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R&D and Productivity in the US and the EU:
Sectoral Specificities and Differences in the Crisis

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ABSTRACT

Using data on the US and EU top R&D spenders from 2004 until 2012, this paper investigates the sources of the US/EU productivity gap. We find robust evidence that US firms have a higher capacity to translate R&D into productivity gains (especially in the high-tech macro sector), and this contributes to explaining the higher productivity of US firms. Conversely, EU firms are more likely to achieve productivity gains through capital-embodied technological change, at least in the medium- and low-tech macro sectors. Our results also show that the US/EU productivity gap has worsened during the crisis period, as the EU companies have been more affected by the economic crisis in their capacity to translate R&D investments into productivity. Based on these findings, we make a case for a learning-based and selective R&D funding, which, instead of purely aiming at stimulating higher R&D expenditures, works on improving the firms' capabilities to transform R&D into productivity gains.

Key words: R&D; productivity; economic crisis; US; EU
JEL codes: O33, O51, O52

1. Introduction

While productivity trends were broadly stable between the 1980s and the first half of the 1990s, both in Europe and the US, we can observe a substantial change since the second half of the 1990s. In particular, during the last two decades, there has been a widening productivity gap between European countries and the United States that has now reached considerable size. In addition, as a consequence of the great recession that followed the 2008/2009 global financial crisis, productivity has been curbed more obviously in Europe than in the US (OECD, 2015a, 2016 and 2017, see Fig.1). Indeed, OECD macroeconomic data (OECD, 2015b) report that in 2014 the labor productivity (measured as GDP per hour worked) in EU-28 was $ (2010 PPP) 46.6, meanwhile it was $ (2010 PPP) 63 in the US (see Fig.1).

As shown by Broadberry and O'Mahony (2004) and van Ark *et al.* (2008), the source of this widening gap has been a slowdown in the European productivity growth, implying that the post-WW2 European catch-up process has not only stopped but is actually now reversing. Even for the latest figures, this gap appears to be widening. The OECD data report an annual productivity growth rate (2014 *vs*. 2013) of 0.5% for the US as compared to 0.3% for the European Union (OECD, 2015b).

There is little consensus on causes of these trends, which is also due to the fact that most analyses refer to aggregate data. The literature has pointed out to different possible reasons probably jointly contributing to the widening gap, ranging from the different level of flexibility in labor markets (Gomez-Salvador *et al.,* 2006; Grimalda, 2016), the quality of human capital (Gu *et al*., 2002) or better North-American managerial practices (Bloom and Van Reenen, 2010; Bloom *et al*., 2012).

However, the main strand of the literature drew attention to the role of the differentials in the introduction and diffusion of new technologies between the two sides of the Atlantic (Oliner and Sichel, 2000; Daveri, 2002; Wilson, 2009; Bacchiocchi and Montobbio, 2010)[1]. In particular, there is a well-documented gap in the relative level of R&D spending, which may have played an important role in explaining the productivity gap (Rogers, 2010). Considering the EU-28, the BERD/GDP[2] ratio was 1.11% in 2002. It has remained almost constant until 2008 (1.14%), while slightly increasing in the following years up to 1.24% in 2012. Meanwhile, the US R&D intensity was 1.77% in 2002,

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[1] Andrews *et al.* (2015) underline how productivity growth of the globally most productive firms has remained robust in the 21st century, despite the slowdown in aggregate productivity. At the same time, the rising productivity gap between the global frontier and other firms raises key questions about why seemingly non-rival technologies do not diffuse to all firms. Their analysis reveals a highly uneven process of technological diffusion consistent with a model where global frontier technologies diffuse to laggards once they are adapted to country-specific circumstances by the most productive firms within each country (i.e. national frontier firms). This interpretation may also help to understand the persistent productivity gap between Europe and the US.
[2] BERD = Business Enterprise Expenditure on R&D.

reached 1.97% in 2008, slowed down in the following years to get back to 1.95% in 2012 (the latest available value, OECD, 2014).

On the one hand, some scholars have argued that the lower European R&D spending is mainly due to differences between industries (the so-called *structural composition effect)* and have provided evidence supporting their thesis. This structural composition effect arises because the R&D-intensive manufacturing and R&D-intensive service industries are under-represented in the European economy in comparison to the US (European Commission, 2007; Mathieu and van Pottelsberghe de la Potterie, 2008; Lindmark *et al.*, 2010; Ortega-Argilés and Brandsma, 2010). This view therefore treats the differences in R&D spending rather as an artifact of differences in industry composition.

On the other hand, other authors have stressed the so-called *intrinsic effect* and they have also provided convincing empirical evidence in support of their view. These authors pointed out that a general difficulty of European firms in investing in R&D and in achieving productivity gains can be detected. According to this view, EU firms *within* each industry are characterized by a lower R&D intensity in comparison with their US counterparts (Erken and van Es, 2007; Ortega-Argilés *et al*., 2010, 2011). In addition, Ortega-Argilés *et al*. (2014) argue that there is also a lower capacity to translate R&D investment into productivity gains. In a sense, European companies might be still affected by a sort of modern Solow's (1987) paradox, *i.e.* by a difficulty to translate their own investments in R&D into increases in productivity. In summary, there could be an issue both in the *level* and in the productivity *impact* of R&D spending within European firms, irrespective of their industry belonging.

However, much of the scientific and policy discussion seems to be focused on the level effect. European policy makers were very explicit that it is necessary to augment R&D investments to foster productivity and, therefore, to support the recovery of growth and jobs in a 'knowledge-based' economy (European Commission 2010a and 2010b). However, precisely knowing the mechanisms sustaining the productivity gap is crucial for policy-making. In particular, if there are differential abilities to translate R&D into productivity gains, the lower levels of R&D spending may be a rational response by the firms, because their expected pay-off is lower. This may imply that policies aiming purely at increasing R&D spending (namely, the EU 3% target in the R&D/GDP ratio is a prime example) may be not enough if policies are not simultaneously aiming at increasing the capabilities to make efficient use of R&D inputs.

Accounting for the role of these different explanations for the EU-US productivity gap requires the ability to control for industry composition in Europe and the US, as well as for R&D and productivity at the level of the firm. Most existing analyses of the European-US productivity gap have, however, made reference to aggregate data. We therefore propose an empirical analysis based

on a unique longitudinal database comprising comparable samples of European and US companies for a total of 1,112 top-R&D performing firms. Together with comparisons for the overall sample of firms, we will also split our analysis by two macro sectors (high-tech and medium- and low-tech), in order to better investigate the nature and source of the transatlantic productivity gap, with particular reference to the respective roles of the *structural* and the *intrinsic* effect. Moreover, the time-period available (2004-2012) also allows us to investigate the R&D-productivity dynamics before and after the recent worldwide economic crisis. Thus, our paper also sheds light on a particular critical period of the economic development in Europe, which has not been investigated by earlier studies.

The rest of the paper is organized as follows. Section 2 discusses the extant literature on the subject and states the hypotheses to be tested. Section 3 outlines how the dataset was constructed and presents the empirical methodology used to pursue the analysis. Section 4 discusses results, while the final section concludes and puts forward some policy implications.

2. Literature review and hypotheses

Back in 1979, Zvi Griliches started a prosperous empirical literature devoted to investigate the relationship between R&D and productivity (for a comprehensive survey, see Mohnen and Hall, 2013; for a very recent synthesis, based on a meta-regression analysis, of the available evidence on the subject, see Ugur *et al.,* 2016). Overall, this micro-econometric literature has provided robust evidence of a positive and significant impact of R&D on productivity at the firm level, with an elasticity ranging from 0.05 to 0.25[3]. Indeed, the consensus about the existence of a positive and significant impact of R&D on productivity remains strong across almost all studies and methodologies, even if comparable data in more countries are not common and results might be subject to discussion (Sterlacchini, 1989; Hall and Mairesse, 1995; Klette and Kortum, 2004; Loof and Heshmati, 2006; Heshmati and Kim, 2011; Ortega-Argiles *et al.*, 2011; Kumbhakar *et al*., 2012; Gkypali *et al.*, 2015).

This leads to our first baseline hypothesis:

H1. *R&D stocks positively affect firm productivity.*

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[3] As far as we know, the extant literature (see the discussion below, also quoting the magnitude of the estimated coefficients) found R&D/productivity elasticities within these boundaries. However, we cannot exclude different results from studies external to our knowledge.

However, when considering the structural dimension of an economic system, its industrial composition might affect the overall aggregate outcome since technological opportunities and appropriability conditions are very different across industries (see Freeman, 1982; Winter, 1984; Malerba, 2004). This may also involve substantial differences in the industry-specific R&D-productivity links.

In particular, previous literature suggests that more complex and radical product innovation generally relies on formal R&D, while process innovation is much more related to embodied technical change achieved by investment in new machinery and equipment (Parisi et al., 2006; Conte and Vivarelli 2014). Within this interpretative framework, an interesting result from Ortega-Argilés et al. (2014 and 2015) is that in traditional low-tech industries, which focus on process innovation, productivity gains turn out to be more related to capital accumulation rather than to R&D expenditures. Consistently, Montresor and Vezzani (2015), using firm-level data of top world R&D investors over the 2002-2010 time-span and adopting quantile regressions, show that the return of knowledge capital (based on R&D) is the largest in the high-tech industries. They also show how in the non-high-tech industries physical capital is the pivotal factor.

Indeed, previous studies at the industry level (mainly on manufacturing industries) clearly suggest a greater impact of R&D investment on productivity in the high-tech industries rather than in the low-tech ones. Griliches and Mairesse (1982) and Cuneo and Mairesse (1983), who performed two companion studies on French and US firms, found that the impact of R&D on productivity for scientific firms (elasticity equal to 0.20) was significantly greater than for non-scientific firms (0.10). By the same token, Verspagen (1995) carried out a multi-country study involving 9 countries, 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 the high-tech macro sector. 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 industries only, the elasticity increased to 0.1. Consistently, Wakelin (2001), using data on 170 UK quoted firms during the period 1988-1992, found a significant impact of R&D on productivity growth, with firms belonging to industries defined as 'net users of innovations' turning out to experience a higher impact.

A more recent study by Ortega-Argilés *et al.* (2010), looking at the top 577 EU R&D investors, concluded that the coefficient of this impact increases monotonically when moving from the low-tech over the medium-high to the high-tech industries, ranging from a minimum of 0.03/0.05 to a maximum of 0.14/0.17. Consistent with these latter results and using data from OECD countries,

Kancs and Siliverstovs (2016) showed that R&D increases firm productivity with an average elasticity of 0.15, ranging from -0.02 to 0.33 according to the different levels of firms' R&D intensity[4].

This discussion leads to the following hypotheses:

H2a. *The elasticity of productivity to the R&D stock is higher in high-tech firms than in medium-low tech firms.*

Conversely,

H2b. *The elasticity of productivity to the physical capital stock is higher in low and medium-tech firms than in high-tech firms.*

Moving closer to the main topic investigated in this study, Ortega-Argilés *et al.* (2014 and 2015) analyze the transatlantic productivity gap providing evidence of differences among industries. Relying on the COMPUSTAT database covering the period 1990-2008, and comprising 1,809 US and EU companies for a total of 16,079 observations, robust evidence of a significant impact of R&D on productivity is provided. Moreover, the R&D coefficients for the US firms always turn out to be significantly higher. To see to what extent these transatlantic differences in the R&D-productivity relationship may be related to the different industrial structures in the US and the EU, the analysis is differentiated by industries. The result is that both in manufacturing, services and high-tech manufacturing industries US firms are more able to translate their R&D investments into productivity increases.

However, albeit providing very interesting results, previous works seem to lack a comprehensive interpretation of what has been found at the empirical level. Indeed, the revealed transatlantic gap in the R&D/productivity elasticity is actually consistent with three interpretations.

Firstly, the possibility of "threshold" effects in the effectiveness of R&D investment may suggest that large R&D expenditures are necessary to get the best in terms of productivity gains. This means that the average lower level of knowledge stock in the EU firms relative to US firms can be seen as one of the culprits of the revealed weaker impact of R&D on productivity levels in Europe.

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[4] Cincera and Ravet (2014), pursuing a slightly different research objective, assess the impact of both geographic and industrial diversification of economic activities on the performance of European multinational enterprises investing in R&D. Their results indicate a positive impact from globalisation on firms' R&D productivity, especially in the US, while a negative impact for industrial diversification is found.

Secondly, if (as hypothesized above) R&D investments have a higher effect on productivity in the high-tech industries rather than in the medium- and low-tech ones, the *structural composition effect* discussed above may play a key role. In other words, the US advantage in terms of R&D impact may be mainly due to an industry composition effect: in the aggregate, US firms may exhibit higher R&D/productivity elasticities just because they are relatively more concentrated in the high-tech industries where the returns to R&D have revealed to be higher.

Thirdly, the transatlantic productivity gap can be seen as suggestive of the presence of a relevant *intrinsic effect*, that is an intrinsic difficulty of European firms (compared with their US counterparts) in translating R&D investment into productivity gains even *within* each industry, including the high-tech ones. While data limitations prevent us from directly investigating the possible explanations of the insurgence of a significant intrinsic effect in this study, from a theoretical perspective the extant literature suggests at least two interpretative frameworks. On the one hand, a vast literature focuses on the superadditive effects that emerge when R&D investments are combined with an adequate endowment in human capital and with appropriate HRM (Human Resource Management) practices (see Acemoglu, D. 1998; Goldin and Katz, 1998; Bresnahan, Brynjolfsson and Hitt, 2002; Laursen and Foss, 2003; Shipton *et al*., 2006; Añón Higón, Gómez and Vargas, 2017; Hendarman and Cantner, 2018)[5]. In this view, European companies, which are characterized on average by a lower level of human capital, might register a systematic disadvantage in exploiting those complementarities that can make the R&D investment more effective in fostering productivity growth. On the other hand, a well-established strand of literature has pointed out how organizational settings and strategic managerial practices are crucial in affecting productivity trends and significantly vary across countries, with a revealed comparative advantage of US companies (see Brynjolfsson and Hitt, 2000; Black and Lynch, 2001; Guthrie, 2001; Bloom and Van Reenen, 2010; Bloom *et al*., 2012; Amoroso, 2017). If such is the case, the transatlantic managerial gap may well affect the ability of translating the R&D efforts into productivity gains.

These considerations lead to our third (key) hypothesis:

H3. *The elasticity of productivity to R&D stock is higher in US firms relative to EU firms; moreover, this gap is obvious within different macro sectors, as well*[6].

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[5] Indeed, some studies even show that a proper endowment in skills is a sort of pre-condition for a larger and more effective investment in R&D (see Leiponen, 2005; Piva and Vivarelli, 2009).

[6] Taking into account the nature of the available longitudinal data (see Section 3), lack of observations prevented has from testing the intrinsic effect at the single-industry level, while we did it at a more aggregate level of analysis (macro sectors).

Taking into account the extant micro-econometric literature focusing on the relationship between R&D and productivity and the theoretical perspectives discussed above, our empirical study tests the hypotheses listed above using updated microdata and also analyzing a critical time span including pre- and post- world crisis sub-periods. In fact, although both the European and the US-economy have been severely plagued by the economic crisis, large parts of the European economy have found it harder to recover. Thus, it does not seem unreasonable to assume that the crisis might have enforced (or even amplified) the factors contributing to widening the productivity gap, rather than closing it. Moreover, the transatlantic gaps in terms of human capital and managerial practices (see above) have not shown any tendency to shrink in recent times.

This leads to our last hypothesis:

H4. *The elasticity of productivity to R&D stock is higher in US firms relative to EU firms, both before and after the major financial and economic crisis occurred in the years 2008/09.*

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. The microdata used in this study were provided by the JRC–IPTS (Joint Research Centre-Institute for Prospective Technological Studies, Seville) of the European Commission[7]. The dataset is mainly based on the EU Industrial R&D Scoreboard and aggregates information on top R&D spenders worldwide from 2004 until 2012. In particular, the EU Industrial R&D Investment Scoreboard provides the main economic and financial data of the top corporate R&D investors from the EU and from abroad. It uses data extracted directly from each company's Annual Report and consolidated at group level, *i.e.* including all the subsidiaries. It is worth highlighting that a key feature of our data is the availability of using such consolidated information, which allows us to account for the global structure of the company's locations of production and R&D. Indeed, we are able to compare the effect of overall investments in R&D on a

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[7] This longitudinal dataset has been prepared and analyzed in the context of a project on 'European Innovative Companies and Global Value Chains: The Productivity Impact of Heterogeneous Strategies' funded by the JRC-IPTS (European Commission).

firm productivity, regardless of where they are located in the world (see Castellani *et al.,* 2017)[8].
Additional balance sheet information from the Bureau Van Dijk's ORBIS database for the same
period was merged. These data refer to firm sales, employment and capital expenditures.

An important limitation of the used data is that they are biased in favor of large firms (the
median size being 4,683 3mployees), while innovative SMEs (small and medium enterprises) are
under-represented. However, even if the population of innovative companies is not covered
completely, it is important to underline that the companies listed in Scoreboard account for more than
90% of worldwide Business Enterprise Expenditure on R&D (BERD)[9].

Overall, the EU Industrial R&D Scoreboard organized as a panel of over 2,000 companies
worldwide over the years 2004-2012; in this paper we focus on EU and US firms only. The final
sample is unbalanced in nature and comprises 1,355 companies (732 European firms and 623 US
firms) with data from a minimum of 2 years, to a maximum of 9 years. Moreover, outlier observations
have been dropped following the Grubbs test (as discussed in Section 3.2) and leading to a final
sample of 1,112 companies (504 European firms and 608 US firms) and 8,763 observations.

Table 1 reports the distribution of the retained firms and observations across countries,
showing a dominant role of Germany and United Kingdom in Europe, but letting the other major
European countries to be adequately represented in the sample[10].

<INSERT TABLE 1>

Table 2 reports the distribution of the investigated firms (and resulting observations) across
industries (ICB code[11]) both for the whole sample and separately for the EU and the US.

<INSERT TABLE 2>

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[8] In other words, our data take into account the overall global value chain within a given company, including labor outsourcing. From this respect, the investigated link between R&D stock and labor productivity is tested at the global corporate level, under the hypothesis that a US type of corporate governance may positively affect this link (see H3).

[9] Innovative SMEs are only marginally covered by this study not only because of sample selection in size, but also because some SMEs (especially in the low-tech industries) may be innovative without necessarily being R&D-intensive (see Becker and Pain, 2008; Ortega-Argilés,Vivarelli and Voigt, 2009; Link, 2017, Roper and Hewitt-Dundas, 2017).

[10] Obviously enough, R&D and innovation activities are heterogeneously distributed across EU countries and regions (see Maurseth and Verspagen, 2002); however, investigating the differences in the innovative efforts within the EU is out of the scope of the present study.

[11] The Industry Classification Benchmark (ICB) is a definitive system categorizing over 70,000 companies and 75,000 securities worldwide, enabling the comparison of companies across four levels of classification and national boundaries. The ICB system is supported by the ICB Database, an unrivalled data source for global industry-level analyses, which is maintained by FTSE International Limited (http://www.icbenchmark.com/).

3.2 Econometric specification and descriptive statistics

Following a consolidated tradition (e.g. Hall and Mairesse, 1995, pp. 268-69), we test an augmented production function, derived from a standard Cobb-Douglas in three inputs: knowledge capital, physical capital and labor (see also Verspagen, 1995; Ortega-Argilés *et al.*, 2014 and 2015). For comparison with most extant literature on the topic (see Section 2), we express the production function in per worker terms:

$$(1) \quad \ln\left(\frac{NS}{E}\right)_{i,t} = \alpha + \beta \ln\left(\frac{K}{E}\right)_{i,t} + \gamma \ln\left(\frac{C}{E}\right)_{i,t} + \vartheta \ln(E)_{i,t} + \varepsilon_{i,t}$$

with $i = 1,\ldots, 1{,}112;$ $t = 2004,\ldots, 2012;$ ln = natural logarithm.

While our ideal proxy for labor productivity should be expressed as value added over total Employment (E), in our dataset we found that the value-added variable had a very high number of missing values, due to the particular accounting procedures adopted in the US. In order to maintain a reasonable number of observations, we decided to use Net Sales (NS) instead of Value Added to construct the productivity variable. However, over the 3,866 observations for which both Value Added and Net Sales are available, the pairwise correlation coefficient between the two turns out to be 0.88. This high correlation makes us confident in using Net Sales/Employment as a proper proxy for labor productivity.

Turning our attention to the regressors, our pivotal impact variables are the R&D stock (K, for knowledge) per employee and the physical capital stock (C) per employee[12]. Taking per capita values permits both standardization of our data and elimination of possible company's size effects (see, for example, Crépon *et al.*, 1998, p.123). In this framework, total employment (E) is a control variable that indicates increasing returns if θ turns out to be greater than zero and decreasing returns otherwise.

In particular, K/E (R&D stock per employee) captures that portion of technological change which is related to the cumulated R&D investments, while C/E (physical capital stock per employee) is the result of the accumulated investment, implementing different vintages of technologies. So, this

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[12] All the monetary variables are expressed in Euro after applying appropriate exchange rates for companies based in non-Euro countries (i.e. Denmark, Hungary, Sweden, United Kingdom, United States) and in cases of firms whose financial data where expressed in pounds or dollars even if located in the Euro-area.

variable encompasses the so-called embodied technological change, possibly affecting productivity growth.

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 might follow different accounting practices in different countries over the world. In particular, the R&D investment included in the Scoreboard is the cash investment which is funded by the companies themselves, while it excludes R&D undertaken under contract for customers such as governments or other companies. Therefore, our R&D indicator is consistent and homogeneous across all the considered countries and refers to the genuine flow of current additional knowledge resources.

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

Moreover, dealing with stocks, rather than flows, has two additional advantages: on the one hand, since stocks incorporate the accumulated investments in the past, the risk of endogeneity is lower. On the other hand, this allows avoiding the complex (sometimes arbitrary) choice of the appropriate lag structure for the flows.

In our paper, R&D stock (K) is computed using a standard perpetual inventory method (PIM) approach according to the following formula[13]:

(2) $K_t = \frac{K_{t-1}}{(1+\delta)} + R\&D_t$

Where R&D = R&D expenditures; δ = depreciation rate (0.15)

The physical capital stock (C) was instead directly provided in the dataset, as a public information from balance sheets[14].

In order to eliminate outliers, we undertook an outlier detection procedure using the Grubbs (1969) test over NS/E, K/E and C/E. After the outlier detection process, 243 companies were dropped. More in detail, 138 observations for the NS/E variable, 313 for the K/E variable and 294 observations for

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[13] In year 0, $K_0 = \frac{R\&D_0}{(g+\delta)}$ (where g is computed as the average growth rate of the corresponding flow variable in the first three years available and δ is the depreciation rate).

[14] We also computed the physical capital stock starting from the investment flows using the same PIM procedure adopted in the case of the R&D stock. Nevertheless, due to a large number of missing values, we opted for the already available capital stock variable. Overall, the pairwise correlation coefficient between the physical capital stock from balance sheets and the physical capital stock computed with the PIM is 0.72 (over the available 7,056 observations), which supports our choice.

the C/E variable were deleted. The final dataset permits to retain almost the 75% of overall European and US R&D covered by the Scoreboard in 2012. This value represents almost the 65% of total European and US Business Enterprise Expenditure on R&D (BERD).

Specification (1) was estimated through different econometric techniques. First, we ran pooled ordinary least squared (POLS) regressions, augmented with a complete set of country (17 European countries + US), time (9 years), industry (34 ICB codes) dummies and controlling for heteroskedasticity (using the Eicker/Huber/White sandwich estimator to compute robust standard errors). While potentially biased by omitted firm-level characteristics simultaneously correlated with R&D stocks and firm productivity, POLS regressions offer a useful baseline.

Second, to take into account firm specific unobservable time-invariant characteristics, we ran fixed effect (FE) regressions[15]. On the one hand, FE regressions offer the great advantage of allowing to control for both unobserved heterogeneity and the intra-firm dependence structure, which significantly reduce a potential bias in the R&D coefficient. On the other hand, the effect of time invariant variables (in our case country and industry dummies) are not individually identified any more, since they are encompassed by the individual firm-level fixed effects[16].

Table 3 reports the means and standard deviations of the four relevant variables in specification (1). As we are also interested in singling out industry differences in the R&D/productivity relationship, we split our panel into two macro sectors: high-tech vs medium- and low-tech, ranking industries according to their R&D intensity (measured in terms of R&D/employment, see Ortega-Argilés et al., 2011)[17]. Furthermore, we also consider the descriptive statistics in the pre- and post-world crisis sub-periods.

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[15] Random effect (RE) regressions were also run and tested against the FE specification through the Hausman test. According to the outcomes of the test, in all the following investigated cases the FE estimates turned out to be preferable to the RE ones (results available from the authors upon request). It needs to be recognized that while firm fixed effects capture a large number of potential confounders, there can certainly be time-varying firm characteristics that are potentially correlated with both R&D capital stock and firm productivity. This can potentially bias the results in an unknown way, but data limitation prevents us to do any better than we do. In our defense, we submit that our specification mimics previous studies, and this makes our work more closely comparable with them.

[16] It is worth mentioning that several alternative estimators of productivity equations and of the role of R&D in affecting productivity (often considered and measured differently from what done in our paper) have been proposed; see, for instance, Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009; De Loecker, 2011; Doraszelski and Jaumandreu, 2013 and Ackerberg et al., 2015. Although these estimators aim to solve the problem of unobserved heterogeneity shocks, they make strong underlying assumptions about firm behavior, which have led some authors to conclude that the offered seemingly elegant solution to the problem is illusionary (see Eberhardt and Helmers, 2010). As shown in Schubert and Neuhäusler (2018), in many real applications structural TFP estimators perform poorly, for example leading to inflated or deflated elasticities of the physical capital stock. Furthermore, existing studies often reveal that different estimators yield highly correlated TFP measures, thus making the choice of the estimation method less relevant (see Van Bieseboreck, 2007 and 2008; Castellani and Giovannetti, 2010; Van Beveren, 2012). All these things considered, in this paper we decided to prefer simplicity and to avoid potentially questionable assumptions, so opting for POLS and individual fixed effects. Moreover, in so doing our results can be compared to earlier econometric works (see the literature discussed in Section 2), which typically relied on POLS or FE estimates of labor productivity.

[17] As already mentioned (see footnote 6), paucity of observations has prevented us from using a more disaggregated industrial splitting. Moreover, missing values in the value added variable (see above) prevented us from using the

As it can be seen, our sample mainly comprises very large and established corporations, with an average employment of more than 20,000 employees (the median value is 4,683). On average, US companies are characterized by a larger R&D stock per employees as compared to EU companies (+60%). Moreover, US companies are more productive (NS/E) than EU firms, although being smaller on average. This very preliminary evidence is consistent both with a view that relates the transatlantic productivity gap to differences in the level of R&D investments and one which emphasizes the different impact of R&D investments. The econometric analysis (see next section) will allow us to properly investigate this issue.

Considering the sectoral taxonomy, average values suggest that the productivity per employees decreases when shifting from the high-tech macro sector to the medium- and low-tech macro sector (together with the R&D stock per employee, not surprisingly), meanwhile the physical capital per employee increases, suggesting a larger endowment of embodied technologies in the medium- and low-tech industries.

Turning our attention to the pre- and post-crisis subsamples, the statistical evidence suggests that the US/EU divides in both productivity and R&D stock have persisted after the crisis.

4. Econometric results

Table 4 provides the baseline econometric results concerning the whole sample of 1,112 companies (8,763 observations).

R&D/VA ratio as an indicator of R&D intensity, as common in the literature; hence we opted for the R&D/employment ratio (we chose employment as a measure of size instead of net sales since the former is more stable over time and less dependent on the firm's location in the supply chain). The industry R&D intensities and the resulting split into the high-tech *vs* the medium- and low-tech macro sectors are reported in Table A.1 in the Appendix. We chose R&D/E=9.5 as a reasonable threshold both to be consistent with the OECD classification (see Hatzichronoglou, 1997) and to keep an adequate number of companies (409) and observations (3,180) in the medium- and low-tech macro sector. The resulting high-tech macro sector is made by: Aerospace & defense, Automobiles & parts, Chemicals Electronic & electrical equipment, Health care equipment & services, Leisure goods, Pharmaceuticals & biotechnology, Software & computer services, Technology hardware & equipment.

In line with **H1** and with the extensive literature recalled in Section 2, we find robust evidence of a positive and significant impact of the R&D stock on productivity with an elasticity ranging from 0.148 to 0.178, according to the different adopted estimation techniques (POLS vs. FE). These estimates are within the bounds set by previous empirical studies (0.05/0.25; see Section 2). As far as the physical capital stock is concerned, we assess a positive and significant impact ranging from 0.112 (FE) to 0.236 (POLS). Capital formation, embodying vintages of new technologies, emerges as a still important driver of productivity growth.

The following Tables 5 and 6 split the analysis into the high- and the medium- and low-tech macro sectors.

< INSERT TABLES 5 AND 6>

Consistently with **H2a**, in Table 5 and 6 we find that R&D has a larger effect on productivity in the high-tech rather than in the medium- and low-tech macro sector (0.255 *vs* 0.100 in the FE estimates). Instead, as per **H2b**, the effect of the physical capital stock is larger in the latter group (0.195 *vs* 0.082 in the FE estimates). These results support the view that productivity gains can be originated by different types of innovation, with more complex and radical product innovation (more common in the high-tech companies) generally relying on formal R&D, while process innovation (more common in the medium- and low-tech firms) more related to embodied technical change achieved by investment in new machinery and equipment.

Turning our attention to the comparison between the US and the EU, the same model is run separately for US companies and European firms (608 vs. 504 companies). As can be seen in Table 4, our results fully confirm the previous outcomes from the extant literature. 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 two estimation techniques consistently provide European elasticities which are merely about 35% of their US counterparts (see the last column of Table 4). Focusing on the fixed-effects (FE) specification, the US/EU gap is statistically significant at the 99%-level, as reported in the last but one column of Table 4 where a t-test measures whether the FE coefficients referred to the two areas are significantly different. We interpret these unambiguous results as a first support for **H3** (stating a better ability of

US firms to translate R&D investments into productivity gains) and as a signal of the presence of a structural gap that European firms and European policy have to deal with.

As far as the productivity impact of the physical capital stock is concerned, POLS and FE estimates tell a different story: they both show that EU has a relative (although only marginally significant) advantage in productivity from investing in physical capital. In particular, the FE elasticity for the EU is 30% higher than its US counterpart. This evidence suggests that in 2004-2012, European companies have mainly relied on embodied technological change in order to foster their levels of productivity.

Finally, it is worth highlighting that FE estimates reveal a negative correlation between employment and productivity[18]. This is simply an evidence of decreasing returns to scale, which is not uncommon in fixed effects estimation of productivity equations. Interestingly, this is more accentuated for European than for US companies, given that the coefficient associated with the number of employees is more than 2.5 time larger for EU firms; this outcome can be related to the larger size of EU firms in our sample (see Table 3).

Coming back to or main focus of interest, it is important to stress that the revealed transatlantic gap in the R&D/productivity elasticity is actually consistent with all the three interpretations put forward by the previous literature and discussed in Section 2.

Firstly, the possibility of "threshold" effects in the effectiveness of R&D investment may suggest that large R&D expenditures are necessary to get the best in terms of productivity gains. This means that the average lower level of the R&D stock in the EU firms (see Table 3) can be seen as one of the culprits of the revealed weaker impact of R&D on productivity levels in Europe.

Secondly, as detailed in Table 2, our regional subsamples (in so reflecting the actual structural compositions of the US and EU economies) are different as far as the incidence of the high-tech industries is concerned. If we take into account the previous evidence discussed in Section 2 (revealing a greater impact of R&D investment on productivity in the high-tech industries rather than in the medium- and low-tech ones), our results turn out to be consistent with the *structural composition effect* discussed in Sections 1 and 2. Moreover, Table 4 reveals that the Wald test for equality of the industry dummies is always soundly rejected, supporting the idea that productivity differs across industries, even controlling for firms' input choices. In other words, the US advantage in terms of R&D impact may be mainly due to an industry composition effect: in the aggregate, US

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[18] Opposite results turn out from the POLS estimates, but this is not surprising, since failing to control for unobserved firm heterogeneity tends to lead to overestimated labor and capital coefficients, due to their correlation with firm size, and in turn with the error term (Griliches and Mairesse, 1995).

firms may exhibit higher R&D/productivity elasticities just because they are relatively more concentrated in the high-tech industries where the returns to R&D are higher.

Thirdly, results from Table 4 can be seen as suggestive of the presence of a relevant *intrinsic effect* (see Sections 1 and 2), that is an intrinsic disadvantage of European firms in translating R&D investment into productivity gains even *within* each industry, including the high-tech ones (see the qualification of our hypothesis **H3**).

As an attempt to further disentangle the structural and the intrinsic effects, we can look again at Tables 5 and 6. Table 5 displays the US/EU comparison with regard to the high-tech macro sector: as can be seen, the European lag is fully confirmed. As it was the case for the whole economy (see Table 4), in the high-tech macro sector the US coefficients are larger than their European counterparts (0.333 *vs* 0.128). Moreover, focusing on the FE estimates, the R&D gap turns out to be statistically significant at the 99% level of confidence (t-test in the last but one column)[19]. This evidence suggests that the advantage of US companies in translating knowledge into productivity gains is not only driven by their higher concentration in high-tech industries, but also by their higher ability to translate R&D into productivity within those industries; therefore, the qualification of **H3** receives a clear support from this evidence.

However, while the outcome from Table 5 rebalances our interpretation in favor of the *intrinsic effect,* it does not rule out the role of the *structural composition effect* completely. In fact, as it is obvious from Table 2, even the industry compositions *within* the high-tech macro sector remain different between the investigated US *vs* EU subsamples (for instance, ICT industries are over-represented in the US subsample)[20]. Unfortunately, as already mentioned, paucity of observations does not allow us to proceed in a more detailed investigation at the single industry level.

Turning our attention to the medium- and low-tech macro sector, European companies again show (both in the POLS and FE estimates) a lower elasticity of productivity to R&D in comparison with their US counterparts. However, this differential is smaller than in the case of the high-tech macro sector: looking at the FE coefficients, the European one it is about two-thirds (0.65) the one estimated for US firms (while in the case of high-tech it was about two-fifths, 0.38) and only significant at the 95% level. On the other hand, European companies in the medium- and low-tech macro sector seem to be more efficient in transforming investment in physical capital into productivity gains, although the t-test provides only marginal support of a statistical significant

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[19] Differently, the gap in the productivity impact of physical capital stock in favor of the European firms is not confirmed at all.

[20] The fact that the industry dummies keep on being jointly significant within the high-tech subsamples (see the corresponding Wald tests in the POLS estimates in Table 5) gives further support to the possibility of an important residual role of the *structural composition effect.*

difference. On the whole, the finding that US companies are more effective in translating their R&D investments into productivity gains both in the high-tech macro sector and in the medium- and low-tech macro sector can be seen as a further support for the intrinsic effect (**H3**).

In order to test our hypothesis **H4**, we re-ran the previous aggregate estimates, splitting the time-period into a pre-crisis sub-period from 2004 to 2008, and a post-crisis sub-period, from 2009-2012. As can be seen in the next Tables 7 and 8 our data allow us to have adequate and comparable sub-samples to be used for this empirical test[21].

< INSERT TABLES 7 AND 8 >

Results - comparing the whole sample evidence from the FE in the first panel of the two tables - reveal that in the post-crisis period the world top-R&D spenders had a lower capacity to translate investment in R&D into productivity gains (0.158 *vs* 0.243); while showing a slightly better performance in terms of getting productivity improvements from physical capital (0.089 *vs* 0.070). This result may suggest that firm R&D investment is less pro-cyclical than output, so in times of crisis output may suffer from higher volatility than R&D.

Focusing on the comparison between the EU and the US, the evidence that US companies outperform the EU ones in terms of productivity gains from R&D capital persists before and after the crisis, (the t-tests supports at the 95% level of significance the difference among the two coefficients both in 2004-2008 and in 2009-2012). In particular, the gap is still clear in the post-crisis period, even if for both the US and the EU the magnitude of the elasticity lowers (from 0.294 to 0.199 for the US and from 0.194 to 0.093 for the EU). However, the EU companies have been more affected than their US counterparts in their capacity to translate R&D investments into productivity: -52% *vs.* -32%. This has implied that after the crisis the return from R&D investments of EU firms has dropped to 46% of the return of US firms, compared with 66% before the crisis. Indeed, the US/EU efficiency gap in linking R&D and productivity has worsened as a consequence of the global economic crisis. In other words, this evidence not only supports our **H4**, but also points out a further deterioration of the transatlantic gap.

5. Conclusions and policy implications

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[21] On the contrary, running estimates that jointly apply the time splitting and the industry-level splitting is prevented by the scarce number of observations in each of the resulting subsamples.

In this paper, we have tested several hypotheses, based on the extant theoretical and empirical literature (see Section 2). In particular, we have tested our key hypothesis **H3** 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.

As a first step and consistently with the extant literature, we have found robust evidence of a positive and significant impact of the R&D stock on productivity (**H1**). However, the R&D coefficients for the US firms turn out to be consistently and significantly larger than the corresponding coefficients for the European firms: in the overall sample, European elasticities amount to about one third of their US counterparts. We interpret this unambiguous support of **H3** 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 these transatlantic differences may be related to the different industrial structures in the US and the EU (the US economy being disproportionally characterized by high-tech industries), we have differentiated the US/EU comparative empirical exercise by macro-sectors, according to their technological level. Beyond confirming that the elasticity of productivity to the R&D stock is higher in the high-tech macro sector rather than in the medium- and low-tech macro sector (while the opposite occurs for the physical capital stock, so supporting **H2a** and **H2b**), our results also show that the US firms are more capable to translate their R&D investments into productivity gains both in the high-tech and in the medium- and low-tech macro sectors, with the US lead turning out particularly obvious in the former. Therefore, not only US firms are more concentrated in high-tech industries, contributing to a positive structural effect on aggregate productivity, but in those industries they can extract higher productivity gains from their R&D investments (this supports our qualification of the hypothesis **H3**).

In summary, our results suggest that the transatlantic productivity divide can be explained by a) a lower level of R&D investment of EU firms as opposed to their US counterparts (see Table 3), if we assume the presence of threshold barriers; b) a *structural composition effect,* which seems to be significant both in aggregate and even within the high-tech macro sector (see Tables 4 and 5 and the interpretations put forward in the previous section); and c) the presence of an *intrinsic effect*, that is a generalized lower capacity of European firms to translate R&D investments into productivity gains.

Furthermore, our results show that EU companies have been more affected by the economic crisis in their capacity to translate R&D investments into productivity: indeed, the US/EU gap investigated in this study has worsened as a consequence of the global economic crisis (**H4**).

These findings have a considerable impact for the organization of policy support. In fact, a major implication of the decreasing ability of EU firms to translate R&D into productivity after the crisis suggests that EU support for R&D has not proven to be particularly effective in reaching one of its major goals, *i.e.* turning the EU into a more competitive economy in the long-run. Rather the opposite seems to have occurred and this can be due to a myopic EU policy.

Indeed, we find robust evidence of both a quantity effect (relatively lower R&D spending of European firms) and a quality effect (lower ability to transform R&D spending into productivity gains). However, most policy attention has been devoted to the lower levels of R&D spending rather than the lower capabilities to make efficient use of it. This is exemplified by the 3% target (in terms of the R&D/GDP ratio) set by the EU, making reference primarily to increasing the level of R&D spending. Differently, effective policies should, instead of primarily focusing on the symptom (i.e. R&D investments that are perceived as too low), rather take into account the reasons why EU firms obtain less productivity gains from their R&D investments compared to their US counterparts.

In this framework, a renewed EU industrial policy is surely needed: since the *structural composition effect* seems to still play an important role both in general and even within the high-tech macro sector, there is scope for an intervention addressed to twist the EU economy towards the emerging industries where R&D expenditures are more likely to foster productivity.

In addition, our results regarding the *intrinsic effect* call for policies addressed to increase firm's capabilities to turn R&D inputs into productivity gains rather than just increasing business R&D spending, irrespective of whether it pays off or not. One possible option is to make policies more learning-oriented by including fostering knowledge-transfer, learning between firms and R&D cooperation (see Frietsch et al., 2015; Tomasello *et al.*, 2017; Toselli 2017; Rammer and Schubert, 2018).

Obviously enough, this paper leaves a series of open questions.

Firstly, as discussed in the previous sections, paucity of observations does not allow us to proceed in a more detailed investigation at the single-industry level and in this way to better assess the relative importance of the *structural composition effect vs* the *intrinsic effect.*

Secondly*,* in this contribution we could not directly test how important complementarities (such as those with human capital and managerial practices) may affect the firms' ability to convert its R&D investment into productivity gains.

Thirdly, globalization and offshoring may play a role in the ability to translate R&D into productivity, maybe in association with other characteristics of the firm; unfortunately, the lack of available information about the location of the different company's activities prevented us from better investigating this issue.

Fourthly, although accounting for more than 90% of worldwide BERD, the adopted dataset is under-representing the SMEs, that may exhibit interesting peculiarities (particularly in the low-tech industries), worth to be investigated.

Due to data constraints, these topics could not be addressed in this particular study, but they are certainly key issues for promising future avenues of research, based on more comprehensive datasets, also providing complementary information about skills, managerial capabilities, outsourcing and other key factors that may affect firm's productivity.

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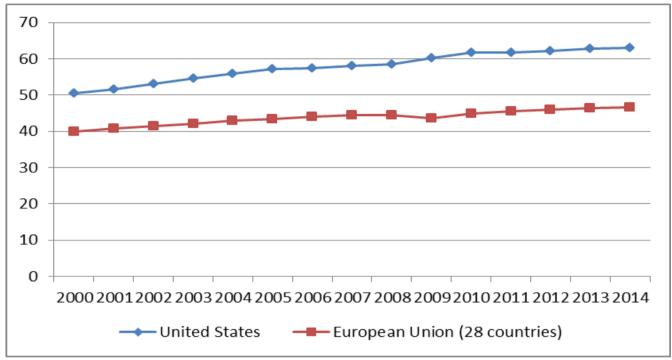
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Figure 1: GDP per hour worked (USD, 2010 PPP) in the period 2000-2014

Source: OECD, 2015b

Table 1: Distribution of firms and observations across countries

COUNTRY	FIRMS	%	OBSERVATIONS	%
AUSTRIA	19	1.71	165	1.89
BELGIUM	18	1.61	140	1.60
DENMARK	22	1.98	176	2.01
FINLAND	31	2.79	272	3.10
FRANCE	79	7.10	642	7.33
GERMANY	113	10.16	990	11.30
GREECE	1	0.09	8	0.09
HUNGARY	1	0.09	9	0.10
IRELAND	10	0.90	82	0.94
ITALY	19	1.71	109	1.24
LUXEMBOURG	3	0.27	15	0.17
MALTA	1	0.09	8	0.09
SLOVENIA	1	0.09	9	0.10
SPAIN	10	0.90	88	1.00
SWEDEN	47	4.23	360	4.11
THE NETHERLANDS	29	2.61	235	2.68
UNITED KINGDOM	100	8.99	791	9.03
EUROPEAN UNION	*504*	*45.32*	*4,099*	*46.78*
UNITED STATES	*608*	*54.68*	*4,664*	*53.22*
TOTAL	*1,112*	*100.00*	*8,763*	*100.00*

Table 2: Distribution of firms and observations across industries

INDUSTRIES (ICB code)	WHOLE SAMPLE				EUROPEAN UNION				UNITED STATES			
	FIRMS	%	OBS.	%	FIRMS	%	OBS.	%	FIRMS	%	OBS.	%
Oil & gas prod. (530)	5	0.45	24	0.27	4	0.79	23	0.56	1	0.17	2	0.04
Oil equip. (570)	9	0.81	75	0.86	6	1.19	48	1.17	3	0.49	26	0.56
Alternative energy (580)	4	0.36	34	0.39	3	0.60	27	0.66	1	0.17	7	0.15
Chemicals (1350)	58	5.22	505	5.76	25	4.96	222	5.42	33	5.43	283	6.08
Forestry & paper (1730)	8	0.72	69	0.79	6	1.19	51	1.24	2	0.33	18	0.39
Ind.metals & min. (1750)	12	1.08	105	1.20	9	1.79	79	1.93	3	0.49	26	0.56
Mining (1770)	6	0.54	34	0.39	4	0.79	17	0.41	2	0.33	17	0.36
Construction & mater. (2350)	24	2.16	213	2.43	17	3.37	151	3.68	7	1.15	62	1.33
Aerospace & defense (2710)	31	2.79	270	3.08	15	2.98	134	3.27	16	2.63	136	2.92
General industrials (2720)	99	8.90	598	6.82	43	8.53	274	6.68	56	9.21	324	6.95
Electronic & el.equip (2730)	91	8.18	748	8.54	44	8.73	378	9.22	47	7.73	370	7.93
Industrial engine. (2750)	98	8.81	845	9.64	62	12.30	537	13.10	36	5.92	308	6.61
Indust.transp. (2770)	3	0.27	27	0.31	3	0.60	27	0.66	0	0	0	0
Support services (2790)	14	1.26	122	1.39	11	2.18	97	2.37	3	0.49	25	0.54
Automob. & parts (3350)	49	4.41	406	4.63	28	5.56	236	5.76	21	3.45	170	3.64
Beverages (3530)	4	0.36	36	0.41	4	0.79	36	0.88	0	0	0	0
Food producers (3570)	28	2.52	227	2.59	17	3.37	140	3.42	11	1.81	87	1.87
House.goods & const. (3720)	19	1.71	169	1.93	8	1.59	72	1.76	11	1.81	97	2.08
Leisure goods (3740)	15	1.35	128	1.46	5	0.99	43	1.05	10	1.64	85	1.82
Personal goods (3760)	13	1.13	113	1.29	7	1.39	61	1.49	6	0.99	52	1.11
Tobacco (3780)	3	0.27	23	0.26	2	0.40	18	0.44	1	0.17	5	0.11
Health care equip. (4530)	66	5.94	539	6.16	18	3.57	156	3.81	48	7.89	383	8.21
Pharma. & bio. (4570)	59	5.31	405	4.63	34	6.75	235	5.73	25	4.11	170	3.65
General retailers (5370)	9	0.81	79	0.90	4	0.79	35	0.85	5	0.82	44	0.94
Media (5550)	10	0.90	81	0.92	5	0.99	39	0.95	5	0.82	42	0.90
Travel & leisure (5750)	8	0.73	62	0.71	4	0.79	33	0.81	4	0.66	29	0.62
Fixed line telec. (6530)	11	0.99	88	1.00	8	1.59	64	1.56	3	0.49	24	0.51

Mobile telec. (6570)	3	0.27	26	0.30	2	0.40	18	0.44	1	0.17	8	0.17
Electricity (7530)	5	0.45	27	0.31	5	0.99	27	0.66	0	0	0	0
Gas, water & multi-ut. (7570)	5	0.45	35	0.40	5	0.99	35	0.85	0	0	0	0
Financial serv. (8770)	8	0.72	59	0.67	3	0.60	21	0.51	5	0.82	38	0.81
Equity inv.instrum. (8980)	1	0.09	9	0.10	0	0	0	0	1	0.17	9	0.19
Software & comp.serv. (9530)	156	14.03	1,212	13.83	54	10.71	432	10.54	102	16.78	780	16.72
Tech.hard & equip. (9570)	178	16.01	1,370	15.63	39	7.74	333	8.12	139	22.86	1,037	22.23
	1,112	*100.00*	*8,763*	*100.00*	*504*	*100.00*	*4,099*	*100.00*	*608*	*100.00*	*4,664*	*100.00*

Table 3: Descriptive statistics

Sample (N. of observations)	Labor Productivity NS/E		R&D stock per employee K/E		Physical capital stock per employee C/E		Employees E	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Whole sample (8,763)	252.18	199.20	66.98	85.98	130.94	120.08	21,371.09	50,965.21
US (4,664)	261.72	191.50	81.31	92.35	133.29	113.60	16,973.35	40,843.24
EU (4,099)	241.32	207.10	50.68	74.86	128.27	127.01	26,375.02	60,070.24
High-tech (5,583)	248.21	184.22	82.75	88.49	122.02	108.57	17,069.86	43,928.71
Medium- and low-tech (3,180)	239.15	222.95	39.31	73.66	146.60	136.60	28,922.59	60,672.77
Whole sample 2004-2008 (4,949)	244.23	192.36	53.31	77.13	122.96	116.25	20,455.02	48,766.52
US (2,652)	253.54	194.05	64.51	82.16	124.51	107.84	16,333.93	38,902.62
EU (2,297)	233.49	189.88	40.39	68.65	121.17	125.26	25,213.03	57,753.02
Whole sample 2009-2012 (3,814)	262.49	207.30	84.72	93.34	141.30	124.12	22,559.77	53,667.32
US (2,012)	272.51	187.59	103.46	100.06	144.86	119.81	17,816.15	43,263.81
EU (1,802)	251.29	226.83	63.80	80.23	137.32	128.69	27,856.20	62,885.47

Table 4: Dependent variable: log(Labor Productivity); WHOLE SAMPLE

	WHOLE SAMPLE	UNITED STATES	EUROPEAN UNION	WHOLE SAMPLE	UNITED STATES	EUROPEAN UNION	EU –US^	EU/US
	POLS	POLS	POLS	FE	FE	FE	FE	FE
Log(R&D stock per employee)	0.148*** (0.007)	0.234*** (0.010)	0.083*** (0.012)	0.178*** (0.013)	0.267*** (0.019)	0.094*** (0.018)	-0.173*** [0.000]	0.35
Log(Physical capital stock per employee)	0.236*** (0.009)	0.174*** (0.011)	0.293*** (0.015)	0.112*** (0.007)	0.099*** (0.009)	0.129*** (0.012)	0.030* [0.060]	1.30
Log(Employees)	0.027*** (0.005)	0.031*** (0.006)	0.032*** (0.007)	-0.143*** (0.012)	-0.082*** (0.016)	-0.223*** (0.019)	-0.141*** [0.000]	2.71
Constant	3.773*** (0.170)	5.872*** (0.095)	3.437*** (0.165)					
Wald time-dummies (p-value)	5.2*** (0.000)	6.5*** (0.000)	2.3** (0.017)	21.8*** (0.000)	15.3*** (0.000)	11.9*** (0.000)		
Wald country-dummies (p-value)	13.5*** (0.000)		10.8*** (0.000)					
Wald industry-dummies (p-value)	41.9*** (0.000)	198.3*** (0.000)	22.3*** (0.000)					
R^2 (overall) R^2 (within)	0.35	0.38	0.38	0.20	0.22	0.19		
Obs.	8,763	4,664	4,099	8,763	4,664	4,099		
N. of firms	1,112	608	504	1,112	608	504		

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

For time-dummies, country-dummies and industry-dummies, Wald tests of joint significance are reported.

^ The absolute difference between the EU and US coefficients (from the FE estimates) is reported, together with the p-value (in squared brackets) of the t-test on the significance of this difference. In the last column the ratio of the EU coefficient with respect to the US one is reported.

Table 5: Dependent variable: log(Labor Productivity); HIGH-TECH MACRO SECTOR

	WHOLE SAMPLE	UNITED STATES	EUROPEAN UNION	WHOLE SAMPLE	UNITED STATES	EUROPEAN UNION	EU-US^	EU/US
	POLS	POLS	POLS	FE	FE	FE	FE	FE
Log(R&D stock per employee)	0.229*** (0.010)	0.277*** (0.011)	0.154*** (0.020)	0.255*** (0.016)	0.333*** (0.019)	0.128*** (0.026)	-0.205*** [0.000]	0.38
Log(Physical capital stock per employee)	0.181*** (0.009)	0.153*** (0.012)	0.219*** (0.017)	0.082*** (0.007)	0.088*** (0.009)	0.062*** (0.015)	-0.026 [0.129]	0.70
Log(Employees)	0.015*** (0.005)	0.019** (0.008)	0.018** (0.008)	-0.142*** (0.014)	-0.096*** (0.017)	-0.243*** (0.024)	-0.147*** [0.000]	2.53
Constant	4.298*** (0.916)	3.914*** (0.098)	3.988*** (0.130)					
Wald time-dummies (p-value)	11.5*** (0.000)	12.2*** (0.000)	2.5*** (0.000)	23.6*** (0.000)	20.1*** (0.000)	7.7*** (0.000)		
Wald country-dummies (p-value)	24.7*** (0.000)		21.7*** (0.000)					
Wald industry-dummies (p-value)	100.5*** (0.000)	99.3*** (0.000)	31.0*** (0.000)					
R^2 (overall) **R^2 (within)**	0.39	0.41	0.37	 0.24	 0.22	 0.22		
Obs.	5,583	3,414	2,169	5,583	3,414	2,169		
N. of firms	703	441	262	703	441	262		

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

For time-dummies, country-dummies and industry-dummies, Wald tests of joint significance are reported.

^ The absolute difference between the EU and US coefficients (from the FE estimates) is reported, together with the p-value (in squared brackets) of the t-test on the significance of this difference. In the last column the ratio of the EU coefficient with respect to the US one is reported.

Table 6: Dependent variable: log(Labor Productivity); MEDIUM- AND LOW-TECH MACRO SECTOR

	WHOLE SAMPLE	UNITED STATES	EUROPEAN UNION	WHOLE SAMPLE	UNITED STATES	EUROPEAN UNION	EU-US^	EU/US
	POLS	POLS	POLS	FE	FE	FE	FE	FE
Log(R&D stock per employee)	0.054*** (0.012)	0.144*** (0.021)	0.027* (0.016)	0.100*** (0.021)	0.133*** (0.041)	0.087*** (0.025)	-0.046** [0.019]	0.65
Log(Physical capital stock per employee)	0.331*** (0.019)	0.222*** (0.025)	0.395*** (0.026)	0.195*** (0.016)	0.162*** (0.025)	0.214*** (0.021)	0.052* [0.100]	1.32
Log(Employees)	0.013 (0.010)	0.037*** (0.012)	0.032*** (0.007)	-0.097*** (0.023)	-0.002 (0.038)	-0.173*** (0.029)	-0.171*** [0.000]	86.5
Constant	3.424*** (0.201)	3.684*** (0.361)	3.544*** (0.284)					
Wald time-dummies (p-value)	2.8*** (0.000)	1.4 (0.174)	1.7* (0.087)	7.8*** (0.000)	2.7*** (0.006)	7.0*** (0.000)		
Wald country-dummies (p-value)	6.9*** (0.000)		5.5*** (0.000)					
Wald industry-dummies (p-value)	20.9*** (0.000)	74.1*** (0.000)	20.4*** (0.000)					
R² (overall) R² (within)	0.42	0.38	0.49	0.18	0.21	0.19		
Obs.	3,180	1,250	1,930	3,180	1,250	1,930		
N. of firms	409	167	242	409	167	242		

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

For time-dummies, country-dummies and industry-dummies, Wald tests of joint significance are reported.

^ The absolute difference between the EU and US coefficients (from the FE estimates) is reported, together with the p-value (in squared brackets) of the t-test on the significance of this difference. In the last column the ratio of the EU coefficient with respect to the US one is reported.

Table 7: Dependent variable: log(Labor Productivity); 2004-2008

	WHOLE SAMPLE	UNITED STATES	EUROPEAN UNION	WHOLE SAMPLE	UNITED STATES	EUROPEAN UNION	EU-US^	EU/US
	POLS	POLS	POLS	FE	FE	FE	FE	FE
Log(R&D stock per employee)	0.143*** (0.010)	0.224*** (0.014)	0.074** (0.023)	0.243*** (0.022)	0.294*** (0.032)	0.194*** (0.030)	-0.100** [0.028]	0.66
Log(Physical capital stock per employee)	0.216*** (0.012)	0.161*** (0.016)	0.265*** (0.039)	0.070*** (0.011)	0.087*** (0.012)	0.034* (0.018)	-0.053** [0.021]	0.39
Log(Employees)	0.036*** (0.007)	0.046*** (0.009)	0.036*** (0.018)	-0.136*** (0.020)	-0.133*** (0.029)	-0.131*** (0.031)	0.002 [0.960]	0.98
Constant	3.565*** (0.126)	3.647*** (0.169)	3.235*** (0.238)					
Wald time-dummies (p-value)	0.6 (0.665)	2.7** (0.028)	0.5 (0.750)	1.5 (0.195)	8.8*** (0.000)	1.5 (0.195)		
Wald country-dummies (p-value)	11.2*** (0.000)		8.5*** (0.000)					
Wald industry-dummies (p-value)	26.5*** (0.000)	27.5*** (0.000)	17.0*** (0.000)					
R^2 (overall) R^2 (within)	0.33	0.59	0.43	0.18	0.22	0.16		
Obs.	4,949	2,652	2,297	4,949	2,652	2,297		
N. of firms	1,090	588	502	1,090	588	502		

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

For time-dummies, country-dummies and industry-dummies, Wald tests of joint significance are reported.

^ The absolute difference between the EU and US coefficients (from the FE estimates) is reported, together with the p-value (in squared brackets) of the t-test on the significance of this difference. In the last column the ratio of the EU coefficient with respect to the US one is reported.

Table 8: Dependent variable: log(Labor Productivity); 2009-2012

	WHOLE SAMPLE	UNITED STATES	EUROPEAN UNION	WHOLE SAMPLE	UNITED STATES	EUROPEAN UNION	EU-US^	EU/US
	POLS	POLS	POLS	FE	FE	FE	FE	FE
Log(R&D stock per employee)	0.164*** (0.011)	0.261*** (0.011)	0.096*** (0.018)	0.158*** (0.026)	0.199*** (0.034)	0.093** (0.041)	-0.106** [0.049]	0.46
Log(Physical capital stock per employee)	0.258*** (0.013)	0.191*** (0.012)	0.323*** (0.024)	0.089*** (0.010)	0.105*** (0.013)	0.058*** (0.018)	-0.047** [0.037]	0.55
Log(Employees)	0.006 (0.007)	0.002 (0.008)	0.020* (0.011)	-0.248*** (0.027)	-0.319*** (0.034)	-0.264*** (0.045)	0.055 [0.327]	0.82
Constant	2.868*** (0.095)	2.699*** (0.105)	3.605*** (0.265)					
Wald time-dummies (p-value)	5.8*** (0.665)	3.2** (0.022)	4.2*** (0.005)	57.7*** (0.000)	37.7*** (0.000)	23.7*** (0.000)		
Wald country-dummies (p-value)	11.9*** (0.000)		7.9*** (0.000)					
Wald industry-dummies (p-value)	19.8*** (0.000)	35.8*** (0.000)	12.0*** (0.000)					
R² (overall)	0.42	0.49	0.43					
R² (within)				0.26	0.20	0.20		
Obs.	3,814	2,012	1,802	3,814	2,012	1,802		
N. of firms	1,024	555	469	1,024	555	469		

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

For time-dummies, country-dummies and industry-dummies, Wald tests of joint significance are reported.

^ The absolute difference between the EU and US coefficients (from the FE estimates) is reported, together with the p-value (in squared brackets) of the t-test on the significance of this difference. In the last column the ratio of the EU coefficient with respect to the US one is reported.

APPENDIX

Table A.1: Classification of ICB industries into the HIGH-TECH and MEDIUM- AND LOW-TECH macro sectors

INDUSTRIES (ICB code)	R&D/Employees (th. € per employee)	Classification
Pharma, & bio, (4570)	66.08	High-Tech
Tech,hard & equip, (9570)	44.16	High-Tech
Software & comp,serv, (9530)	27.66	High-Tech
Leisure goods (3740)	20.49	High-Tech
Health care equip, (4530)	16.12	High-Tech
Electronic & el,equip (2730)	12.99	High-Tech
Aerospace & defense (2710)	9.87	High-Tech
Automob, & parts (3350)	9.74	High-Tech
Chemicals (1350)	9.52	High-Tech
General retailers (5370)	9.39	Medium- and Low-Tech
Financial serv, (8770)	9.03	Medium- and Low-Tech
Mobile telec, (6570)	9.01	Medium- and Low-Tech
Media (5550)	8.94	Medium- and Low-Tech
Alternative energy (580)	7.44	Medium- and Low-Tech
Fixed line telec, (6530)	7.38	Medium- and Low-Tech
Industrial engine, (2750)	6.85	Medium- and Low-Tech
House,goods & const, (3720)	5.53	Medium- and Low-Tech
Travel & leisure (5750)	5.26	Medium- and Low-Tech
Personal goods (3760)	4.41	Medium- and Low-Tech
Equity inv,instrum, (8980)	4.28	Medium- and Low-Tech
General industrials (2720)	4.27	Medium- and Low-Tech
Support services (2790)	4.26	Medium- and Low-Tech
Oil equip, (570)	4.23	Medium- and Low-Tech
Ind,metals & min, (1750)	3.47	Medium- and Low-Tech
Oil & gas prod, (530)	3.38	Medium- and Low-Tech
Food producers (3570)	3.01	Medium- and Low-Tech
Electricity (7530)	2.15	Medium- and Low-Tech
Gas, water & multi-ut, (7570)	2.10	Medium- and Low-Tech
Construction & mater, (2350)	1.99	Medium- and Low-Tech
Tobacco (3780)	1.92	Medium- and Low-Tech
Forestry & paper (1730)	1.83	Medium- and Low-Tech
Indust,transp, (2770)	1.23	Medium- and Low-Tech
Beverages (3530)	1.20	Medium- and Low-Tech
Mining (1770)	1.15	Medium- and Low-Tech