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 the 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 manufacturing sectors US firms are more able to translate their R&D investments into productivity increases.

Keywords: R&D, productivity, embodied technological change, US, EU.
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1. Introduction: aggregate trends and motivation

During the last decade the European industrial and innovation policy initiatives have been driven by the main concern about the revealed lower productivity records that European companies have experienced in comparison with their main competitors, namely US firms. For instance, recent communications released by the European industrial policy authorities make explicit that it is essential to increase R&D investments and knowledge diffusion to foster productivity in manufacturing industry and associated services and therefore to underpin the recovery of growth and jobs in a "knowledge based" EU economy (European Commission, 2010a and 2010b).

The academic literature has pointed to 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; O'Sullivan, 2007; Rogers, 2010). 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, 2010b). More specifically, the European innovation policy advises member countries to strength their knowledge base to remain competitive, and ask European companies to massively invest in research and innovation in order to foster a smart, sustainable and inclusive economic growth.

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 it is well-known, 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. Hence, the labour productivity slowdown in EU15 since the '90s has reversed what was once thought as a long-term pattern of convergence[1].

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. Siegel and Griliches, 1992; Oliner and Sichel, 1994; 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 also Timmer *et al.,* 2003; Corrado *et al.,* 2007; van Ark *et al.*, 2008; McMorrow *et al.*, 2009; Timmer *et al.,* 2010).

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; Gordon, 2000; Jorgenson and Stiroh, 2000; Stiroh, 2002; Turner and Boulhol, 2008; Wilson, 2009). 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 EU has persistently invested around the 60% of the US economy all over the last two decades as far as the total private expenditures in R&D are concerned (see Fig.1).

INSERT FIGURE 1

[1] For updated statistics, see the OECD Statistical Extracts: *http://stats.oecd.org*.

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 Commission, 2002; European Council, 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, 2010a).

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 manufacturing 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,

[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.

2007), that is a structural difficulty of European firms in achieving productivity gains, independently from the sectors considered.

This paper is pursuing these aims through an empirical analysis based on a unique longitudinal database comprising comparable samples of EU and US companies for a total of 1,809 firms, investigated over the period 1990-2008. The rest of the paper is organised as follows: Section 2 summarises the previous microeconometric evidence on the subject; Section 3 outlines how the dataset was constructed and the empirical methodology used to pursue the analysis; Section 4 discusses results and robustness checks, while the final Section 5 concludes and puts forward some policy implications.

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 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 and – more recent - Hall *et al.*, 2009)[3].

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; Winter, 1984; 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, singling

[3] 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; 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.

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. 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 for the high-tech firms, while for the remaining firms the R&D elasticity resulted either not being significant or being significantly lower. Los and Verspagen (2000) found - for a sample of US manufacturing firms - that the average elasticity of the R&D investment to company productivity was 0.014; however, when they run the same analysis for the high-tech sectors only, the elasticity increased to a range spanning from 0.04 to 0.1.

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 (see also Ortega-Argilés *et al.*, 2011).

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[4].

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 Conte and Vivarelli, 2005; Parisi *et al.*, 2006). If such is the case, in traditional low-tech sectors – which are focusing on process

[4] 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. More 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).

innovation – productivity gains might be much more related to capital accumulation rather than to R&D expenditures[5].

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 (see also Kumbhakar *et al.*, 2012). 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

Previous literature has been partly limited by the extreme difficulty to obtain reliable and comparable micro datasets across countries; one of the novelties of this paper is the unique longitudinal database used in the following empirical analysis. More specifically, the microdata used in this study were provided by the JRC–IPTS (Joint Research Centre-Institute for Prospective Technological Studies, Sevilla) of the European Commission. The information provided only concerns large and well established 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[6].

Available data includes:

- Company identification, name and address, industry sector (Global Industry Classification Standard (GICS) that can be translated in the standard SIC classification);

[5] 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.

[6] The original data source being the Compustat Global dataset provided by Standard&Poor's. Compustat collects data on the major quoted companies in the world and, as a consequence, is selecting the main actors as far as corporate R&D is concerned. Indeed, the firms included in our final sample account for the 73 % of US corporate R&D in 2007 and for the 54 % of EU corporate R&D.

- 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. Since R&D measurement follows different accounting practices in different countries over the world, the original data collector (Compustat-Standard&Poor's) has been very stringent in defining and homogenizing what can be considered as corporate R&D. In particular, the collected item represents "all costs incurred during the year that relate to the development of new products and services" (Compustat Research Insight North America Data Guide, p. 264). It is important to notice that this amount is "only the company's contribution" (*ibidem*) and excludes amortization and depreciation of previous investments, so being a good measure of current in-house R&D expenditures[7]. On the whole, the adopted definition of R&D is quite restrictive, is homogeneous across all the considered countries 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.

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 US 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.

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:

[7] 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.

physical capital, labour and knowledge capital (see Hall and Mairesse, 1995, formulas 1-2-3, pp. 268-69)[8].

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

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)[9].

Specification (1) was estimated through different estimation techniques. Firstly, pooled ordinary least squared (POLS) regressions were run to provide 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

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

[9] From a preliminary correlation analysis, some evidence of the expected positive impacts of both K/E and C/E upon VA/E emerges (ρ equal to 0.451 and 0.278 respectively). 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.

of four batteries of dummies, namely country (19 countries), time (19 years), sector (52 two-digit SIC-sectors) and sector by time (773 interactions)[10] 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 additional outcomes, where both individual (randomized) effects are taken into account together with the possibility to retain all the entire batteries of dummies. The disadvantage of the RE methodology is that it provides inconsistent estimators if omitted factors not included in (1) are correlated with the included regressors.

As standard in the microeconometric literature, the FE specification was tested against the alternative RE specification through the Hausman test. According to the outcomes of the test reported in the following Tables 2 to 5, in all the investigated cases the FE estimates turned out to be preferable to the RE ones. Therefore, Tables 2 to 5 report the preliminary POLS outcomes and the results from the preferred FE specification[11].

Table 1 reports the means and standard deviations of the four relevant variables in specification (1)[12]. As can be seen, our sample comprises very large and established corporations, with an average employment of more than 11,000 employees. We will refer to Table 1 – when appropriate – in the following Section 4 that is devoted to discuss the econometric results.

INSERT TABLE 1

[10] Sector by time effects were added to fully take into account the possible impact of idiosyncratic shocks; their number does not amount to 988 because of empty cells.

[11] However, the RE estimates (available from the authors upon request) turned out to be highly consistent with the FE ones.

[12] When referring to the EU, the following tables are based on the observations relative to the 18 countries listed in table A.1 in the Appendix.

4. Econometric analysis

4.1 Main results

From Table 1 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 2 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 the R&D stock on productivity with an elasticity ranging from 0.089 to 0.229, 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 0.126; together with the intangible R&D investment, capital formation – embodying vintages of new technologies – emerges as a still important driver of productivity growth.

Turning our attention to the main aim of this study, the hypothesis to investigate 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 2, 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 two estimation techniques consistently provide European elasticities equal to about 60% of their US counterparts. Focusing on the key fixed-effects (FE) specification, the US/EU gap is obvious and statistically significant, as reported in the last column of Table 2. 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 structural gap that European firms and European policy have to deal with.

INSERT TABLE 2

As far as the productivity impact of the physical capital is concerned, POLS and FE estimates tell us different stories in terms of the US-EU comparison. However, if we rely on the more reliable methodology controlling for the unobservables (FE), it appears that the US reveals an advantage similar to the one that emerged for the intangible R&D investments[13]. Therefore, US firms resulted in being more able to get productivity gains both from their R&D and their physical capital investments.

As discussed in Section 2, previous literature 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 impact 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.

Table 3 displays the US/EU comparison with regard to the manufacturing and service sectors separately. As is obvious, the European delay is fully confirmed: as it was the case for the whole economy, in the manufacturing sectors (first panel of Table 3) the FE relevant US coefficients are significantly larger that their European counterparts. However, focusing on the key estimates, the R&D gap turns out to be statistically significant (0.078 *vs* 0.052 with a significant difference), while the capital gap does not pass the significance threshold (see the last column of Table 3).

The second panel of Table 3, focusing on the service sectors, tells us a similar story, confirming the US advantage both in terms of R&D and capital elasticities (in this case, both the gaps turn out to be statistically significant)[14].

INSERT TABLE 3

[13] Here again, the t-test on the significance of the difference between the US and the EU fixed-effects coefficients turns out to be 99% significant (2.95***).

[14] 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 both the FE and POLS estimates), while in all the other regressions (focusing our attention on the most reliable FE 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).

Hence, at this stage, we can conclude that both US manufacturing and US service firms are more able to translate their R&D investments into productivity increases, while the efficiency gap in terms of physical capital seems to be clearly confirmed only in the service sectors. Therefore, the transatlantic productivity divide can be explained not only by a lower level of corporate R&D investment[15], but also by a lower capacity to translate R&D into productivity gains, and this seems to be obvious both within manufacturing and within services.

Table 4 displays the results concerning the manufacturing firms only, 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.

INSERT TABLE 4

As far as the high-tech sectors are concerned, all the coefficients are positive, fully significant and within the expected magnitude ranges[16]; however, focusing on the more reliable FE estimates, the US coefficients are larger than the corresponding European ones. Not surprisingly, in the high-tech manufacturing the European disadvantage is far less obvious, at least with regard to the key FE outcomes (0.069 *vs* 0.065, with a non-significant differential). The fact that in the high-tech manufacturing European companies manage to partially fill the gap with their American counterparts is an outcome confirming the role of the industrial structure in explaining (part of) the aggregate transatlantic productivity gap.

However, with regard to the rest of the manufacturing sectors (which constitute the bulk of European economies), US firms are clearly regaining their leadership in the impact of the R&D stock (from the FE estimates we get a 99% significant 0.060 coefficient in the US case *vs* a 90% significant 0.035 coefficient in Europe[17]). Interestingly enough and in contrast with the previous estimations, embodied technological change seems instead to play a more relevant role in the European firms (0.093 in the EU *vs* 0.063 in the US, with a 99% significant differential). On the whole, US companies are leading in terms of the R&D effect regardless of the sectors, while embodied technological change appears the most effective in the US high-tech manufacturing sectors and in the EU non-high-tech manufacturing sectors.

[15] Looking at Table 1, the European R&D 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.
[16] With the only exception of ln(C/E) in the European FE panel data estimation, turning out not significant.
[17] In this case, the t-test on the difference fails to be significant mainly as a consequence of the non-significance of one of the two compared coefficients and cannot be interpreted as an evidence against the emergence of a clear gap between the US and the EU.

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

Within the US, high-tech manufacturing sectors display larger productivity elasticities both with regard to the R&D and the capital investment (all the four 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 ability 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, while the reverse happens as far as physical capital is concerned (the FE estimate in the high-tech sectors is even not significant). This picture largely confirms what has emerged from a previous work based on different (UK-DTI) European microdata (Ortega-Argilés *et al.*, 2010). In that study, the R&D coefficient was found to increase 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 into productivity gains is detected across all the sectors of the economy, with the partial exception of the high-tech manufacturing sectors where the EU shows a catching-up capacity. Turning our attention to capital formation, the US advantage is clear in the service sectors, while it fades away in manufacturing where – in the non-high tech sectors – the embodied technological change turns out to be more effective in the EU.

4.2 Robustness checks

In this subsection, a number of possible concerns about the adopted specification and the results discussed in the previous section are addressed.

Firstly, one can cast some doubts about specification (1) where contemporaneous values of the relevant variables are considered; in particular – since investment decisions about knowledge and physical capital are jointly taken by firms – possible problems of simultaneity and endogeneity may arise. Although the use of stock variables may mitigate this possible problem in a considerable way (since what are considered are not the contemporaneous investment decisions on flows but rather the cumulated stocks), the likely presence of path-dependence and persistence in the investment decisions suggests to control for endogeneity to be on a safer side.

With this purpose in mind, Table 5 shows, in its first panel, the results of a first robustness check consisting in replicating the estimates of (1) with the stock of physical capital lagged one period, in order to split the two main investment decisions. As can be seen, results remain very stable, both in terms of significance and order of magnitude of the relevant coefficients and – more important – in terms of the US/EU comparison. For space reasons, we only report the outcome from the regressions over the whole sample, but the same high degree of consistency have been found with regard to the four sectoral specifications[18].

Secondly, we tried to control for the possible important role of spillovers. As commonly done in the literature (see Bernstein and Nadiri, 1989; Los and Verspagen, 2000; Medda and Piga, 2007), we proxied intra-sectoral spillovers[19] through total sectoral R&D expenditures. We obtained the relevant national/sectoral figures from the OECD-ANBERD database, which is the only official source to provide reliable and comparable sectoral data concerning company R&D activities. This statistical source is updated up to 2008 for most countries; for the remaining (namely Denmark updated to 2006; France, Greece, the Netherlands and Sweden, updated to 2007) we extrapolated figures for the last years using the compounded average rates of change over the previous four-year period. Then flows were transformed into sectoral stocks per employee using the same procedures described in the Appendix (fifth step). Unfortunately, the ISIC sectoral classification adopted by the OECD is more aggregate than the SIC classification adopted in our study; this means that our additional spillover variable is affected by a non-negligible measurement error, being the same value repeated for all the SIC subsectors belonging to the same ISIC sector.

As can be seen from the second panel of Table 5[20], the inclusion of the additional spillover regressor leaves our main results virtually unchanged[21]. Contrary to the expectations, sectoral spillovers seem to negatively affect firms' productivity, although the relevant coefficient becomes non-significant once the US and the EU data are split[22].

INSERT TABLE 5

Thirdly, one may wonder how much of the estimated difference between US and EU productivity is due to the average levels of the key regressor (notably corporate R&D) and how

[18] Results available from the authors upon request.

[19] With our data we have no way of controlling for inter-sectoral spillovers; however, given our relatively low level of sectoral disaggregation (52 two-digit sectors), it can legitimately be assumed that most spillovers are intra-sectoral.

[20] In replicating our aggregate and sectoral regressions, we were forced to drop the interaction dummies, since their inclusion, together with the new sectoral spillover values, rendered collinearity unacceptable in the US case.

[21] This is also the case for the four batteries of sectoral estimates (results available upon request).

[22] However, the unexpected result for the whole sample may be due to the measurement error discussed above.

much is due to the difference in the estimated R&D coefficients in the US and the EU respectively. Obviously enough, our conclusion that European economies not only invest *less in R&D,* but also *get less* from their R&D investment would be proved if and only if a substantial portion of the productivity gap is explained by the difference in the estimated R&D coefficients.

With this aim in mind, we put forward a decomposition analysis based on the methodology developed by Blinder (1973) and Oaxaca (1973) and on the recent computational devices put forward by Jann (2008). This decomposition splits the estimated differential (in our case the productivity gap, equal to about 24%[23]) between two groups (in our case the US and the EU) into a part that is explained by the difference in the level of the observed characteristics and a part attributable to the difference in the estimated coefficients (a third residual part being the interaction of the two effects, see Table 6).

INSERT TABLE 6

As can be seen, an overwhelming contribution to the revealed US-EU productivity differential can be ascribed to the R&D coefficient, confirming that the transatlantic productivity divide can be explained not only by a lower level of corporate R&D stocks in Europe, but also by a lower capacity of European companies to translate R&D expenditures into productivity gains.

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, on aggregate we find robust evidence of a positive and significant impact of the R&D stock on productivity. However, although uniformly positive and statistically significant, the R&D coefficients for the US firms turn out to be consistently and

[23] This productivity differential (0.2378) can be computed using the whole sample estimations reported in Table 2; the threefold Oaxaca decomposition has been applied to this specification.

significantly larger than the corresponding coefficients for the European firms. Indeed, the whole sample estimations provide European elasticities equal to about 60% of their US counterparts. We interpret this unambiguous outcome 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 structural gap 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 have differentiated the US/EU comparative empirical exercise by sectors. It results that both US manufacturing and US service firms are more able to translate their R&D investments into productivity increases. Within manufacturing, the US advantage is obvious in the non high-tech manufacturing sectors (which constitute the bulk of the European manufacturing structure), while in the high-tech ones, some evidence of a European catching-up emerges. On the whole, the transatlantic productivity divide can be explained not only by a lower level of corporate R&D investment by European companies, but also by a lower capacity to translate R&D into productivity gains across all sectors of the economy.

With regard to capital formation, the US advantage turns out to be obvious and significant on the aggregate and in the service sectors, while it fades away once only manufacturing is taken into account; in particular, while US companies still appear to be more effective in translating investments into productivity gains in the high-tech sectors, the reverse happens in the non-high-tech manufacturing sectors.

Although necessarily tentative, some policy advices and implications can be derived from the empirical results obtained in this study, in order to contribute to the debate on the importance of increasing European productivity and therefore underpinning the competitiveness of a "knowledge based" European economy.

Firstly, the results obtained show that the US economy is uniformly superior in getting productivity advantages from investments in R&D activities[24]. 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.

[24] With the partial exception of the high-tech manufacturing companies.

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, with the notable exception of the traditional manufacturing sectors where the opposite is detected: embodied technological change appears crucial in increasing productivity within European non-high-tech firms. Therefore, a European innovation policy aiming to increase productivity in the medium/low-tech manufacturing sectors should support overall capital formation at least as much as R&D expenditures.

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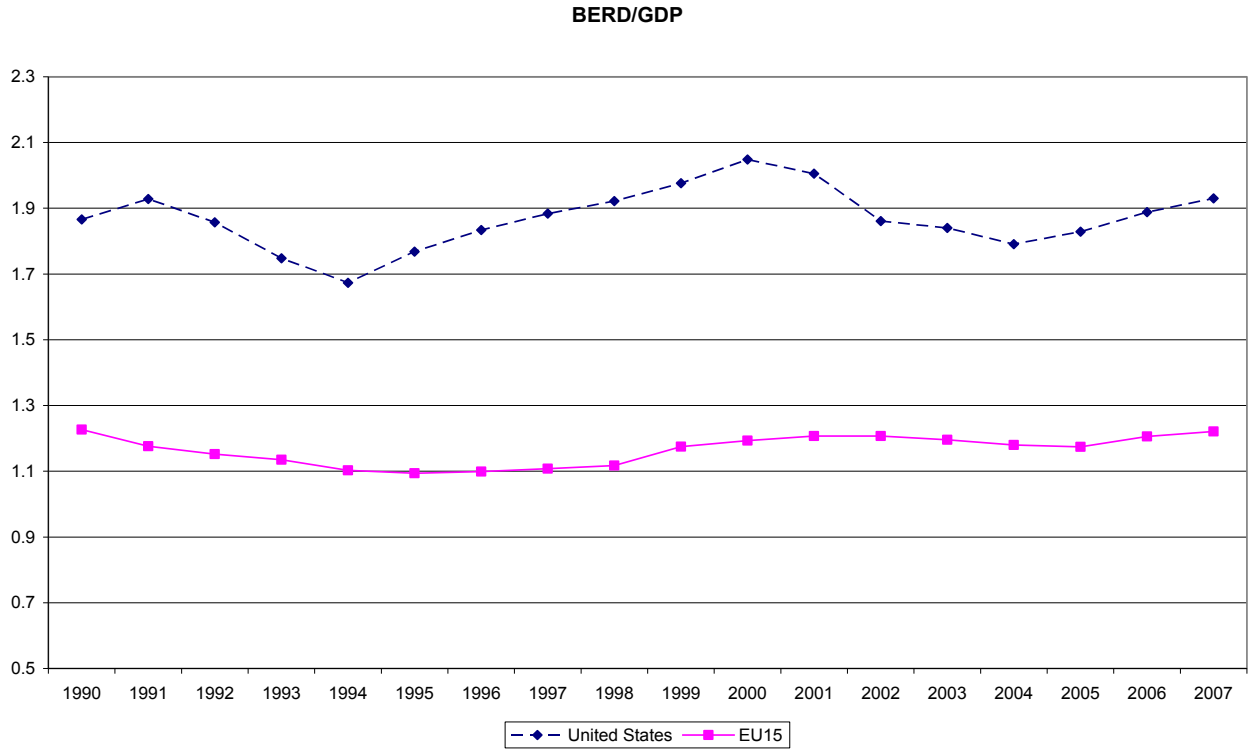
Figure 1: Private R&D (BERD)/GDP in the US and in the EU15: 1990-2007



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

Table 1: Descriptive statistics (in PPP-2000 US $)

Sample (N. of observations)	*VA/E*		*K/E*		*C/E*		*E*	
	Mean	**Standard deviation**	**Mean**	**Standard deviation**	**Mean**	**Standard deviation**	**Mean**	**Standard deviation**
Whole sample (16,079)	102.781	91.008	86.076	105.899	81.026	80.542	11,204	35,302
US (12,605)	108.793	96.475	93.467	110.310	81.567	79.633	9,124	31,064
EU (3,474)	80.965	62.912	59.267	82.701	79.065	83.742	18,752	46,846
Manufacturing (12,876)	99.565	92.914	82.470	106.904	84.886	81.585	11,951	35,250
High-tech manufacturing sectors (7,693)	112.038	108.275	110.748	119.007	78.142	76.709	8,179	23,264
Other manufacturing sectors (5,183)	81.050	58.938	40.497	66.507	94.895	87.380	17,551	47,237
Services (3,203)	115.709	81.648	100.574	100.478	65.512	74.222	8,199	35,356
US Manufacturing (10,214)	104.18	98.355	88.593	110.932	84.785	81.171	9,714	31,116
EU Manufacturing (2,662)	81.324	65.678	58.974	85.842	85.272	83.167	20,535	46,937
US High-tech manufacturing (6,462)	116.125	112.525	114.977	121.210	79.272	77.609	7,298	21,294
EU High-tech manufacturing (1,231)	90.583	79.089	88.545	103.958	72.208	71.535	12,803	31,259
US Other manufacturing sectors (3,752)	83.983	61.733	70.251	43.153	94.279	86.153	13,876	42,752
EU Other manufacturing sectors (1,431)	73.359	50.093	33.536	54.921	96.510	90.532	27,187	56,244
US Services (2,391)	127.907	86.000	114.286	105.119	67.819	71.089	6,600	30,718
EU Services (812)	79.789	52.858	60.199	71.483	58.718	82.433	12,908	46,096

Note: The number of observations is reported in brackets

Table 2: Whole sample, US vs. EU

	Whole sample		US		EU		T-test on US vs. EU coefficient differences
	POLS	FE	POLS	FE	POLS	FE	
Log(R&D stock per employee)	0.207***	0.089***	0.229***	0.098***	0.150***	0.058***	3.68***
	(0.006)	(0.007)	(0.007)	(0.008)	(0.014)	(0.011)	(0.000)
Log(Physical stock per employee)	0.114***	0.093***	0.104***	0.100***	0.126***	0.053***	2.95***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.013)	(0.011)	(0.000)
Log(Employees)	0.032***	-0.049***	0.037***	-0.034***	0.017**	-0.162***	3.92***
	(0.003)	(0.007)	(0.004)	(0.008)	(0.008)	(0.017)	(0.000)
Constant	2.413***	3.529***	2.620***	3.523***	-1.030***	3.744***	-2.54**
	(0.124)	(0.038)	(0.119)	(0.036)	(0.378)	(0.079)	(0.011)
Wald time-dummies	0.9	11.4***	1.2	9.6***	1.2	2.4***	
(p-value)	(0.589)	(0.000)	(0.288)	(0.000)	(0.260)	(0.001)	
Wald country-dummies	40.7***	-	-	-	11.8***	-	
(p-value)	(0.000)				(0.000)		
Wald sectoral-dummies	1,201.2***	-	6,808.2***	-	159.5***	-	
(p-value)	(0.000)		(0.000)		(0.000)		
Wald time*sectoral dummies	557.5***	-	144.1***	-	2,202.6***	-	
(p-value)	(0.000)		(0.000)		(0.000)		
Hausman test (p-value)#	52.14 (0.000)		53.00 (0.000)		71.94 (0.000)		
N. of observations	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 (18), Country-dummies (18), Sectoral-dummies (51) and Time-Sectoral dummies interacted (772). Wald tests of joint significance are reported

Table 3: Manufacturing and Services sectors

	Whole sample Manufacturing		US Manufacturing		EU Manufacturing		T-test on US vs. EU coefficient differences
	POLS	FE	POLS	FE	POLS	FE	
Log(R&D stock per employee)	0.211***	0.073***	0.230***	0.078***	0.149***	0.052***	2.29**
	(0.007)	(0.008)	(0.007)	(0.009)	(0.017)	(0.013)	(0.020)
Log(Physical stock per employee)	0.109***	0.086***	0.098***	0.089***	0.135***	0.059***	0.48
	(0.007)	(0.007)	(0.008)	(0.008)	(0.016)	(0.013)	(0.620)
Log(Employees)	0.026***	-0.078***	0.028***	-0.069***	0.028***	-0.166***	2.65***
	(0.004)	(0.009)	(0.004)	(0.010)	(0.009)	(0.022)	(0.000)
Constant	1.273***	3.559***	2.577***	3.560***	2.132***	3.769***	-2.06**
	(0.481)	(0.036)	(0.122)	(0.040)	(0.192)	(0.093)	(0.039)
Hausman test (p-value) #	45.89 (0.000)		40.18 (0.000)		45.30 (0.000)		
N. of observations	12,876		10,214		2,662		
N. of firms	1,383		914		469		
	Whole sample Services		**US Services**		**EU Services**		
	POLS	FE	POLS	FE	POLS	FE	
Log(R&D stock per employee)	0.184***	0.114***	0.215***	0.125***	0.141***	0.086***	2.27**
	(0.014)	(0.014)	(0.018)	(0.017)	(0.027)	(0.024)	(0.025)
Log(Physical stock per employee)	0.142***	0.115***	0.146***	0.140***	0.115***	0.045**	2.91***
	(0.014)	(0.014)	(0.018)	(0.016)	(0.027)	(0.022)	(0.000)
Log(Employees)	0.066***	0.021	0.088***	0.051***	-0.014	-0.141***	5.66***
	(0.009)	(0.014)	(0.010)	(0.016)	(0.017)	(0.030)	(0.000)
Constant	-1.022***	3.744***	2.967***	3.755***	-1.265***	3.623***	0.64
	(0.394)	(0.085)	(0.459)	(0.093)	(0.392)	(0.185)	(0.522)
Hausman test (p-value) #	19.29 (0.000)		31.01 (0.000)		28.22 (0.000)		
N. of observations	3,203		2,931		812		
N. of firms	426		256		170		

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

- POLS have been controlled for time, country, sectoral and time-sectoral dummies, while FE have been controlled just for time-dummies. The Wald test for each set of dummies provides evidence that dummies are jointly significant (1%), with the exception of time-dummies and country-dummies in POLS-whole manufacturing, time-dummies in POLS-US manufacturing and time-dummies in POLS-EU manufacturing.

- The outcomes of the t-tests on the significance of the differences between the US *vs.* the EU (FE coefficients) are reported in the last column (p-values in brackets).

The Hausman statistic results correspond to the model specification comparing FE and Random Effects (not reported in the table) without dummy sets.

Table 4: High-tech manufacturing and Other manufacturing sectors

	Whole sample High-tech manufacturing		US High-tech manufacturing		EU High-tech manufacturing		T-test on US vs. EU coefficient differences
	POLS	FE	POLS	FE	POLS	FE	
Log(R&D stock per employee)	0.238***	0.070***	0.253***	0.069***	0.134***	0.065***	1.02
	(0.011)	(0.012)	(0.010)	(0.013)	(0.026)	(0.020)	(0.321)
Log(Physical stock per employee)	0.118***	0.092***	0.112***	0.101***	0.172***	0.029	1.96**
	(0.011)	(0.010)	(0.012)	(0.011)	(0.033)	(0.022)	(0.050)
Log(Employees)	0.042***	-0.086***	0.041***	-0.081***	0.054***	-0.155***	2.06**
	(0.005)	(0.012)	(0.005)	(0.013)	(0.014)	(0.033)	(0.041)
Constant	2.911***	3.514***	3.049***	3.525***	2.853***	3.499***	0.15
	(0.118)	(0.051)	(0.114)	(0.055)	(0.525)	(0.166)	(0.881)
Hausman test (p-value)[#]	37.73 (0.000)		34.77 (0.000)		15.62 (0.000)		
N. of observations	7,693		6,462		1,231		
N. of firms	804		591		213		
	Whole sample Other manufacturing		**US Other manufacturing**		**EU Other manufacturing**		
	POLS	FE	POLS	FE	POLS	FE	
Log(R&D stock per employee)	0.161***	0.053***	0.178***	0.060***	0.116***	0.035*	1.31
	(0.008)	(0.009)	(0.009)	(0.010)	(0.018)	(0.015)	(0.185)
Log(Physical stock per employee)	0.092***	0.070***	0.073***	0.063***	0.138***	0.093***	-2.03**
	(0.008)	(0.008)	(0.009)	(0.012)	(0.018)	(0.016)	(0.042)
Log(Employees)	-0.010	-0.107***	-0.006	-0.087***	-0.012	-0.209***	3.23***
	(0.006)	(0.015)	(0.007)	(0.015)	(0.011)	(0.028)	(0.000)
Constant	0.502***	3.758***	2.604***	3.763***	1.873***	4.006***	-1.45
	(0.165)	(0.049)	(0.625)	(0.054)	(0.297)	(0.159)	(0.147)
Hausman test (p-value)[#]	28.68 (0.000)		14.83 (0.000)		43.70 (0.000)		
N. of observations	5,183		3,752		1,431		
N. of firms	579		323		256		

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

- POLS have been controlled for time, country, sectoral and time-sectoral dummies, while FE have been controlled just for time-dummies. The Wald test for each set of dummies provides evidence that dummies are jointly significant (1%), with the exception of time-dummies and time-sectoral dummies in POLS-whole high-tech manuf., time-dummies and time-sectoral dummies in POLS-US high-tech manuf., time-dummies in POLS-EU high-tech manuf. and time-dummies in FE-EU other manuf.

- The outcomes of the t-tests on the significance of the differences between the US *vs.* the EU (FE coefficients) are reported in the last column (p-values in brackets).

[#] The Hausman statistic results correspond to the model specification comparing FE and Random Effects (not reported in the table) without dummy sets.

Table 5: Whole sample, US vs. EU – robustness checks

	Whole sample		US		EU		T-test on US vs. EU coefficient differences
	POLS	FE	POLS	FE	POLS	FE	
Log(R&D stock per employee)	0.246***	0.098***	0.263***	0.111***	0.182***	0.043***	3.88***
	(0.007)	(0.008)	(0.007)	(0.009)	(0.020)	(0.015)	(0.000)
Log(Physical stock per employee -1)	0.084***	0.042***	0.077***	0.044***	0.095***	0.025**	1.46
	(0.006)	(0.006)	(0.007)	(0.007)	(0.014)	(0.011)	(0.163)
Log(Employees)	0.032***	-0.085***	0.035***	-0.073***	0.021**	-0.188***	5.24***
	(0.004)	(0.008)	(0.004)	(0.009)	(0.009)	(0.020)	(0.000)
Constant	2.148***	3.704***	3.816***	3.688***	4.027***	3.992***	3.29***
	(0.120)	(0.035)	(0.098)	(0.038)	(0.145)	(0.084)	(0.000)
Hausman test (p-value) #	42.18 (0.000)		63.25 (0.000)		62.98 (0.000)		
N. of observations	13,987		11,311		2,676		
N. of firms	1,678		1,136		542		
	Whole sample		**US**		**EU**		
	POLS	**FE**	**POLS**	**FE**	**POLS**	**FE**	
Log(R&D stock per employee)	0.205***	0.089***	0.228***	0.098***	0.143***	0.058***	2.94***
	(0.006)	(0.007)	(0.007)	(0.008)	(0.013)	(0.011)	(0.000)
Log(Physical stock per employee)	0.115***	0.093***	0.106***	0.100***	0.125***	0.053***	3.60***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.012)	(0.011)	(0.000)
Log(Spillover R&D stock per employee)	-0.026**	-0.036***	0.034	-0.058	0.013	-0.021*	-0.75
	(0.011)	(0.013)	(0.065)	(0.048)	(0.007)	(0.011)	(0.452)
Log(Employees)	0.031***	-0.049***	0.036***	-0.034***	0.015**	-0.164***	6.91***
	(0.003)	(0.007)	(0.004)	(0.008)	(0.007)	(0.017)	(0.000)
Constant	1.813***	3.682***	2.037***	3.783***	1.873***	3.804***	-0.24
	(0.492)	(0.063)	(0.541)	(0.022)	(0.297)	(0.085)	(0.810)
Hausman test (p-value) #	202.18 (0.000)		173.76 (0.000)		69.93 (0.000)		
N. of observations	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%.

- POLS have been controlled for time, country and sectoral dummies in the second panel as well as for time-sectoral dummies in the first panel, while FE have been controlled just for time-dummies. The Wald test for each set of dummies provides evidence that dummies are jointly significant (at 1%), with the exception of time-dummies in the POLS in the first robustness check.
- The outcomes of the t-tests on the significance of the differences between the US *vs.* the EU (FE coefficients) are reported in the last column (p-values in brackets).

The Hausman statistic results correspond to the model specification comparing FE and Random Effects (not reported in the table) without dummy set.

Table 6: Blinder-Oaxaca decomposition

	Full model
Difference in productivity between US and EU	0.2378
Endowments	*0.0908 (38.2 %)*
Log(R&D stock per employee)	.0757
Log(Physical stock per employee)	.0177
Log(Employees)	-.0026
Coefficients	*0.0916 (38.5 %)*
Log(R&D stock per employee)	.4092
Log(Physical stock per employee)	-.1843
Log(Employees)	.0191
Constant	-.1524
Interaction	*0.0554 (23.3 %)*
Log(R&D stock per employee)	.0724
Log(Physical stock per employee)	-.0059
Log(Employees)	-.0111

APPENDIX: The construction of the dataset

First step: data extraction

All data provided by Compustat-Standard&Poor's are taken from the consolidated balance sheets at the firm's headquarters.
In guiding the extraction of the data from what provided[25], 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 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 expenditures;
    - 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)[26]. 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

[25] All data are taken from the consolidated balance sheets at the firm's headquarter.
[26] 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).

(Denmark, Estonia and the UK) were excluded as well[27]; while the 58 European companies reporting in US dollars were kept as such.

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[28]:

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

where R&D = R&D expenditures

(A.2) $C_{t0} = \dfrac{I_{t0}}{(g+\delta)}$ 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, both because companies have entered the original Compustat database gradually over time and because of missing information due to incompleteness of the collected balance sheets data (for instance, some firms are missing in 2008 due to postponed accounting registration procedures, while for some firms some key information are available only in a subset of the considered years). As a consequence, only a

[27] 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.

[28] The standard OECD classification was taken (see Hatzichronoglou, 1997) and extended 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.

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 contrast, sample selection due to firms' exit does not seem to be a problem in our database: indeed, the included firms are very large and well established companies and – once entered the database – are tracked until the final period[29].

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 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[30]. 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[31].

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; Hall, 2007 and Hall *et al*., 2009 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.

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[29] In fact, in the year 2007 – displaying the last fully updated balance sheet data strings - 1796 companies are recorded, out of 1,809.

[30] This means that for firms characterized 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 assign – in the econometric estimates – a single fixed or random effect to all of the spans belonging to the same company history.

[31] 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,...".

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[32].

Once computed according to the formulas (A.1) and (A.2) and the adopted g and δ rates, the resulting stocks were checked and negative ones were dropped[33]. Moreover, we excluded a minority of unreliable data such as those indicating negative sales and cost of goods equal to zero.

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. A.1 and A.2).

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[34]: 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:

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

with $\overline{Y}$ 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[35].

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

[32] These depreciation rates were chosen in order to be consistent with previous literature (see above); however, Hall *et al*., 2009 (Section 3.2) show that the R&D elasticity is not sensitive to the choice of the depreciation rate. Indeed, our results turned out to be robust to marginal changes in the adopted depreciation rates for both R&D and physical capital figures (results available upon request).

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

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

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

- test whether the minimum value is an outlier: $G = \frac{\overline{Y} - Y_{\min}}{s}$ with Ymin denoting the minimum value;

- test whether the maximum value is an outlier: $G = \frac{Y_{\max} - \overline{Y}}{s}$ with Ymax denoting the maximum value.

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

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

Seventh step: the final sample composition

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

Tab. A.1: Geographical distribution (whole sample)

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**

Table A.2 reports the distribution of the retained firms and observations across sectors.

SIC Classification	WHOLE SAMPLE N. of companies	%	US N. of companies	%	EU N. of companies	%
10: Metal mining	8	0.44	1	0.09	7	1.10
12: Coal mining	1	0.06	1	0.09	0	0.00
13: Gas extraction	9	0.50	3	0.26	6	0.94
14: Quarrying of non-metallic minerals	4	0.22	4	0.34	0	0.00
15: Building construction	4	0.22	0	0.00	4	0.63
16: Heavy construction	9	0.50	4	0.34	5	0.78
20: Food	34	1.88	16	1.37	18	2.82
21: Tobacco products	7	0.39	5	0.43	2	0.31
22: Textile mill products	6	0.33	3	0.26	3	0.47
23: Apparel made from fabrics	4	0.22	0	0.00	4	0.63
24: Lumber and wood products	4	0.22	2	0.17	2	0.31
25: Furniture and fixtures	13	0.72	8	0.68	5	0.78
26: Paper	24	1.33	16	1.37	8	1.25
27: Printing	7	0.39	5	0.43	2	0.31
28: Chemicals (without 283)	82	4.53	45	3.85	37	5.79
283: Drugs	176	9.73	118	10.09	58	9.08
29: Petroleum refining	9	0.50	4	0.34	5	0.78
30: Rubber and miscellaneous plastics products	32	1.77	20	1.71	12	1.88
31: Leather	6	0.33	3	0.26	3	0.47
32: Stone, clay, glass	21	1.16	9	0.77	12	1.88
33: Primary metal	35	1.93	18	1.54	17	2.66
34: Fabricated metal products	43	2.38	26	2.22	17	2.66
35: Industrial and commercial machinery (without 357)	137	7.57	76	6.50	61	9.55
357: Computer and office equipment	87	4.81	72	6.15	15	2.35
36: Electronic and other electrical equipment (without 366)	216	11.94	162	13.85	54	8.45
366: Communications equipment	85	4.70	64	5.47	21	3.29
37: Transportation equipment (without 372-376)	59	3.26	39	3.33	20	3.13
372-376: Aircrafts to space vehicles	21	1.16	14	1.20	7	1.10
38: Measuring, analyzing and controlling instruments	219	12.11	161	13.76	58	9.08
39: Miscellaneous manufacturing industries	21	1.16	15	1.28	6	0.94
44: Water transportation	2	0.11	0	0.00	2	0.31
45: Transportation by air	12	0.66	0	0.00	12	1.88
47: Transportation services	2	0.11	2	0.17	0	0.00
48: Communications	31	1.71	14	1.20	17	2.66
49: Electric, gas, and sanitary services	12	0.66	1	0.09	11	1.72
50: Wholesale trade-durable goods	7	0.39	2	0.17	5	0.78
51: Wholesale trade-non-durable goods	7	0.39	6	0.51	1	0.16
52: Building materials	10	0.55	0	0.00	10	1.56
54: Food stores	1	0.06	1	0.09	0	0.00

58: Eating and drinking places	2	0.11	2	0.17	0	0.00
59: Miscellaneous retail	7	0.39	5	0.43	2	0.31
62: Security and commodity brokers	1	0.06	1	0.09	0	0.00
67: Holding and other investment offices	7	0.39	7	0.60	0	0.00
70: Hotels	1	0.06	1	0.09	0	0.00
73: Business services	278	15.37	190	16.24	88	13.77
78: Motion pictures	1	0.06	1	0.09	0	0.00
79: Amusement and recreation services	5	0.28	1	0.09	4	0.63
80: Health services	10	0.55	7	0.60	3	0.47
82: Educational services	1	0.06	1	0.09	0	0.00
87: Engineering, accounting, research	25	1.38	12	1.03	13	2.03
89: Miscellaneous services	1	0.06	1	0.09	0	0.00
99: Non-classifiable establishments	3	0.39	1	0.26	2	0.63
TOTAL	1,809	100	1,170	100	639	100
MANUFACTURING	*1,383*	*76.45*	*914*	*78.12*	*469*	*73.40*
SERVICES	*426*	*23.55*	*256*	*21.88*	*170*	*26.60*
HIGH-TECH MANUFACTURING	*804*	*44.44*	*591*	*50.51*	*213*	*33.34*
OTHER MANUFACTURING	*579*	*32.01*	*323*	*27.61*	*256*	*40.06*