reverse happens as far as physical capital is concerned (all the three coefficients are higher in the non-high-tech manufacturing sectors, while the FE estimate in the high-tech sectors is even not significant). This picture largely confirms what has emerged from a previous study based on different (UK-DTI) European microdata (Ortega-Argilés *et al.*, 2010), where the R&D coefficient was found to increase

[12] Looking at Table 3, the European underinvestment in comparison with the US is obvious and spread across the sectors: the whole sample K/E is 59 in the EU vs. 93 in the US; 59 vs. 89 in the manufacturing sectors; 89 vs. 115 in the high-tech manufacturing sectors; 34 vs. 70 in the other manufacturing sectors; 60 vs. 114 in the service sectors.

monotonically moving from the low-tech to the medium and high-tech sectors, while the capital coefficient was found to be characterised by an opposite pattern. One possible interpretation is that productivity growth in the European non-high-tech firms is still heavily dependent on the investment in physical capital (embodied technological change).

On the whole, the US revealed better capacity to translate R&D and capital investments into productivity gains is detected across all the sectors of the economy, with the only exception being non-high tech manufacturing sectors where embodied technological change turns out to be more effective in the EU. Therefore, our evidence supports the presence of an obvious and significant intrinsic effect; in particular, US firms are better able to get productivity gains from their R&D expenditures, no matter which sector they belong to.

Tab.9: US versus EU: High-tech manufacturing sectors

	Whole sample			US High-tech manufacturing			EU High-tech manufacturing		
	POLS	**FE**	**RE**	**POLS**	**FE**	**RE**	**POLS**	**FE**	**RE**
Log(R&D stock per employee)	0.205*** (0.006)	0.089*** (0.007)	0.107*** (0.007)	0.251*** (0.010)	0.069*** (0.013)	0.105*** (0.012)	0.172*** (0.032)	0.065*** (0.020)	0.081*** (0.019)
Log(Physical stock per employee)	0.115*** (0.006)	0.093*** (0.006)	0.099*** (0.006)	0.112*** (0.011)	0.101*** (0.011)	0.105*** (0.010)	0.127*** (0.025)	0.029 (0.022)	0.061*** (0.020)
Log(Employees)	0.031*** (0.003)	-0.049*** (0.007)	-0.012** (0.007)	0.041*** (0.005)	-0.08*** (0.013)	-0.03*** (0.010)	0.054*** (0.013)	-0.155*** (0.033)	-0.026 (0.023)
Constant	0.860* (0.493)	3.529*** (0.038)	1.115 (0.984)	3.147*** (0.074)	3.525*** (0.055)	3.060*** (0.205)	2.691*** (0.226)	3.499*** (0.166)	3.579*** (1.022)
Wald time-dummies [p-value]	4.5*** [0.000]	11.41*** [0.000]	165.4*** [0.000]	2.2*** [0.002]	8.3*** [0.000]	112.8*** [0.000]	2.0*** [0.009]	2.4*** [0.000]	25.6* [0.081]
Wald country-dummies [p-value]	52.5*** [0.000]	-	67.2*** [0.000]	-	-	-	11.5*** [0.000]	-	10.7 [0.710]
Wald sectoral-dummies [p-value]	38.2*** [0.000]	-	233.1*** [0.000]	78.8*** [0.000]	-	31.2*** [0.000]	14.4*** [0.000]	-	2.4 [0.790]
R^2 (overall)	0.32	0.18	0.29	0.28	0.12	0.23	0.26	0.01	0.13
Obs.	16,079			6,462			1,231		
N. of firms	1,809			591			213		

Notes: - (Robust in POLS) standard-errors in parentheses; * significance at 10%, ** 5%, *** 1%.

- For Time-dummies, Country-dummies and Sectoral-dummies Wald tests of joint significance are reported (p-values in square parentheses).

Tab. 10: US versus EU: Other manufacturing sectors

	Whole sample			US Other manufacturing			EU Other manufacturing		
	POLS	**FE**	**RE**	**POLS**	**FE**	**RE**	**POLS**	**FE**	**RE**
Log(R&D stock per employee)	0.205*** (0.006)	0.089*** (0.007)	0.107*** (0.007)	0.175*** (0.008)	0.060*** (0.010)	0.079*** (0.010)	0.112*** (0.013)	0.035** (0.015)	0.056*** (0.014)
Log(Physical stock per employee)	0.115*** (0.006)	0.093*** (0.006)	0.099*** (0.006)	0.074*** (0.009)	0.063*** (0.012)	0.066*** (0.009)	0.146*** (0.016)	0.093*** (0.016)	0.118*** (0.016)
Log(Employees)	0.031*** (0.003)	-0.049*** (0.007)	-0.012** (0.007)	-0.007 (0.007)	-0.087*** (0.015)	-0.049*** (0.011)	-0.014 (0.009)	-0.209*** (0.028)	-0.075*** (0.017)
Constant	0.860* (0.493)	3.529*** (0.038)	1.115 (0.984)	2.351*** (0.446)	3.763*** (0.054)	2.501*** (0.487)	3.815*** (0.172)	4.006*** (0.159)	-0.245 (0.362)
Wald time-dummies [p-value]	4.5*** [0.000]	11.4*** [0.000]	165.4*** [0.000]	4.2*** [0.000]	9.9*** [0.000]	171.0*** [0.000]	0.8 [0.718]	1.1 [0.397]	30.8** [0.030]
Wald country-dummies [p-value]	52.5*** [0.000]	-	67.2*** [0.000]	-	-	-	28.7*** [0.000]	-	18.5 [0.237]
Wald sectoral-dummies [p-value]	38.2*** [0.000]	-	233.1*** [0.000]	79.5*** [0.000]	-	207.3*** [0.000]	12.6*** [0.000]	-	44.3*** [0.001]
R^2 (overall)	0.32	0.18	0.29	0.44	0.12	0.41	0.35	0.01	0.27
Obs.	16,079			3,752			1,431		
N. of firms	1,809			323			256		

Notes: - (Robust in POLS) standard-errors in parentheses; * significance at 10%, ** 5%, *** 1%.

- For Time-dummies, Country-dummies and Sectoral-dummies Wald tests of joint significance are reported (p-values in square parentheses).

5. Conclusions and policy implications

The role of corporate R&D investment has been recognised as a fundamental engine for productivity growth both at the macro and microeconomic level. As shown in Section 1, the EU has spent notably less on R&D than the US in the last two decades, particularly as far as the private business sector is concerned. However, in this paper we have tested the hypothesis that the transatlantic productivity gap may be due not only to a lower level of corporate R&D expenditures by European firms, but also to a possible lower capacity to translate corporate R&D expenditures into productivity gains. Indeed, it may be well the case that European economies not only invest *less in R&D,* but also *get less* from their R&D investment.

Consistent with previous literature, we found robust evidence of a positive and significant impact of R&D on productivity with an elasticity ranging from 0.089 to 0.205, according to the different adopted estimation techniques. However, although uniformly positive and statistically significant, the R&D coefficients for the US firms turn out to be consistently larger than the corresponding coefficients for the European firms. Indeed, the three estimation techniques consistently provide European elasticities equal to about 60% of their US counterparts. We interpreted these unambiguous results as a clear evidence of the better ability of US firms in translating R&D investments into productivity gains and as a signal of a gap of efficiency that European firms and European policy have to deal with.

To see to what extent the transatlantic differences may be related to the different sectoral structures in the US and the EU (the US economy being disproportionally characterised by high-tech manufacturing and ICT-intensive services), we differentiated the US/EU comparative empirical exercise by sectors. It results that both US manufacturing and US service firms are more efficient in translating their investments (both in R&D and in physical capital) into productivity increases. In addition, this US efficiency advantage is obvious both in the high-tech manufacturing sectors and in the rest of the manufacturing sectors. On the whole, US firms are leading in terms of R&D efficiency regardless of the sectors. Hence, the transatlantic productivity divide can be explained not only by a lower level of corporate R&D investment, but also by a lower capacity to translate R&D into productivity gains across all sectors of the economy.

Looking inside the American and the European aggregates, within the US, high-tech sectors display larger productivity elasticities both with regard to the R&D and the capital. Hence, in the US manufacturing, high-tech sectors appear to be characterized by a higher efficiency in translating investments into productivity advantages.

Differently, European firms in the high-tech sectors turn out to be characterised by larger coefficients concerning the productivity elasticity of the R&D stock, while the reverse happens as far as physical capital is concerned. Hence, productivity growth in the European non-high-tech firms is still heavily dependent on the investment in physical capital (embodied technological change).

Although necessarily tentative, some policy implications can be derived from the empirical results obtained in this study.

Firstly, the results obtained show that the US economy is uniformly more efficient in getting productivity advantages from investments in R&D activities; while this is obvious for the whole economy, the efficiency gap is confirmed separately in services and manufacturing and – within manufacturing – both in the high-tech sectors and in the other industrial sectors. Hence, the transatlantic divide is not only a matter either of a lower R&D investment in Europe or of an European industrial structure specialised in middle and low-tech sectors (*structural effect*): European firms are structurally less able to translate R&D expenditures into productivity gains. This *intrinsic effect* can be due to a lower level of human capital or to a lag in those organizational changes that are crucial complements of technological change. While these perspectives are beyond the scope of the present study, this conclusion has a first important policy implication: just increasing R&D is a necessary but not a sufficient policy if the overall increase in productivity is the target.

Secondly, the paper shows that R&D investment is not the sole source of productivity gains; technological change embodied in capital formation is of comparable importance. However - also with regard to the relationship between physical capital and productivity - the US economy exhibits an advantage, similar to the one detected for the R&D activities. Here again, European firms appear to lack of those complementary factors – such as adequate human resources and updated organizational layouts – which fuel the productivity increases resulting from both tangible and intangible investments.

Thirdly, embodied technological change appears to be crucial within European non-high-tech firms; hence, a European innovation policy aiming to increase productivity in the medium/low-tech sectors should support overall capital formation at least as much as R&D expenditures.

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APPENDIX: The construction of the dataset

First step: data extraction

In guiding the extraction of the data from what provided, the following criteria were adopted:

- Selecting only those companies with R&D>0 in, at least, one year of the available time span;
- Selecting only those companies located in the US and in the EU 27 countries;
- Extracting information concerning R&D, sales, cost of goods (the difference between sales and cost of goods allowed to obtain value added), capital formation, R&D expenditures, and employment. More specifically, this is the list of the available information for each firm included in the obtained workable dataset:
    - Country of incorporation (location of the headquarter);
    - Industry code at 2008;
    - R&D expenses;
    - Capital expenditures;
    - Net turnover;
    - Cost of goods sold;
    - Employees.
- All the value data were expressed in the current national currency in millions (for instance: countries which are currently adopting Euro have values in Euro for the entire examined period).

Second step: deflation of current nominal values

Nominal values were translated into constant price values through GDP deflators (source: IMF) centred in year 2000. For a tiny minority of firms reporting in currencies different from the national ones (namely: 41 British firms, 9 Dutch firms, 4 Irish firms, 2 Luxembourg firms, 1 German and 1 Swedish firms reporting in US dollars and 7 British firms, 2 Danish firms and 1 Estonian firm reporting in euro), we opted for deflating the nominal values through the national GDP deflator, as well.

Third step: values in PPP dollars

Once we obtained constant 2000 price values, all figures were converted into US dollars using the PPP exchange rate at year 2000 (source: OECD)[13]. 9 companies from 4 countries (Lithuania, Latvia, Malta and Romania) were excluded, due to the unavailability of PPP exchange rates from the OECD. The 10 companies reporting in euros but located in non-euro countries (Denmark, Estonia and the UK) were excluded as well[14]; while the 58 European companies reporting in US dollars were kept as such.

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[13] This procedure is consistent with what suggested by the Frascati Manual (OECD, 2002) in order to correctly adjust R&D expenditures for differences in price levels over time (*i.e.* intertemporal differences asking for deflation) and among countries (*i.e.* interspatial differences asking for a PPP equivalent). In particular "...the Manual recommends the use of the implicit gross domestic product (GDP) deflator and GDP-PPP (purchasing power parity for GDP), which provide an approximate measure of the average real "opportunity cost" of carrying out the R&D." (*ibidem*, p. 217).

[14] Given the very small number of firms involved, it was decided not to take the arbitrary choice of using either the national or the Euro PPP converter.

Fourth step: the format of the final data string

The obtained unbalanced database comprises 2,777 companies, 2 codes (country and sector) and 5 variables (see the bullet points above) over a period of 19 years (1990-2008).

Since one of the purposes of this study is to distinguish between high-tech and medium/low-tech sectors, a third code was added, labelling as High-tech the following sectors[15]:

- SIC 283: Drugs (ISIC Rev.3, 2423: Pharmaceuticals);
- SIC 357: Computer and office equipments (ISIC Rev. 3, 30: Office, accounting and computing machinery);
- SIC 36 (excluding 366): Electronic and other electrical equipment and components, except computer equipment (ISIC Rev. 3, 31: Electrical machinery and apparatus);
- SIC 366: Communication equipment (ISIC Rev. 3, 32: Radio, TV and communications equipment);
- SIC 372-376: aircraft and spacecraft (ISIC Rev. 3, 353: Aircraft and spacecraft);
- SIC 38: measuring, analyzing and controlling instruments (ISIC Rev. 3, 33: Medical, precision and optical instruments)

Fifth step: computation of the R&D and capital stocks.

Consistent with the reference literature (see Section 2), the methodology adopted in this study requires us to compute the R&D and capital stocks, accordingly with the *perpetual inventory method*. In practice, the following two formulas have to be applied:

(A.1) $K_{t0} = \frac{R\&D_{t0}}{(g+\delta)}$ and $K_t = K_{t-1} \cdot (1-\delta) + R\&D_t$

where R&D = R&D expenditures

(A.2) $C_{t0} = \frac{I_{t0}}{(g+\delta)}$ and $C_t = C_{t-1} \cdot (1-\delta) + I_t$

where I = gross investment

where g is generally computed as the *ex ante* pre-sample compounded average growth rate of the corresponding flow variable and δ is a depreciation rate.

However, our dataset spans 19 years and is unbalanced in nature. This means that only a minority of firms display continuous information all over the entire period, while many firms have information only for one or more spans over the 1990-2008 period and these spans may be either very short or even isolated data. In addition, many firms display left-truncated data; for instance, the majority of European firms have data only for the most recent years.

Given the unbalanced structure of the dataset, to strictly apply the formulas (1) and (2) for computing initial stocks (using – say – the first three years to obtain the *ex-ante* growth rates) would have implied the loss of a huge amount of information. In the best case - say a firm with a complete set of 19 data over the period - this methodology would have implied the loss of 3 observations out

[15] The standard OECD classification was taken (see Hatzichronoglou, 1997) and extended it including the entire electrical and electronic sector 36 (considered as a medium-high tech sector by the OECD). We opted for this extension taking into account that we just compare the high-tech sectors with all the other ones and that we need an adequate number of observations within the sub-group of the high-tech sectors.

of 19; in the worst case - say a firm characterized by data available only for some spells of three years each – this computation would have implied the loss of all the available information for that particular firm.

In order to avoid this severe loss of available data, we adopted the following criteria. First, it was decided to compute a rate of growth using the initial three years of a given spell and then apply it to the initial flow and not to the fourth year (that is our t_0 is the very first year of the spell and so g is an "ex post" 3-year compound growth rate). Second, we iteratively applied this methodology to all the available spans of data comprising at least three consecutive years[16]. The combination of these two choices allowed us to keep all the available information, with the only exceptions of either isolated data or pairs of data.

Although departing from the usual procedure, to rely on *ex-post* growth rates appears acceptable in order to save most of the available information in the dataset; however, the impact of this choice on the values assumed by the stocks is limited, since they are also affected by the flow values and the depreciation rates. Finally, the chosen growth rate affects only the initial stock and its impact quickly smoothes out as far as we move away from the starting year[17].

Therefore, - in order to be able to compute R&D and capital stocks according to the procedure described above – only R&D and capital expenditure flows data with at least 3 observations in consecutive years were retained. This implied that 354 companies (mainly European) had to be dropped because they were lacking 3 R&D observations in successive years, while 30 additional companies were lacking 3 capital expenditure observations in successive years. Thus, a total of 2,393 firms were retained at the end of this stage of the cleaning process.

Turning the attention to the depreciation rates (δ), we differentiated both between R&D and capital and between the high-tech sectors *vs.* the other sectors, taking into account what is common in the reference literature which assumes δ = 6% for computing the capital stock and δ = 15% for computing the R&D stock (see Nadiri and Prucha, 1996 for the capital stock; Hall and Mairesse, 1995 and Hall, 2007 for the R&D stock).

Indeed, depreciation rates for the R&D stocks have to be assumed to be higher than the corresponding rates for physical capital, since it is assumed that technological obsolescence is more rapid than the scrapping of physical capital.

However, depreciation rates for the high-tech sectors have to be assumed to be higher than the corresponding rates for medium and low-tech sectors under the assumption that technological obsolescence – both related to R&D efforts and to the embodied technologies incorporated in physical capital - is faster in the high-tech sectors. Specifically, depreciation rates were assumed to be equal to 6% and 7% with regard to physical capital in the low-medium and high-tech sectors respectively, while the corresponding δ for R&D stocks were assumed equal to 15% and 18% respectively.

Once computed according to the formulas (1) and (2) and the adopted g and δ rates, the resulting stocks were checked and negative ones were dropped[18]. Moreover, we excluded a minority of unreliable data such as those indicating negative sales and cost of goods equal to zero.

[16] This means that for firms characterised by breaks in the data we computed different initial stocks, one for each available time span, consistent with Hall (2007); however, differently from Hall (2007), we consider the different spans as belonging to the same firm and so we will assign – in the following econometric estimates – a single fixed or random effect to all of the spans belonging to the same company history.

[17] Options for the choice of g - different from the standard one - have been implemented by other authors, as well. For instance, Parisi *et al.* (2006), assume that the rate of growth in R&D investment at the firm level in the years before the first positive observation equals the average growth rate of industry R&D between 1980 and 1991 (the time-span antecedent to the longitudinal micro-data used in their econometric estimates). In general terms, the choice of a feasible g does not significantly affect the final econometric results of the studies. As clearly stated by Hall and Mairesse (1995, p.270, footnote 9): "In any case, the precise choice of growth rate affects only the initial stock, and declines in importance as time passes,...".

[18] The occurrence of negative stocks happens when g turns out to be negative and larger – in absolute value – than δ.

After these further removals of data, we ended up with 1,884 companies (1,210 US and 674 EU, for a total of 17,064 observations).

Sixth step: outliers.

At this point, in order to check for the presence of outliers (*i.e.* observations that appear to deviate markedly in terms of standard deviations from the relevant mean, possibly implying a bias in the econometric estimates), the Grubbs test (Grubbs, 1969) was run on the two critical variables in the analysis: the R&D stock (K) and the physical capital stock (C).

Since the outlier test has to be applied to the variables used in the regression analysis, the test was run on the two normalised stock variables: K/E and C/E (see eq. 5 in Section 3.3).

In detail, the Grubbs test - also known as the maximum normed residual test, (Grubbs, 1969; Stefansky, 1972) - is used to detect outliers in a dataset, either creating a new variable or dropping outliers out of the data set. Technically, the Grubbs test detects one outlier at each iteration[19]: the outlier is expunged from the data set and the test is iterated until no outliers remain.

The Grubbs test is defined under the null hypothesis (H_0) that there are no outliers in the dataset; the test statistic is:

$$\textbf{(A.3)} \quad \boldsymbol{G} = \frac{\max\limits_{\boldsymbol{i}=1,..,\boldsymbol{N}} \left| \boldsymbol{Y_i} - \overline{\boldsymbol{Y}} \right|}{\boldsymbol{s}}$$

with $\overline{\boldsymbol{Y}}$ and s denoting the sample mean and standard deviation, respectively. Therefore, the Grubbs test detects the largest absolute deviation from the sample mean in units of the sample standard deviation[20].

With a two-sided test, the null hypothesis of no outliers is rejected if:

$$\textbf{(A.4)} \quad \boldsymbol{G} > \frac{(\boldsymbol{N}-1)}{\sqrt{\boldsymbol{N}}} \sqrt{\frac{\boldsymbol{t}^2_{(\boldsymbol{\alpha}/(2\boldsymbol{N}),\boldsymbol{N}-2)}}{\boldsymbol{N}-2+\boldsymbol{t}^2_{(\boldsymbol{\alpha}/(2\boldsymbol{N}),\boldsymbol{N}-2)}}}$$

with $\boldsymbol{t}^2_{(\boldsymbol{\alpha}/(2\boldsymbol{N}),\boldsymbol{N}-2)}$ denoting the critical value of the t-distribution with *(N-2)* degrees of freedom and a significance level of $\alpha/(2N)$.

After running the Grubbs test, 426 observations turned out to be outliers for the K/E variable and 613 for the C/E variable (54 outliers turned out to be common to both the variables).

Therefore, at the end of the process, we ended up with a final dataset comprising 1,809 companies (1,170 US and 639 EU, for a total of 16,079 observations).

Table A.1 reports the distribution of the retained firms and observations across countries.

[19] The default number of iterations is 16,000.

[20] The Grubbs test can also be defined as one of the following one-sided tests:

- test whether the minimum value is an outlier: $\boldsymbol{G} = \frac{\overline{\boldsymbol{Y}} - \boldsymbol{Y}_{\min}}{\boldsymbol{s}}$ with Ymin denoting the minimum value;
- test whether the maximum value is an outlier: $\boldsymbol{G} = \frac{\boldsymbol{Y}_{\max} - \overline{\boldsymbol{Y}}}{\boldsymbol{s}}$ with Ymax denoting the maximum value.

Tab. A.1: Distribution of firms and observations across countries in the final version of the dataset

COUNTRY	FIRMS	OBSERVATIONS
AUSTRIA	16	51
BELGIUM	20	82
CZECH REPUBLIC	1	4
DENMARK	21	152
ESTONIA	1	3
FINLAND	41	157
FRANCE	54	279
GERMANY	141	749
GREECE	11	41
HUNGARY	3	12
IRELAND	8	55
ITALY	5	19
LUXEMBOURG	3	9
NETHERLANDS	25	165
SLOVENIA	1	4
SPAIN	3	7
SWEDEN	62	386
UNITED KINGDOM	223	1,299
EU	**639**	**3,474**
USA	**1,170**	**12,605**