EXPLORING EUROPE’S R&D DEFICIT RELATIVE TO THE US: DIFFERENCES IN THE RATES OF RETURN TO R&D OF YOUNG LEADING R&D FIRMS

Authors

Michele Cincera, Université Libre de Bruxelles, Solvay Brussels School of Economics and Management, iCite, Brussels, Belgium.

Reinhilde Veugelers, Faculty of Economics & Business, Department of Management Strategy & Innovation, University of Leuven (K.U.L.), Leuven, Belgium, Senior Fellow at Bruegel; Research Fellow at CEPR

iCite Working Paper 2013 - 001

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Exploring Europe’s R&D deficit relative to the US: differences in the rates of return to R&D of young leading R&D firms

Michele Cincera*a and Reinhilde Veugelersb

aUniversité Libre de Bruxelles, Solvay Brussels School of Economics and Management, iCite, Brussels, Belgium; bFaculty of Economics & Business, Department of Management Strategy & Innovation, University of Leuven (K.U.L.), Leuven, Belgium, Senior Fellow at Bruegel; Research Fellow at CEPR

This version: 14.11.2012

Abstract

This paper examines the sources of the EU’s lagging business R&D performance relative to the US, particularly the contribution of missing young leading innovators in high technology intensive sectors in Europe. It investigates through econometric analysis whether the lower presence in the EU of young leading innovators and in high-tech sectors is due to lower rates of return to R&D as compared to their US counterparts. The analysis indeed finds such lower rates of return.

Key words: age of firms, rate of return to R&D, EU-US R&D gap

JEL codes: O33

* Corresponding author. mcincera@ulb.ac.be
1. Introduction

Innovation in the European Union remains weak, especially R&D investment by the business sector. Furthermore, there are relatively few signs of progress despite the 3% Barcelona target established since 2000 (European Commission, 2012).

A common explanation raised for the EU’s tame business R&D performance is its specialization in medium-tech, rather than in high-tech, sectors. The EU is especially lagging in key information technology sectors, which were the drivers of growth in the late 1990s in the US (O’Mahoney and van Ark, 2003; Denis et al., 2005; European Commission, 2007; Moncada et al., 2010).

Further firm-level evidence suggests that the EU’s business R&D deficit may reflect constraints on the rapid growth of new, technology-based entrants in the EU compared to the US (Aghion et al., 2008). Cohen and Lorenzi (2000) already argued that the US economy is a more hospitable environment than the EU for new firms to grow large, particularly in Information Technology.

The continued business R&D deficit seems a symptom rather than a cause of the EU’s weakness in innovation. The cause of Europe’s innovation gap seems rooted in an inappropriate industrial structure in which new firms fail to play a significant role in the dynamics of the industry, especially in the high-tech sectors. This is illustrated by their inability to enter and grow to become world market leaders.

This structural EU innovation deficit story has attracted many supporters (O’Sullivan, 2007). But it has received little or no thorough empirical investigation. In a recent contribution, Cincera and Veugelers (2012) use the EC-JRC-IPTS Industrial R&D Scoreboard (European Commission, 2008) of largest global R&D spending firms to examine the contribution of young leading innovators to the EU’s lagging business R&D performance relative to the US. Their findings confirm that the EU has fewer young firms among its leading innovators and that the EU has less of its young leading innovators in new high technology intensive sectors. Missing ‘yollies’ in the right sectors is the largest contributing factor to the EU’s overall R&D deficit relative to the US.

This paper draws further on these results. It investigates through econometric analysis whether the lower presence in the EU of young leading innovators and in high-tech sectors is due to lower rates of return to R&D as compared to their US counterparts. The analysis indeed finds such lower rates of return. This is an important finding for policy making in Europe. In order to nurture more young new firms in young high-tech sectors, the factors that reduce the rates of return to R&D for these firms need to be tackled. This implies that demand-side innovation

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2 Based on an analysis of the top 1000 global firms in terms of market capitalisation which were listed in Business Week in 1999, Cohen and Lorenzi (2000) show that of the 355 US firms included in this list, 33 percent were created after 1950. In contrast, of the 181 firms EU firms in the list, 14 percent were created after 1950. Information technology accounted for more than 70 percent of the difference between the two geographical regions (Cohen and Lorenzi, 2000, p. 125).
instruments needs to play an as important role as stimulating the supply of new firms, by reducing the costs of start-up of new firms.

This paper proceeds as follows. After a review of the literature on young innovative companies in Section 2, Section 3 presents the scoreboard data being used. Section 4 presents the main findings from a descriptive analysis on the contribution of young leading innovators to the EU-US gap in R&D. Section 5 presents our econometric findings on differences in rates of return to R&D for young leading innovators in the EU versus the US. A final section summarises, discusses policy implications of our findings and suggests further research.

2. Young companies and R&D: insights from the literature

The innovation literature provides multiple points of view as to why having young firms might matter for R&D investments. Dating back to Schumpeter, young entrepreneurial firms are at the heart of the creative destruction process (Schumpeter, 1934; the so-called Schumpeter Mark I). Young entrepreneurial firms are more likely to be introducing innovations, particularly of the radical type, displacing existing products and processes. This is because young small lenient firms, unlike their large incumbent counterparts are not bothered by safeguarding incumbent positions and suffer less from bureaucratization of the innovation process (Reinganum 1983; Henderson and Clark, 1990).

At the same time, arguments abound on why large incumbent firms are the driver of innovations (Schumpeter, 1943; Schumpeter Mark II). Large incumbent firms can benefit from economies of scale and scope in the R&D process and complementarities with other competences needed to commercialize the innovations. Large incumbent firms can benefit from learning by doing, having accumulated experience to drive down costs (Malerba, 1992). With higher liquidity at their disposal and collateral, they have easier access to finance (Cincera and Ravet, 2010). Small and particularly young firms, lacking internal funds, collateral and reputation are more likely to be financially constrained, particularly if they are looking to finance high growth-high risk projects (Cincera, 2003; Hall and Lerner, 2010). Large incumbent firms may also find it easier to appropriate the benefits from innovation, having the scale for developing a portfolio of appropriation strategies (Schneider and Veugelers, 2012) and complementary assets (Teece, 1986; Gans and Stern, 2000). And finally, the incentive to preempt displacing entrants pushes incumbent’s innovations, thus countering the fear of cannibalization of existing profits (Gilbert and Newbery, 1982).

One should not see large incumbents and small entrants as purely substitutes. Both types of firms complement each other, with the small new entrepreneurial firms introducing the new drastic innovations on which the large incumbent firms build further with their follow-up innovations, thus further improving and developing the full potential of these innovations. Baumol (2004) notes that although most of the breakthrough innovations occur in small young firms, the improvements on those innovations and wide-scale dissemination occurs through large firms. He notes how fortunate the US has been to exploit the complementarities between large and small firms.

Whether entrants will spend more on innovation than incumbents and which indirect effect entry will have on incumbents’ innovations depends inter alia on the likelihood of entry, the possibility for licensing (Gans and Stern, 2000), the strength of intellectual property protection (Anton and Yao, 1994), the stage in the industry life cycle (Klepper, 1996), the effectiveness of the market for ideas, the control over complementary assets, the association with venture capital, the likelihood of cooperation between entrants and incumbents (Gans et al., 2002).
Overall, with theoretical arguments in favour as well as against young innovators, it remains an empirical question to identify whether and in which circumstances young firms will be more innovative than large incumbent firms.

Much of the multivariate empirical analysis on the relationship between firm size, age and innovation, incorporating a wide set of firm and industry characteristics as control, has failed to find significant results for a positive (or negative) effect of firm size and age (Kamien and Schwartz, 1982; Cohen and Levin, 1989). Characteristics like market concentration, technological opportunities, the stage of the technology life cycle, all matter as intervening variables for the effect of firm size and age for innovation. Small young firms are more important for innovation in less concentrated industries (Acs and Audretsch, 1987) and in the early stages of the life cycle of an industry (Utterback, 1994).

When it comes to radical innovations, there is more support to be found for small, new firms compared to large incumbents. Henderson (1993) examined two theories of why large incumbent firms fail to create radical innovations: (1) lack of motivation (the economic perspective), and (2) lack of ability (the organizational perspective). Her analysis, using data from the semiconductor photolithography equipment industry, showed support for both theories. Shane (2001) similarly finds evidence in favor of small firms introducing radical innovations. His research on MIT based patents finds that radical patents have a higher probability that the invention will be commercialized through start-ups.

Schneider and Veugelers (2010) provide micro-econometric evidence from German CIS data in support of young, small highly-innovative companies (YICs) for the introduction of more radical innovations. Controlling for other firm and industry characteristics that might explain innovative performance, they find that YICs achieve on average a higher level of innovation performance than other innovators. This difference is substantially more pronounced for the measure of sales with market novelties, suggesting that young highly-innovative firms are most differentially successful when it comes to introducing more radical innovations. Pellegrino et al. (2011) using Italian CIS data find young innovative companies to rely more on embodied technical change from external sources compared to large incumbent firms.

The empirical analysis of the growth performance of new technology based firms identifies a mixture of firm, founder, founding team and environment characteristics to be of relevance for explaining post-entry growth (Almus and Nerlinger, 1999; Acs and Audretsch, 1990). There is firm age (Jovanovic, 1982), start-up size (Evans, 1987), the education and experience of the founder and founding team (Colombo and Grilli, 2005), partnerships with other innovation actors, local agglomeration effects among others. An important barrier for growth identified in the literature is the presence of liquidity constraints, as shown by the impact of start-up capital, internal funds and the availability of external financing, in casu most notably venture capital backing (Bertoni et al., 2011).

If young leading innovators are more R&D intensive and/or their presence incites other firms to be more R&D intensive, then a nation that fails to generate new innovative firms and let them grow to a worldwide leading R&D position, will suffer in terms of its overall innovative capacity. And as young firms will be particularly important in the early stages of new markets being developed, a nation that fails to nurture young leading innovators, will be particularly weak in developing innovative capacity in new sectors where the largest opportunities are for technological growth.
If young firms are indeed found to play this role, with their higher R&D intensity, could they then also be behind the EU’s gap in R&D intensity relative to the US and the persistence of this gap? Is the story behind EU’s persistent EU-US gap due to Europe missing young firms with a deep R&D intensity in new sectors? And if the EU has less young leading innovators and particularly less in new sectors, why is this so? Is this because these firms have fewer incentives to invest in R&D as compared to their US counterparts? Are their returns to R&D investments lower, reflecting structural barriers to innovate for these companies in the EU? These are the questions addressed in the remainder of this paper. To this end we use data from the largest R&D investors worldwide, as collected in the EU-JRC-IPTS Industrial R&D Investment Scoreboard.

3. Data

We start from the set of firms which belong to the European Union (UE)-1000 and non-EU-1000 largest\(^3\) R&D spenders in the 2008 edition of the EU-JRC-IPTS Industrial R&D Investment Scoreboard\(^4\).

This data set has been augmented with information on the age of the creation of firms. The sources used for retrieving the age information are mainly the websites of companies (86.0% of firms) and Wikipedia (78.7%). These sources have been crosschecked with the Amadeus database (for the EU companies only, 25.6%), the dataset of Veron (2008) which is publicly available\(^5\) (9.6%) and other sources (less than 10% of firms) such as Business Week, FinanceYahoo, LinkedIn.

To construct the age of the firms we use the very first year of the firms' creation, i.e. ex-nihilo creation. In case of a merger and acquisition (14.9% of the cases), the oldest age of the merged entities is considered.

The information on the age of the firms allows us to distinguish between young and old firms. It should be noted that the “young firms” in this paper, are not small start-ups. Indeed, the average size for the young firms is 10,000 employees worldwide. Hence our “young firms” are a group of firms that managed on their own, i.e. without being taken over, in a relatively short time span since birth, to grow to a world scale leading position deploying substantial R&D resources. These firms have managed to overcome not only any barriers to entry but also barriers to growth to world leading innovator status. As a corollary of this, the dataset is not suited to check for a start-up or SME dimension as it includes (almost) no firms with less than 250 employees.

Besides the age of foundation of firms, the dataset also contains information on the following variables: main industrial sector (according to the Industry Classification Benchmark, ICB), country of origin of the firm, net sales, number of employees, and R&D investment for each

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\(^3\) By large, we mean companies with R&D investments higher than 35 millions € in 2007.

\(^4\) The European Commission JRC-IPTS collects since 2004 annual data on companies investing the most in R&D worldwide (the EU Industrial R&D Investment Scoreboards).

See: http://iri.jrc.ec.europa.eu/research/scoreboard.htm

\(^5\) http://spreadsheets.google.com/pub?key=pDNVZRRJsKO4qJaOogboxbg&gid=0
year of the period 2004-2007. The geographic classification of firms is done on the basis of ownership.\footnote{All activities of the firm are being consolidated in the R&D Scoreboard. We have no information on the geographic and sectoral distribution of firm’s activities.}

Due to missing data for some firms, the final sample includes 1034 firms. The data set is representative of 96.1\% of the R&D carried out in 2007 by the top 2000 worldwide corporations’ listed in the EU-JRC-IPTS 2008 industry R&D Scoreboard which is itself representative of more than 80\% of the worldwide R&D in the private sector (Business Enterprise R&D)\footnote{See for instance European Commission (2008).}. 29\% of our sample firms are from the EU, 38\% from the US, 19\% from Japan and 14\% from the Rest of the world.

In terms of the age of the companies, 22\% of the firms were created before 1900, 27\% between 1900 and 1945, 18\% between 1946 and 1974, 18\% between 1975 and 1990 and 16\% after 1990.

We define young companies as the ones that were created after 1975. We will label them as young leading innovators (Yollies) compared to old leading innovators (Ollies). We have 363 Yollies, i.e. 34\% of our sample of which 59 are from the EU, 218 from the US, 3 from Japan and 83 from the Rest of the Word.
4. Descriptive analysis

In this section we briefly present some descriptive statistics on the position of EU versus US based and old versus new firms in the data set of leading world R&D spenders. For a more indepth analysis of these descriptives, see Cincera & Veugelers (2012).

4.1. Young Leading Innovators and their R&D, sales and employment profile

Thirty-four percent of all leading innovating firms in our sample are ‘young’, i.e. were born after 1975. Sixteen percent are ‘very young’, i.e. born after 1990. The share of Yollies in number of firms is larger than their share in net sales, employment and R&D. Yollies represent 10 percent of net sales, 12 percent of employment and 19 percent of R&D in our sample. Yollies are typically smaller in size, employment and R&D budget than Ollies. As their share is larger in R&D than in net sales, Yollies are more R&D oriented than Ollies. The average R&D intensity of Yollies is 6.3 percent relative to the 3.2 percent for old firms, almost twice as high.

4.2. Young Leading Innovators and their sectoral distribution

A number of industry and services sectors are particularly associated with Yollies. Table 1 illustrates these sectors in which Yollies are prominently present. These sectors are Internet, biotechnology, software, semiconductors, telecom equipment, computer hardware, computer services, health equipment & services. The Internet sector has no firms born before 1975.

--- INSERT TABLE 1 ABOUT HERE ---

All these ‘young’ sectors are also high R&D intensive sectors, i.e. their R&D intensity is above twice the total average in the sample. The only exceptions are computer hardware and computer services. The high-R&D intensive sectors which have relatively less young firms are health equipment and pharmaceuticals.

With the exception of biotechnology (and Internet by default), young firms are not significantly more R&D intensive than their older counterparts in the same sector. This seems to suggest that if we ignore biotechnology and Internet, albeit two important sectors, the higher overall R&D intensity of Yollies can mostly be attributed to their presence in R&D intensive sectors rather than being more R&D intensive than their older counterparts within their sector. Table 1 shows that old firms in young sectors are also more R&D intensive (8%) than average old firms (3%). They are most likely incited by the competition of the young firms in their sector, and/or doing the follow-up innovations on the breakthrough innovations launched by the young firms. The importance of this sectoral dimension for explaining the difference in R&D intensity between young and old firms is more rigorously examined in Cincera and Veugelers (2011).\(^8\)

4.3 Young leading innovators and EU’s R&D gap relative to the US

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\(^8\) Using a statistical decomposition exercise, the authors show that the difference in R&D intensity between Yollies and Ollies is mostly a structural effect, i.e. due to a stronger presence of Yollies in High-Tech sectors, rather than an intrinsic effect, i.e. Yollies being more R&D intensive than their older counterparts in their sector. The structural effect accounts for 78% of the overall difference in R&D intensity.
With young firms being more R&D intensive and being the driving force in most high-tech sectors, young firms are obvious candidates to explain differences between the EU and the US.

--- INSERT TABLE 2 ABOUT HERE ---

Among the US’s leading innovators in the R&D Scoreboard, more than half of them are Yollies. By contrast, Europe has only one out of five leading innovators as ‘young’. For the US, Yollies account for 35 percent of total R&D, for the EU this is a mere seven percent! Yollies have a higher R&D intensity compared to their older counterparts in both regions. But for the US this is more evident, leaving a higher R&D intensity differential for US Yollies as compared to the EU.

The lower overall R&D intensity of EU leading innovators compared to the US can thus be explained by the combination of the following factors:

1. The EU has less Yollies than the US. This matters because Yollies have a higher R&D intensity;
2. The EU-based Yollies are less R&D intensive than their US counterparts;
3. Also the EU-based Ollies are less R&D intensive than their US counterparts.

Cincera and Veugelers (2012) calculate the exact size of these effects, using a decomposition analysis. This exercise shows that all three effects contribute to explaining the lower R&D intensity of EU leading innovators. It matters that the EU has fewer Yollies than the US. This effect is responsible for about one third of the overall gap. But it matters even more that European Yollies are less R&D intensive compared to the US. This factor accounts for 55 percent of the total EU-US R&D intensity differential. That Europe’s Ollies are less R&D intensive as compared to their US counterparts only accounts for only 11% of the total R&D intensity gap, leaving 89% of the gap explained by Europe’s missing yollies and their lower R&D intensity.

Why are EU firms less R&D intensive than their US counterpart, and particularly EU Yollies? Is it a case of wrong sectoral specialisation? Table 2 shows clearly that Europe has fewer of its yollies in High-Tech sectors: 59% compared to 83% in the US. Cincera and Veugelers (2012) identify how much of the difference in R&D intensity between EU Yollies and their US counterparts is due to this different sectoral composition. They find that almost all of the difference (i.e. 98%) is due to a structural effect. Europe simply has fewer Yollies in the high R&D intensive sectors. Interestingly, this sectoral specialisation story also explains the difference in R&D intensity between the EU and the US for old companies and even more so, as the intrinsic effect for old companies turns out to be negative, i.e. within sectors, old EU leading innovators are performing better than their US old counterparts. Therefore, the reason why EU Ollies are performing on average worse than their US counterparts is entirely due to a different sectoral composition. Once corrected for this, EU Ollies are performing better than their US counterparts. The Ollies differential effect is however of only minor importance in explaining the overall EU-US gap (11%, cfr. supra).

In sum, the descriptive evidence clearly confirms that Europe’s persistent business R&D gap with the US is mostly due to it missing young leading innovators, particularly in high-tech sectors. This raises the question why EU has less young leading innovators and particularly less in high-tech sectors. Is this because these firms have fewer incentives to invest in R&D as compared to their US counterparts? Are their returns to R&D investments lower, reflecting
structural barriers to innovate for these companies in the EU? These are the questions addressed in the next section, using econometric analysis.

5. Econometric analysis

In this section, we estimate the rates of return for firms investing in R&D, particularly in high-tech sectors. We are mostly interested in any differences between young and old firms, and between the US and the EU.

5.1. The econometric specification

Most of the econometric studies that have assessed rates of return to R&D adopt a general version of the Cobb-Douglas production function (Hall et al., 2010).

\[ Y_t = \lambda L_t^\alpha C_t^K R_t^\gamma e^{\epsilon_t} \]  

where: \( Y \) is output (value added or net sales\(^9\)); \( L \) and \( C \) are the traditional inputs, i.e. labor and physical capital; \( K \) is the knowledge capital; \( \alpha, \beta, \) and \( \gamma \) are the parameters of interest, i.e. the elasticities of output with respect to each of the inputs.

Usually equation (1) is taken in logarithm to implement the estimation of \( \alpha, \beta \) and \( \gamma \). This leads to the following linear regression model:

\[ \ln Y_t = \lambda \ln L_t + \alpha \ln C_t + \beta \ln K_t + \gamma \ln R_t + \epsilon_t \]  

where lower case letters denote logarithms of variables. The parameter \( \gamma \) reflects the elasticity of output with respect to the R&D capital.

A difficulty raised by the Cobb-Douglas specification rests in the construction of the knowledge capital\(^10\). In order to get around this issue an alternative specification consists in directly estimating the rate of return to R&D instead of its elasticity (Griliches, 1973; Terleckij, 1974). Approximating the growth rate of variables in equation (1) by the first difference of their logarithms, assuming that the rate of depreciation of the R&D capital is close to zero, and given that by definition the elasticity of R&D with respect to output is equal to:

\[ \gamma = \frac{\Delta Y_t}{\Delta Y_t} = \frac{Y_t}{Y_t} \]  

equation (1) expressed in growth rates, can be re-written as:

\[ \Delta Y_t = \lambda \Delta L + \alpha \Delta C + \beta \Delta K + \rho \frac{R_t}{Y_t} + \epsilon_t \]  

where \( \rho \) is the gross (i.e. net of depreciation) rate of return to R&D.

Estimating the elasticity of output with respect to R&D, with its requirement of constructing the firm’s R&D capital stock is not well suited for our purpose as the time series available is not

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\(^9\) If sales is the left-hand variable, then materials should be added in the list of inputs. However, this last variable is not always available at the firm level. Value added is sometimes proxied by gross output, i.e. output less changes in inventories of finished goods.

\(^10\) In general, the R&D capital stock is constructed on the basis of the perpetual inventory method and assuming a 15% depreciation rate of the R&D capital stock of the previous period common to all firms in the sample (Griliches, 1979).
very long and its length is not the same from one firm to the other (i.e. the panel is unbalanced). Furthermore the depreciation rates for the R&D capital stocks across sectors and of Yollies and Ollies are probably not the same.

There are two other well-known problems when estimating the contribution of R&D. The first problem is the so called ‘double counting’ of R&D. This double counting arises since the conventional inputs generally already include the R&D-labor and R&D-capital components of R&D expenditures. As shown by Schankerman (1981) and Mairesse and Hall (1996) for instance, this double counting reflects itself in downward estimates of R&D elasticities and rates of return. As a consequence, when the other inputs are not cleaned from their R&D components, the rate of return to R&D has to be interpreted as an excess rate\footnote{Quoting Mairesse and Hall (1996: p.5), “Conceptually, the value added, labor, and capital measures used to estimate [the productivity equation] should be purged of the contribution of R&D materials, physical capital used in R&D laboratories, and R&D personnel, since these inputs do not produce current output, but are used to increase the stock of R&D capital. If this is not done, the cross section estimates [...] will not necessarily be incorrect, but the measured R&D coefficient will be some kind of ‘excess’ elasticity of output to R&D rather than a total elasticity, i.e. the incremental productivity of R&D rather than a total elasticity.”}.

The second issue is related to the way output and inputs, including R&D investments have to be deflated. Price deflators are usually not available at the firm level and specifically for the various inputs. Also price deflators do not incorporate output quality changes and as a result underestimate the ‘real’ output (Mairesse and Hall, 1996). However, as Mairesse and Mohnen (1995) emphasize, with panel data, quality differences can be captured by time and sector dummies. However, there remain the inter-firm differences, which are not captured by these dummies. The R&D estimates are thus biased but only to the extent that sector prices or dummies do not fully capture the quality differences and the latter are correlated with the explanatory variables.

5.2. Econometric results

The major approach used and discussed in this contribution is the estimation of rates of return to R&D (equation (4)), rather than the R&D elasticities obtained through equation (2-3).

Tables 3 and 4 report the main findings of the econometric analysis of the links between R&D, traditional inputs and firms' productivity performance. In all specifications, we obtain estimated rates of return to R&D globally in line with the results generally reported in the R&D production function literature (Hall et al., 2010).

The second column of Table 3 exhibits the estimates of our benchmark median regression. The estimated rate of return to R&D obtained for the full sample of firms is equal to 0.07. Column 3 of Table 4 presents the estimated rates of return to R&D for the Yollies companies only. Yollies exhibit much higher rates of return to their R&D than the average firm. When an average company irrespective of her age invests one euro in R&D she receives, once we control for the other inputs, 7 cents in terms of additional generated output. For Yollies, this additional value amounts to almost the double, i.e. 13 cents.

Table 4 also reports the results obtained for all firms in the EU and all firms in the US. While positive for the US firms, the rate of return to R&D of EU companies is not statistically significant for the average EU firm.

In terms of firms operating in high-tech sectors compared to medium- and low tech sectors, only the former have a positive and significant rate of return.
We are particularly interested in any difference between the EU and the US in terms of rates of return, and this particularly for Yollies. The results presented in Table 4 allow one to examine this question. When comparing the estimated rates of return to R&D of all yollies across regions, US Yollies exhibit higher rates of return (18 cents) compared to the average US firm (9 cents). For EU firms, the estimated rates of return to R&D turn out to be not statistically significant.

Table 4 adds a further sectoral dimension by reporting the estimated rates of return to R&D of Yollies that operate in the high tech sectors. Here also a higher rate of return (15 cents) is found for the yollies compared to the average firms (9 cents). Results are also presented for EU and US high-tech yollies. The rates of return to high-tech R&D US yollies are clearly outperforming the other US firms (21 cents vs. 15 cents). For the EU companies, here also no direct comparison can be made as none of the estimates for rates of return to R&D are statistically different from zero, not for yollies, but also not in general, even not in high-tech sectors.

5.3. Robustness tests

Table A1 in the Appendix compares the estimated rate of returns to R&D estimated from a simple OLS and median regression models. The estimated coefficients associated with the R&D intensity are much lower in the second model, i.e. 0.07, which can be explained by the presence of some outliers in the data.

Table A1 in the Appendix presents additional results based on GMM first difference (F.D.) and GMM system estimators (Blundell and Bond, 1998). These models allow one to control for the possible endogeneity of some of the regressors\(^{12}\). The Hansen over-identification test validates the set of instruments used (two and higher lagged values of regressors) only in the case of the GMM F.D. estimates. For this model, the rate of return associated with the R&D intensity is statistically significant and positive, albeit larger than the estimate obtained for the median regression.

Table A2 in the Appendix reports the results of median regression based on alternative specifications containing interaction terms between our variables of interest, i.e. R&D intensity and dummy variables representing the fact that a firm is a Yollie or not, is based in the EU or in the US, operates in a high-tech sector or not or a combination of these categories\(^ {13}\). Whatever the model estimated, the results shown in Table A2 again confirm the higher rates of return to R&D for Yollies, US firms and firms that operate in the high-tech sectors. When these dimensions are combined, i.e. US yollies, US high-tech firms or US high-tech yollies, these rates of returns are significantly higher.

Table A3 in the Appendix provides results as regards the R&D elasticities for all firms in the sample. The elasticities associated with the stock of R&D (constructed on the basis of a Perpetual Inventory Method assuming a 15% depreciation rate) indicate a positive and important contribution of R&D to firms' productivity growth. The results based on the median

\(^{12}\) See Aldieri and Cincera (2009) for an application and discussion.

\(^{13}\) One advantage of this type of specifications is that the sample of firms is held constant across models. Hence the differences in the estimated rates of returns to R&D are not due to differences in the samples’ composition.
regression are not very different than the ones we obtain with a simple OLS regression. The F-tests reject however the absence of firms’ specific unobserved effects which may be correlated with the errors terms and as a result may bias the estimates. In order to accommodate for this situation, we also perform within and random panel data regressions (two last columns of Table A3). The Hausman test rejects the random model in favor of the within one, hence confirming the possibility of correlated unobserved effects with the disturbance terms. The estimated elasticities based on the within model and associated with the R&D stock are in line with OLS results: a one percent increase of the stock of R&D results in an increase of more than 0.20% of output (0.28% with the within-estimates).

The main findings of the econometric analysis can be summarized as follows. Yollies exhibit higher rates of return to R&D as compared to the average leading innovators. This holds particularly in the US. In particular US Yollies are performing better than the average US leading innovator (R&D rate of return twice as high). These results are to a large extent robust to alternative specifications and models.

In the next section, we discuss some implications of these results.

6. Implications

The analysis has shown that the EU’s business R&D deficit with the US can be almost entirely explained by the EU having fewer young leading innovators and, even more importantly, having fewer of these in new high-R&D intensive sectors. Why there are less EU young leading innovators and in the high R&D intensive sectors can be related to their non-significant rates of return to R&D as compared to their US counterparts. While in the US, young firms succeed in realizing significantly higher rates of return to R&D as compared to their older counterparts, and this significantly more so in high-tech sectors, European firms fail to generate significant rates of return, even if they are yollies and even if they are in high-tech sectors.

The evidence presented here, when corroborated in further analysis, has important implications for the EU’s innovation policy agenda. The evidence suggests that policies need to address the lower rates of return to R&D in Europe. To do this, policies need to address the specific barriers to development of new high R&D-intensive firms and sectors, as the evidence has shown how pivotal these sectors and firms are for a nation’s persistent R&D performance. Perhaps the most pressing issue for tackling Europe’s deficient capacity for change, are the lower returns to R&D for young leading innovators. This may impede the development of European Yollies more than any other entry costs. Addressing these lower returns would be a more important policy avenue than further reducing administrative burden for innovative start-ups.

Lower returns from innovation may not only hamper innovative firms from entering and growing, they may also reduce the appetite of those financing young risky highly innovative projects. Poorer rates of return relative to risk significantly impede early stage venture capital investing in Europe. Addressing these lower rates of return may be a most effective policy route for developing deeper European venture capital markets.

How to address these lower rates of return? What explains the lower rates of return for European Yollies? The analysis presented here does not provide much help here. But other evidence and analysis on barriers for innovation do provide useful insights (for a survey, see e.g. Veugelers, 2009). Beyond the already mentioned access to early risk financing, access to risk-taking lead customers as well as access to frontier research, specialised know-how and skills, can go a long way to explain the barriers to innovation faced by firms in Europe, especially young innovative firms, aspiring to become Yollies. And when intellectual property regimes are not clear, open and affordable, innovators and again especially aspiring young
innovators will be hampered in their search for partners to develop, finance, produce, market, distribute and sell their breakthrough innovations.

With respect to incentives and uncertain demand as barrier for innovation, an important impediment for innovators in Europe is the more fragmented nature of Europe’s markets compared to the US. The higher mobility of capital, labour and knowledge in the integrated US market enables combinations of factors that respond rapidly to shifts of the technological frontier, and allow full exploitation of innovative activities. In the European Union, by contrast, imperfect market integration, in products, services, labour, capital and knowledge markets together with institutional and cultural barriers across the European countries produce a less dynamic configuration. This holds particularly for Europe’s services markets. Because the US is capable of rapidly reallocating resources in line with new technological paradigms, its economy has a higher capacity for “shifting” to new technologies and markets.

For new firms in new sectors, what matters particularly is access to early users willing to take up and co-develop innovations. A particular early customer is the government. In many of the health and ICT sectors, history has shown US public institutions to have been an important early user, pivotal in leveraging further private markets through public procurement (Mowery, 2009). In Europe, the use of public procurement as policy tool to foster innovations and structural change is much less developed and far from being integrated on a European scale.

When considering creative destruction capacity, there are is the more competitive markets and lower exit and re-entry costs for firms in the US. Mowery (2009) notes how critical antitrust policy has been for the development of ICT sectors in the US, by reinforcing a competitive environment for companies conducting R&D and commercialising the results. But they were also contributing to relatively weak enforcement of intellectual property rights in the early years, which permits easier inter-firm diffusion and the entry of new firms. This generally more favourable business environment allows a more effective adjustment of the sectoral structure of the economy with the prompt start-up of new firms in response to new market opportunities in emerging sectors.

Major constraints also arise from European labour markets, which lead to mismatches between staffing patterns and the true demand for skills. They slow down recomposition of research staff from old to new sectors in response to technology and market shifts. They also slow down the recomposition of research staff from the public to the private sector. The greater flexibility of the US labour market, with more mobility between public and private innovation actors, helps to supply skills for the emergence of new firms and industries in the US.

Part of the story is also the shortcomings of the EU’s innovation 'eco-system', which does not effectively link the institutions and organisations that are active in innovation. In particular, a well-functioning interface between the science system and the corporate sector is important for new emerging technologies, which are often built on insights from frontier research.

What types of EU policy intervention are needed to address these specific barriers? And how targeted do they need to be? Innovation policy should further the integration of the EU’s capital, labour, product and services markets, strengthen the EU’s public research base, make it easier for players in the innovation system to interact, ensure healthy competition and clear and affordable intellectual property regimes, ease access to risk financing. Activating demand side instruments, such as procurement, should be high on the agenda.

These policy recommendations, aimed at overcoming barriers that are particularly but not exclusively important to young firms in highly R&D intensive sectors, do not require targeted, sectoral approaches. However, at this stage of the analysis, when there are still too many
unknowns about whether and which interventions are effective, European policy-makers are advised to engage in close monitoring of emerging innovative markets. This is in order to evaluate if the right mix of policy instruments is present and if the mix is effective in ensuring the smooth development of new firms in new high-tech sectors, and so that policies can be adapted or dropped if ineffective. Monitoring should include a strong prospective angle, able to identify potential bottlenecks well in advance.

References


Schneider, C., R. Veugelers, 2012. How young firms protect the returns from their innovations, mimeo.


Table 1. Yollies and their presence in high-tech sectors (in %)

<table>
<thead>
<tr>
<th>Sector</th>
<th>Share of Yollies</th>
<th>R&amp;D by Yollies</th>
<th>R&amp;D Intensity of Yollies</th>
<th>R&amp;D Intensity of Ollies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internet</td>
<td>100</td>
<td>100</td>
<td>10.9</td>
<td></td>
</tr>
<tr>
<td>Biotechnology</td>
<td>91</td>
<td>92</td>
<td>26.7</td>
<td>9.2</td>
</tr>
<tr>
<td>Software</td>
<td>86</td>
<td>88</td>
<td>15.3</td>
<td>13.8</td>
</tr>
<tr>
<td>Semiconductors</td>
<td>71</td>
<td>53</td>
<td>15.2</td>
<td>13.8</td>
</tr>
<tr>
<td>Telecom equipment</td>
<td>64</td>
<td>34</td>
<td>13.5</td>
<td>12.0</td>
</tr>
<tr>
<td>Computer hardware</td>
<td>63</td>
<td>36</td>
<td>3.8</td>
<td>4.6</td>
</tr>
<tr>
<td>Computer services</td>
<td>64</td>
<td>13</td>
<td>4.6</td>
<td>5.5</td>
</tr>
<tr>
<td>Pharmaceuticals</td>
<td>28</td>
<td>3</td>
<td>15</td>
<td>16</td>
</tr>
<tr>
<td>Health equipment</td>
<td>26</td>
<td>29</td>
<td>10.6</td>
<td>6.0</td>
</tr>
<tr>
<td><strong>Average all Sectors</strong></td>
<td><strong>34</strong></td>
<td><strong>19</strong></td>
<td><strong>6</strong></td>
<td><strong>3</strong></td>
</tr>
</tbody>
</table>

Note: See Veugelers & Cincera (2010b) for a version of Table 1 with all sectors.

Table 2: Yollies: EU versus the US

<table>
<thead>
<tr>
<th></th>
<th>EU</th>
<th>US</th>
<th>World Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of Yollies in number of region’s leading innovators</td>
<td>23%</td>
<td>51%</td>
<td>34%</td>
</tr>
<tr>
<td>Share of Yollies in region’s leading R&amp;D</td>
<td>7%</td>
<td>35%</td>
<td>19%</td>
</tr>
<tr>
<td>R&amp;D intensity of Yollies</td>
<td>4%</td>
<td>10%</td>
<td>6%</td>
</tr>
<tr>
<td>R&amp;D intensity of Ollies</td>
<td>3%</td>
<td>4%</td>
<td>3%</td>
</tr>
<tr>
<td>Share of the region’s Yollies in High-Tech Sectors</td>
<td>59%</td>
<td>83%</td>
<td>84%</td>
</tr>
<tr>
<td>Share of the region’s Ollies in High-Tech Sectors</td>
<td>37%</td>
<td>53%</td>
<td>46%</td>
</tr>
</tbody>
</table>

Sources: Authors’ own calculations, the 2008 EU Industrial R&D Investment Scoreboard, EC, JRC/DG RTD and companies’ publicly available information
Table 3. Production function – All firms vs. Yollies; by region (EU vs. US) and by R&D intensity of sectors (High- vs. non High-Tech sector)

<table>
<thead>
<tr>
<th>sample</th>
<th>All firms</th>
<th>Yollies</th>
<th>EU</th>
<th>US</th>
<th>High-Tech</th>
<th>Low+Medium-Tech</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.010 (0.004)</td>
<td>0.022 (0.012)</td>
<td>-0.038 (0.005)</td>
<td>0.010 (0.004)</td>
<td>0.011 (0.007)</td>
<td>0.011 (0.005)</td>
</tr>
<tr>
<td>Δ ln Employees</td>
<td>0.467* (0.008)</td>
<td>0.501* (0.020)</td>
<td>0.595* (0.012)</td>
<td>0.433* (0.014)</td>
<td>0.483* (0.013)</td>
<td>0.465* (0.009)</td>
</tr>
<tr>
<td>Δ ln Physical capital</td>
<td>0.282* (0.017)</td>
<td>0.271* (0.036)</td>
<td>0.258* (0.024)</td>
<td>0.301* (0.024)</td>
<td>0.281* (0.024)</td>
<td>0.265* (0.020)</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>0.070* (0.014)</td>
<td>0.127* (0.030)</td>
<td>0.020 (0.017)</td>
<td>0.088* (0.020)</td>
<td>0.089* (0.019)</td>
<td>-0.047 (0.059)</td>
</tr>
<tr>
<td># of observations</td>
<td>4505</td>
<td>1431</td>
<td>1278</td>
<td>1909</td>
<td>2515</td>
<td>1990</td>
</tr>
<tr>
<td>R²</td>
<td>0.19</td>
<td>0.19</td>
<td>0.26</td>
<td>0.19</td>
<td>0.19</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Notes: Least absolute deviation (median) regressions; *(**,***) = stat. significant at the 1% (5%, 10% level); standard errors in brackets; all equations include time dummies.

Table 4. Production function – Yollies by region (EU vs. US) and by R&D intensity of sectors (High- vs. non High-Tech sector); High-Tech firms by region (EU vs. US)

<table>
<thead>
<tr>
<th>sample</th>
<th>EU</th>
<th>US</th>
<th>High tech</th>
<th>EU &amp; High-tech</th>
<th>US &amp; High-tech</th>
<th>EU</th>
<th>US</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.050** (0.024)</td>
<td>0.058* (0.013)</td>
<td>0.007 (0.014)</td>
<td>0.002 (0.029)</td>
<td>0.046 (0.015)</td>
<td>-0.032* (0.011)</td>
<td>0.024* (0.009)</td>
</tr>
<tr>
<td>Δ ln Employees</td>
<td>0.615* (0.046)</td>
<td>0.505* (0.022)</td>
<td>0.523* (0.023)</td>
<td>0.750* (0.054)</td>
<td>0.517* (0.025)</td>
<td>-0.713* (0.024)</td>
<td>0.419* (0.009)</td>
</tr>
<tr>
<td>Δ ln Physical capital</td>
<td>0.297* (0.089)</td>
<td>0.281* (0.036)</td>
<td>0.270* (0.041)</td>
<td>0.215** (0.095)</td>
<td>0.284* (0.042)</td>
<td>-0.187* (0.048)</td>
<td>0.317* (0.020)</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>-0.010 (0.055)</td>
<td>0.176* (0.033)</td>
<td>0.147* (0.033)</td>
<td>0.042 (0.063)</td>
<td>0.205* (0.038)</td>
<td>0.023 (0.029)</td>
<td>0.145* (0.059)</td>
</tr>
<tr>
<td># of observations</td>
<td>236</td>
<td>937</td>
<td>1174</td>
<td>177</td>
<td>811</td>
<td>560</td>
<td>1302</td>
</tr>
<tr>
<td>R²</td>
<td>0.23</td>
<td>0.20</td>
<td>0.19</td>
<td>0.26</td>
<td>0.21</td>
<td>0.25</td>
<td>0.19</td>
</tr>
</tbody>
</table>

Notes: Least absolute deviation (median) regressions; *(**,***) = stat. significant at the 1% (5%, 10% level); standard errors in brackets; all equations include time dummies.
### Appendix – Table A1. Production function - Full sample – OLS, LAD, F.D. and SYS-GMM regressions

<table>
<thead>
<tr>
<th>Method</th>
<th>OLS</th>
<th>LAD</th>
<th>F.D. GMM</th>
<th>GMM-SYS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.005 (0.010)</td>
<td>0.010 (0.004)</td>
<td>-0.025* (0.006)</td>
<td>-0.409 (0.450)</td>
</tr>
<tr>
<td>Δ ln Employees</td>
<td>0.446* (0.047)</td>
<td>0.467* (0.008)</td>
<td>0.663* (0.109)</td>
<td>0.804* (0.084)</td>
</tr>
<tr>
<td>Δ ln Physical capital stock</td>
<td>0.522* (0.076)</td>
<td>0.282* (0.017)</td>
<td>0.021 (0.101)</td>
<td>0.150* (0.064)</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>0.245* (0.073)</td>
<td>0.070* (0.014)</td>
<td>0.190*** (0.106)</td>
<td>-0.029 (0.061)</td>
</tr>
<tr>
<td># of observations</td>
<td>4505</td>
<td>4468</td>
<td>5508</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.19</td>
<td>0.19</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AR1 test</td>
<td></td>
<td></td>
<td>[0.194]</td>
<td>[0.034]</td>
</tr>
<tr>
<td>AR2 test</td>
<td></td>
<td></td>
<td>[0.870]</td>
<td>[0.850]</td>
</tr>
<tr>
<td>Sargan test</td>
<td></td>
<td></td>
<td>[0.000]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Hansen test</td>
<td></td>
<td></td>
<td>[0.108]</td>
<td>[0.014]</td>
</tr>
</tbody>
</table>

Notes: OLS = Ordinary Least square; LAD = Least absolute deviation (median) regression; F.D. GMM = First difference Generalized Method of Moments; SYS-GMM = System GMM; *(**,***) = stat. significant at the 1% (5%, 10% level); standard errors in brackets (robust for OLS); P-values in square brackets; instruments lagged 2, 3 and 4 periods; all regressions include time dummies; OLS and LAD regressions include country and industry dummies.

### Table A2. Production function – interaction terms with Yollies, US and High-Tech

<table>
<thead>
<tr>
<th>sample</th>
<th>All firms</th>
<th>All firms</th>
<th>All firms</th>
<th>US</th>
<th>High-tech</th>
<th>US &amp; high-tech</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.040* (0.004)</td>
<td>0.011* (0.004)</td>
<td>0.009 (0.006)</td>
<td>0.068* (0.006)</td>
<td>0.046* (0.006)</td>
<td>0.063* (0.008)</td>
</tr>
<tr>
<td>Δ ln Employees</td>
<td>0.469* (0.008)</td>
<td>0.475* (0.007)</td>
<td>0.472* (0.008)</td>
<td>0.431* (0.013)</td>
<td>0.476* (0.012)</td>
<td>0.423* (0.015)</td>
</tr>
<tr>
<td>Δ ln Physical capital stock</td>
<td>0.281* (0.015)</td>
<td>0.280* (0.015)</td>
<td>0.280* (0.016)</td>
<td>0.300* (0.023)</td>
<td>0.282* (0.023)</td>
<td>0.327* (0.027)</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>-0.054** (0.025)</td>
<td>0.008 (0.019)</td>
<td>-0.051 (0.080)</td>
<td>-0.029 (0.046)</td>
<td>-0.059*** (0.035)</td>
<td>0.005 (0.054)</td>
</tr>
<tr>
<td>Yollies</td>
<td>0.007** (0.003)</td>
<td>0.009* (0.003)</td>
<td>0.004 (0.006)</td>
<td>0.004 (0.006)</td>
<td>0.007 (0.005)</td>
<td>0.009 (0.007)</td>
</tr>
<tr>
<td>US</td>
<td></td>
<td></td>
<td></td>
<td>0.005 (0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High-tech</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D intensity x Yollies</td>
<td>0.163* (0.030)</td>
<td>0.080* (0.025)</td>
<td>0.144*** (0.081)</td>
<td>0.215* (0.052)</td>
<td>0.191* (0.041)</td>
<td>0.219* (0.054)</td>
</tr>
<tr>
<td># of observations</td>
<td>4505</td>
<td>1909</td>
<td>2515</td>
<td>1302</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
</tr>
</tbody>
</table>

Notes: Least absolute deviation (median) regression; *(**,***) = stat. significant at the 1% (5%, 10% level); standard errors in brackets; all equations include time dummies.

### Table A3. Production function - Full sample – Elasticities of R&D

---

20
<table>
<thead>
<tr>
<th>Method</th>
<th>OLS</th>
<th>LAD</th>
<th>OLS</th>
<th>LAD</th>
<th>Between</th>
<th>Within</th>
<th>Random</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.416*</td>
<td>-0.463*</td>
<td>0.500*</td>
<td>0.412*</td>
<td>-0.209</td>
<td>-0.875*</td>
<td>-0.519*</td>
</tr>
<tr>
<td>In Employees</td>
<td>0.601*</td>
<td>0.614*</td>
<td>0.521*</td>
<td>0.534*</td>
<td>0.593*</td>
<td>0.510*</td>
<td>0.549*</td>
</tr>
<tr>
<td>In Physical capital</td>
<td>0.313*</td>
<td>0.293*</td>
<td>0.233*</td>
<td>0.228*</td>
<td>0.322*</td>
<td>0.322*</td>
<td>0.319*</td>
</tr>
<tr>
<td>In R&amp;D capital</td>
<td>0.079*</td>
<td>0.083*</td>
<td>0.214*</td>
<td>0.213*</td>
<td>0.083*</td>
<td>0.277*</td>
<td>0.164*</td>
</tr>
<tr>
<td>Industry and country dummies</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td># of observations</td>
<td>5508</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.90</td>
<td>0.73</td>
<td>0.94</td>
<td>0.78</td>
<td>0.90</td>
<td>0.63</td>
<td>0.63</td>
</tr>
<tr>
<td>Hausman test</td>
<td>Chi²(7) 59.54*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: OLS = Ordinary Least square; LAD = Least absolute deviation (median) regression; *(**,***) = stat. significant at the 1% (5%, 10% level); standard errors in brackets (robust for OLS); P-values in square brackets; instruments lagged 2, 3 and 4 periods; all regressions include time dummies.
001 - Exploring Europe’s R&D deficit relative to the US: Differences in the rates of return to R&D of young leading R&D firms - Michele Cincera and Reinhilde Veugelers