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The Impact of Investment in Intangible Assets on Productivity Spillovers

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The impact of investment in intangible assets on productivity spillovers

Final report for the Department for Business, Innovation and Skills

Prepared by London Economics

The views expressed in this report are the authors' and do not necessarily reflect those of the Department for Business, Innovation and Skills.

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London Economics is one of Europe's leading specialist economics and policy consultancies and has its head office in London. We also have offices in Brussels, Dublin, Cardiff and Budapest, and associated offices in Paris and Valletta.

We advise clients in both the public and private sectors on economic and financial analysis, policy development and evaluation, business strategy, and regulatory and competition policy. Our consultants are highly-qualified economists with experience in applying a wide variety of analytical techniques to assist our work, including cost-benefit analysis, multi-criteria analysis, policy simulation, scenario building, statistical analysis and mathematical modelling. We are also experienced in using a wide range of data collection techniques including literature reviews, survey questionnaires, interviews and focus groups.

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Glossary

Spillovers (used interchangeably with **externalities**, **indirect effects**, and **external effects**)	**Spillovers** refer to situations in which the activities of one agent in the market induce external effects (either positive or negative) on other agents in that market. While negative externalities comprise cases in which the effects of an agent's actions are detrimental to the well-being of others, positive externalities represent benefits to the well-being of others. Any external effects that are mediated, reflected or accounted for through prices do not constitute true externalities or spillovers. For example, the spillover effect associated with a firm's investment in an individual worker's training would be the enhanced productivity resulting from the training achieved by *other* co-workers stemming from interactions between employees (such as imitation, learning- by-doing, social pressure or leading-by-example). The spillover effects described are independent of whether these gains are appropriated by the firm or the workers themselves.
Direct effects (used interchangeably with **internal effects** or **private effects**)	The **direct effect** associated with an investment in intangible assets refers to the impact of the investment on the agent undertaking the investment. For example, the direct effect associated with a firm's investment in an individual worker's training would be the enhanced productivity resulting from the training achieved by that worker (again irrespective of whether these gains are appropriated by the firm or the worker). Throughout the report, we sometimes describe a component of the direct effect as being ***internal***, which in this case would represent the element of the direct effect that is appropriated by the employer only (and not the component of the direct effect appropriated by the employee or the spillover effect).
Social effects	The **social effect** of a particular action comprises the *combined* direct *and* indirect effect
Tangible assets	Assets that are physical in nature (such as land, machinery and capital)
Intangible assets	Assets that are not physical in nature. In the context of this analysis, these are grouped into three categories: **computerised information; innovative property; and economic competencies.**
Computerised information (used interchangeably with **ICT capital**)	**Computerised information** refers to outlays on knowledge included in computer software developed for a businesses' own use, and in computerised databases

Innovative property	**Innovative property** takes account of both spending on scientific R&D and on the exploration of new mineral reserves, as well as expenditures on research in less scientific but more creative research. The latter include investments in copyrights in patents, as well as in the development of other products related to the financial industry, architectural and engineering designs, and social sciences and humanities research
Economic competencies	**Economic competencies** take into account the value of firm-specific human capital, the costs of firms' organisational structure, with both the expenses on external consulting and own-account structural change from within the company, and outlays on advertising and market research related to a company's brand equity
Absorptive capacity	**Absorptive capacity** is defined as the ability of an agent to identify, assimilate and exploit existing external knowledge
Agglomeration	**Agglomeration** refers to interactions that are facilitated through geographical proximity of workers. Agglomeration effects are normally discussed in respect of human capital spillovers.
Growth accounting exercises	**Growth accounting exercises** assess the relative contributions of factors of production (e.g. land, labour, capital, intangible assets etc.) in explaining economic growth rates.
Labour productivity	**Labour productivity** is defined using some measure of output or value added per worker (and is (or can be) measured using a monetary value). Taking an example, If labour productivity is assumed to be £30,000, then the identification of a 0.5% increase in labour productivity following from investment in intangible assets, labour productivity might be expected to be £30,150 (0.5% of £30,000), corresponding to a change of £150.
Labour productivity growth	**Labour productivity growth** is the rate of change of labour productivity over time and is measured in percentage terms, Using the previous example, if labour productivity growth is 3.0% per annum (between 1950 and 2010, labour productivity growth in the United Kingdom has averaged 3.1%), then this implies that labour productivity would be expected to increase from £30,000 to £30,900 over the course of a year.

Elasticity	The **elasticity** is defined as the percentage change in one variable (e.g. quantity demanded) following a given percentage change in another (e.g. price). The elasticity measures the degree of responsiveness or sensitivity of one particular variable to another. In this report, a number of analyses estimate the elasticity of output per worker with respect to some form of investment in intangible assets. In other words, the estimates indicate the percentage change in labour productivity following a given percentage change in investment in intangible assets.
Total factor productivity	The standard economic growth model is based on an aggregate production function relating aggregate output to tangible capital (such as machinery and equipment) and labour. In addition, output is assumed to depend on a technology variable, so-called **total factor productivity**, which captures the advances in technological development that result in a more efficient use of inputs in the production of output
Inter-firm spillovers	**Inter**-firm spillovers refer the outcomes occurring *between* firms. For instance, if an employer trains a particular worker, and there is a resulting increase in productivity a number of employees in *different* firms within the same industry (as a result of informal networks and knowledge transfer), then the indirect productivity impact on the employees employed in the non-training firm would be defined as an inter-firm spillover.
Intra- firm spillovers	**Intra**-firm relates the outcomes occurring *within* firms. For instance, if an employer trains a particular worker, and there is a resulting increase in productivity for a number of co-workers in the *same* firm (as a result of learning-by-example for instance), then the indirect productivity impact of the co-workers would be defined as an intra-firm spillover.

Executive summary

London Economics were commissioned by the Department for Business, Innovation and Skills to conduct a literature review of the evidence regarding the impact of investment in intangible assets on productivity spillovers. The review provides a summary of the theory underpinning the concepts of intangible assets, their measurement, as well as the theory of spillovers. We also review the available evidence relating to the channels through which spillovers occur and how spillovers are facilitated. In the empirical section of the report, we review and assess a very large number of articles that consider the direct effect and/or the indirect effect associated with the investment in intangible assets, further disaggregated according to the nature of the intangible asset (so called *economic competencies*, *scientific and creative property* and *computerised information*), as well as the level at which the impact occurs (i.e. individual, firm, industry, and region etc). Finally, we attempt to illustrate the relative effect of the direct impact of intangible assets to the indirect effect.

Investment in intangible assets - identification and measurement

The revolution of information technology over recent decades, as illustrated by the introduction of the Internet, advanced telecommunications and the accelerating launch of new technological products, has significantly contributed to economic growth; however, until recently, this contribution has not been recognised in traditional **growth accounting** exercises, which explain the relative role of the factors of production in explaining economic growth rates, and are based on production functions developed by economic growth theory. **Neoclassical economic growth** theory treats technological progress as exogenous, i.e. no assumptions are made concerning the origin of and mechanisms behind technological change, leaving it as an unexplained and automatic process. As a consequence, when taking account of the relative contribution of production factors to economic growth, technological progress remains as an unexplained residual in traditional growth accounting exercises. The development of various **endogenous growth** theories has attempted to incorporate the effect of technological progress in determining productivity growth (for instance, through the inclusion of measures of human capital in modelling exercises). The incorporation of these variables reduces the residual in the model (i.e. the component of growth that cannot be explained by the various factors of production) implying that the reduction in the residual is accounted for by technological progress[1].

Despite this recent incorporation of technological progress in economic growth theory, expenditures on **intangible assets** (i.e. capital that is not physical in nature) have continuously been expensed as intermediate inputs in firm and National Accounts, which is an approach that effectively removed intangible assets as a determinant of economic growth, rather than recognising their contribution. A significant strand of the recent empirical literature has focused on the resulting bias in common economic growth accounting, and has argued that outlays on intangible assets should be considered as

[1] The estimates of the contribution to productivity growth do not identify the exact source of the growth (i.e. resulting directly from the human capital or through spillover effects)

investments rather than intermediate inputs. As such, a framework for the exact definition, identification and measurement of these **intangible investments** has been developed and applied.

The main contribution to the literature in this respect is authored by Corrado et al. (2005), whose framework has been recognised and applied by the majority of studies relating to intangible assets. In their methodology, the authors group investments in intangible capital into three main components, and measure them according to this classification:

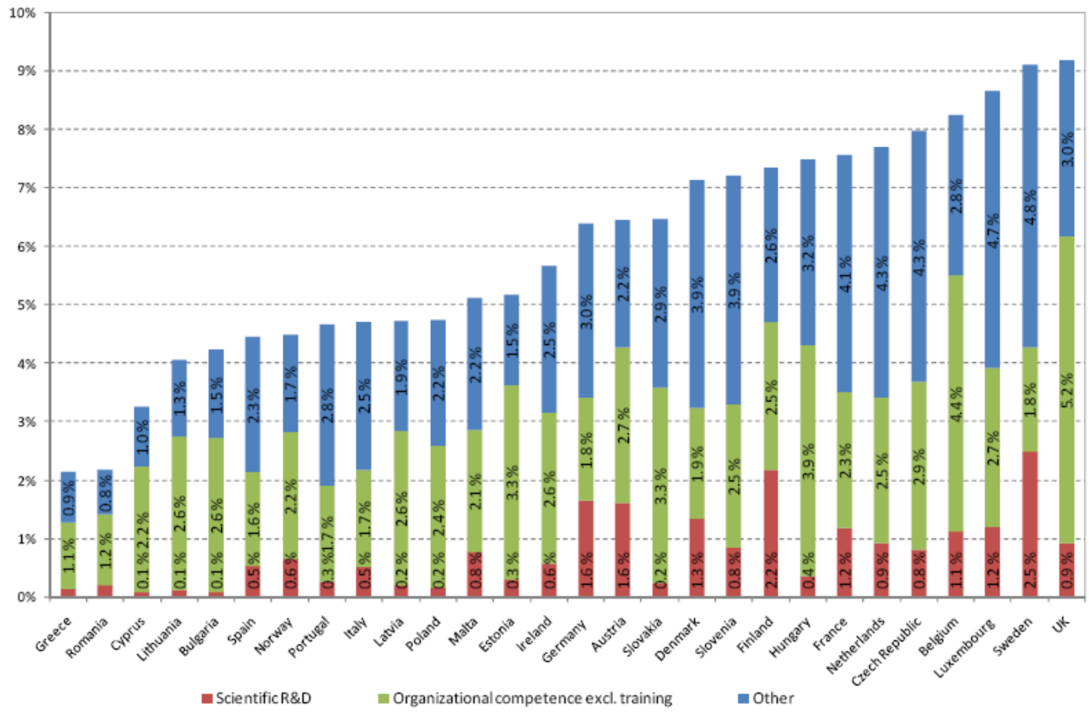
1. **Computerised information** includes expenditures on knowledge embedded in computer software that has been developed, purchased or customised for a firm's use, as well as computerised databases.

2. **Scientific and creative property** takes account of both outlays on scientific R&D, covering the scientific knowledge embodied in patents, licenses and unpatented general know-how and the exploration of mineral reserves, as well as non-scientific R&D efforts. The latter refer to spending on commercial copyrights, licenses and designs, and on the development of products related to the financial industry, architectural and engineering designs, and research regarding social sciences and humanities.

3. **Economic competencies** relate to the value of firm-specific human capital, the costs of developing the organisational structure of firms (regarding both the expenses on external consulting and own-account structural change), and expenditures on advertising and market research related to a company's brand equity.

A comparison of national levels of investment in intangible assets across various countries, taken from one of the more recent works exploring the international measurement of intangibles, is provided in Figure 1 and demonstrates that intangible assets make up between 2% and 9% of GDP (with the UK at the very top of the range (see Majcen et al. (2011), Jona-Lasinio (2011)). Although this demonstrates the aggregate investment in intangibles at a national level, a key question raised is the extent to which total investment in intangible assets is **optimal** given the potential economic benefits resulting from that investment.

Figure 1: Intangibles as a percentage of GDP using the INNODRIVE macro database



Source: Majcen et al. (2011) based on INNODRIVE macro database and Jona-Lasinio (2011)

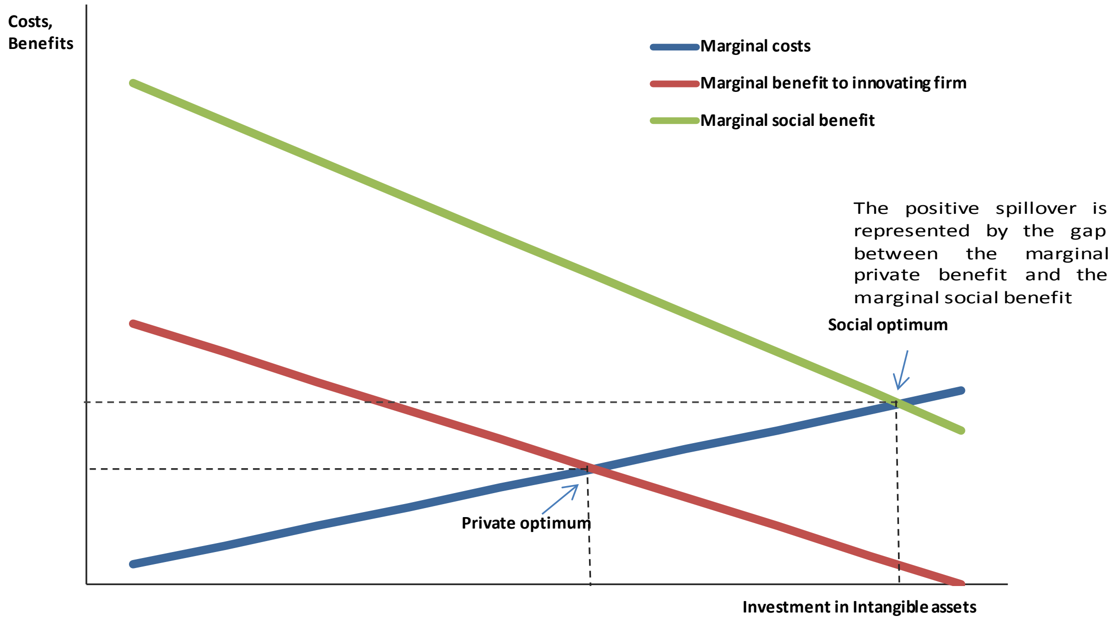
What is a spillover?

There is a significant volume of literature that indicates that investments in intangible assets result in substantial increases in productivity to those making the investment. As with any investment, in addition to the **direct** effect, these particular investments in intangible assets may elicit **spillovers**. Spillovers refer to situations in which the activities of one agent in the market induce an **indirect** effect (of either a positive or negative character) on one or more other agents in the market. While negative spillovers comprise cases in which the effects of an agent's actions are detrimental to the well-being of others, positive spillovers represent benefits to the well-being of others.

An assertion of the theory is that any indirect effects that are mediated, reflected or accounted for through price mechanisms do not constitute true spillovers. In other words, if an outcome appears to be a spillover (i.e. the higher productivity achieved by employees following the provision of **firm-funded** training), but is reflected or accounted for through higher wages, then it is not in fact a spillover (and is considered a direct effect and not an indirect effect).

Spillovers of productivity and knowledge between different actors and levels of the economy constitute examples of positive externalities. For example, investments in R&D activities by one firm in the market might benefit other firms if they can apply the newly-developed technology in their own production processes to reduce costs, without the beneficiary firms contributing to the expenses of the innovating company. However, given the absence of a market mechanism, the innovating firm does not take account of the external benefits it provides to its rivals (presented below). As such, the existence of substantial spillovers or external benefits may lead to substantial under-investment in intangible assets (from a social perspective). For instance, employers are incentivised to pay for the benefits they themselves receive but not the benefits that other firms or individuals receive or indeed the benefits that employees receive. The potential for sub-optimal investment provides an economic rationale for the government for intervention.

Figure 2: Illustration of a positive externality



Source: London Economics

Do externalities result in sub-optimal outcomes and how big is the problem?

The information presented in Figure 1 illustrates the aggregate investment in intangibles at a national level. A key question this raises is the extent to which total investment in intangible assets is optimal given the total benefits. Particularly pertinent for micro-policy is whether and to what extent do spillovers potentially result in sub-optimal outcomes (i.e. sub-optimal investment by employers and individuals).

A commonly cited spillover at firm level relates to *poaching* externalities, whereby a training firm faces an under-incentive to invest in training (especially in relation to general transferable skills), given the fact that the trained employee may have the option to move firm after the training has occurred and potentially reap some of the gains associated with the training. Although there may be positive spillovers from investing in training, and some firms will benefit from hiring employees trained by other firms, there is a free-rider problem, where according to standard game theoretic models, all firms will have an incentive to rely on other firms to invest in training in the expectation of *poaching* more productive workers trained elsewhere. Even in an imperfectly competitive labour market, all firms will face the same incentives, resulting in a sub-optimal level of investment in training.

A number of authors have demonstrated the extent of poaching externalities. Muehlemann and Wolter (2011) hypothesise that the density of regional labour markets might adversely affect firms' training decisions (in the sense that higher labour market density might increase the threat of competitors poaching trained employees). The results suggest that a 1% increase in regional labour market density in Switzerland results in a **0.15% decrease** in the number of apprentices trained by those firms offering training (i.e. the extent of the training provided by firms). However the authors find evidence of poaching externalities only when firms incur net costs from training. When training generates a net benefit for firms, local labour market density appears to have no effect on the number of apprenticeships offered.

Similarly, Brunello and De Paola (2006)[2] use firm data on training in the Italian provinces and find that a 1% increase in local labour market density reduces the percentage of trained employees across firms by approximately **0.146%**[3]. Using individual data, Brunello and Gambarotto (2007) examine the effect of local labour market density on training participation in the United Kingdom. The results of their analysis suggest that, when evaluated at the average firm size, a 1% increase in labour market density reduces the probability of employer-provided training by 0.014, which corresponds to approximately 4% of the average value for this type of training in the UK[4].

Spillover channels – how do spillovers occur?

R&D and innovation

Labour mobility

The academic literature considers a wide range of mechanisms or channels through which these productivity spillovers might occur. The first of these refers to the **mobility of skilled and experienced labour**, which is considered as a channel for spillovers between and within industries and regions, and between foreign multinational enterprises and domestic firms in the host countries they operate in. Authors considering labour mobility as the main channel for knowledge externalities assert that knowledge regarding production processes, organisational structures, and new technologies etc. is embodied in individual workers through training and work experience with their employers. This channel operates for firms' investments in innovative activities and training, with potential externalities arising from the firms' inability to appropriate all the returns generated from their investment. While the basic mechanism is the same for both types of investment (i.e. innovation and training), the existence and the magnitude of the disincentive to invest may vary according to the type of investment. Investment in innovative activities such as R&D (the effect on training decisions is discussed below) generate knowledge fully appropriable by the firm through patents, but also increase the stock of human capital for the research workers involved. This accumulated knowledge may not be fully appropriable by the investing firm if the worker then decides to leave their current employer for a new job at a different firm

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[2] Brunello and De Paola's results refer to off-the-job training provided by specialised external organisations, paid for or organised by firms. However, the authors argue that their results should not change significantly if applied to on-the-job training.

[3] These findings are also supported by work relating to Germany (Harhoff and Kane (1997)).

[4] The authors find an average incidence of employer-provided training in the UK of 32% in the sample considered

(either an existing firm or a start-up firm). Conversely, the hiring firm may experience a positive externality, increasing their stock of knowledge without having to bear the cost of the investment. However, two factors should be taken into account when assessing the existence of externalities and the potential disincentive to invest affecting firms. On the one hand, the extent of externalities may be smaller than expected if potential externalities are internalised by labour market mechanisms such as higher wage payments. On the other hand, the presence of externalities may not necessarily discourage firm-level investment in R&D if firms are subject to both labour market threats and opportunities (i.e. employees leaving and joining the firm) and the two effects on firm-level productivity cancel each other out. However, even in this latter case, in the presence of labour mobility, the decision of firms to invest in R&D becomes more risky than would otherwise be the case, which will in itself potentially reduce the level of R&D undertaken by firms to a sub-optimal level.

International knowledge spillovers

The literature identifies three main mechanisms explaining how international knowledge and productivity spillovers occur. First, knowledge might be diffused through **international trade in intermediate inputs**, where domestic companies importing the input will benefit from its technology, as developed by foreign companies. Concerning this mechanism, different authors disagree whether domestic firms will benefit only from the knowledge that is produced in the countries they trade with, or whether it is the stock of knowledge available in the trading countries (more generally) that matters, undermining the relevance of bilateral trade relationships. Secondly, it has been asserted that knowledge spillovers might be the result of **foreign direct investment (FDI)**, where domestic firms achieve productivity increases via purchases from foreign-owned multinational subsidiaries, or multinationals deliberately initiate operations abroad in order to benefit from local firm knowledge in the host countries. Finally, international knowledge spillovers might also result from **direct learning about foreign technologies** by domestic companies, through the exchange of blueprints at prices which are lower than the costs originally incurred by the innovator.

Focusing on intra-industry spillovers, **interactions between workers** are considered as the primary channel through which knowledge is diffused between firms from the same industry. The literature emphasises how **formal knowledge** exchange, e.g. through patents, conferences and patents, as well as **informal** contacts and knowledge-sharing between workers, will lead to intra-industry spillovers. Further, several studies elaborate on spillover channels that are deliberately initiated by companies intending to benefit from their competitors' knowledge. For example, spillovers might occur if firms decide to enter into R&D collaborations with universities or rival companies, in an attempt to internalise the externalities arising from each others' research efforts. In addition, companies might poach their rivals' R&D employees to reap benefits from their competitors' R&D activities. At intra-industry level, in addition to the diffusion of knowledge within firms (such as the adoption of new technology and organisational improvements, but wider than straightforward human capital accumulation), some studies consider the external sectoral restructuring effect resulting to firms entering or exiting the market (see Disney et al (2003)). These studies demonstrate that the external effects account for a significantly greater proportion of productivity growth at sectoral level compared to the within firm effects.

Human capital spillovers: agglomeration effects and labour mobility

A significant strand of the literature investigates the extent to which human capital externalities, as a particular type of knowledge externalities, are prone to **agglomeration effects**. It is argued that working alongside highly educated and experienced workers will induce knowledge spillover effects through interactions between employees (such as imitation, learning-by-doing, social pressure or leading-by-example). Arguing that these interactions are facilitated through geographical proximity of workers, it is asserted that the size of human capital spillovers crucially depends on the geographical proximity of the workers concerned, thereby facilitating spillovers between workers within the same region, city, or firm.

Although agglomeration effects may be positive, these need to be traded off against the potential for poaching externalities, similarly to that described for investment in R&D activities. Firms may under-invest in training given that they cannot avoid the possibility of the employee leaving the firm and thus not fully internalising the benefits from training. As emphasised above, Brunello and De Paola (2006) and Brunello and Gambarotto (2007) analyse the **net effect** of agglomeration and poaching externalities on training outcomes, and find that it is **negative**, implying that poaching externalities are strong enough to outweigh any positive effects of agglomeration on firm incentives to invest in training. The evidence presented indicates that the threat of labour poaching significantly decreases firms' incentives to provide training for their workers, leading to sub-optimal levels of firm investments in training.

Spillover facilitators

A large number of studies analyse how **geographical proximity** influences the effectiveness of some of the identified knowledge spillover channels, and the size of the resulting spillovers. The widely-used approach of trailing patent citations to identify the impact of proximity on the size of knowledge externalities demonstrates that knowledge externalities remain mostly localised (and similar to the discussion relating to human capital above).

An additional factor influencing the size of knowledge spillovers and the effectiveness of spillover channels is the extent to which a company's R&D activities enhance its ability to absorb any existing external knowledge; a notion referred to as **absorptive capacity**. In particular, while investment in human capital increases the extent of spillovers, e.g. from one firm to the other, they also raise the rate at which spillovers from other intangible assets are absorbed within the investing firm (i.e. a double spillover). Hence, investments in human capital by a firm influence the extent to which it can benefit directly from increased productivity gains; indirectly through productivity spillovers between workers; and (indirectly) by the extent to which external knowledge can be absorbed within the firm and utilised in the firm's ongoing economic activities.

An issue directly related to absorptive capacity is the presence of **threshold effects** in knowledge absorption: for example adopting a new technological solution at firm-level may be beneficial to the firm only if all employees adopt it and receive training on how to use it. Likewise, the diffusion of human capital spillovers may be enhanced by the fact that all workers receive at least a certain level of basic education. In this sense ensuring that all members of the relevant population (e.g. all employees in a firm, all individuals in the workforce) share at least a minimum common knowledge may act as a key enhancer for the diffusion of spillovers.

In the next sections, we summarise the empirical evidence relating to the direct effect of investment in intangible assets, followed by the evidence relating to the indirect effects.

Empirical research - key findings on the direct effect from the investment in intangible assets

Economic competencies

In terms of the **direct** impact of investments in intangible assets on productivity, the analyses reviewed consistently demonstrate the positive impact of the various elements of intangible assets on productivity, but particularly stress the role of **economic competencies** (incorporating human capital and skills) in explaining productivity growth and levels. Some summary information is presented in Table 10 of the main report. The literature assessing the impact of investments in intangible assets on firm-level productivity in the United Kingdom consist of two primary strands of literature:

- Studies from the first of these strands involve growth accounting exercises, and show that economic competencies account for approximately **0.1-0.2** percentage points of **labour productivity growth** at firm-level (e.g. Riley and Robinson (2011b), Riley and Robinson (2011c)). This corresponds to between **3.2%** and **6.4%** of total labour productivity growth[5].

- Economic competencies make a comparatively greater contribution to **labour productivity growth** than other forms of intangible capital. According to Jona-Lasinio *et al*. (2011), economic competencies account for **0.30%** of productivity growth, compared to **0.15%** for ICT and **0.11%** for R&D (corresponding to **9.7%**, **4.8%** and **3.5%** of total labour productivity growth respectively).

- In the second stream of literature, which considers the impact of human capital on firm or industry **productivity levels**, the analyses generally indicate that an increase in the level or structure of human capital within industries increases industry-level productivity (by **0.1-0.3%** following a 1 percentage point increase in human capital (e.g. Galindo-Rueda and Haskel (2005), Mason et al. (2007)), or by as much as **0.6%** for labour productivity following a 1 percentage point increase in the volume of training (Dearden et al. (2005)).

Research and Development

The literature on the direct impact of **R&D** and productivity is very rich and covers both macro and micro evidence. In all studies considered by the authors, R&D is invariably found to have a significant and positive effect on output growth. However, the range of estimates of the elasticity of output with respect to R&D does vary across studies to some extent, depending on the approach adopted, the data considered and the extent of disaggregation. Some summary information is presented in Table 13 of the main report.

[5] Between 1950 and 2010, labour productivity growth in the United Kingdom has averaged 3.1%

- Looking at firm-level evidence, in one of the first studies to address the issue, Griliches (1979) found that the elasticity of output to R&D in US manufacturing was around **0.07** on average (implying a 10% increase in R&D increases output by 0.7%). Other authors present estimates of the US output elasticity to R&D of **0.10** to **0.16** (Schankerman (1981)), up to **0.19** (Griliches and Mairesse (1983)), and **0.20** (Jaffe (1986)), and between **0.09** and **0.33** in France (Cueno and Mairesse (1983)).

- The evidence relating to the United Kingdom indicates that the direct effect of R&D is lower than the estimates generated internationally. For instance, Griffith et al. (2006) estimate output elasticities to R&D which are lower than those estimates for the United States, and approximates **0.029** (implying that a 10% increase in the firm-level stock of R&D would increase output by approximately 0.29%). Similar results for the United Kingdom (approximately **0.03**) are presented in Bloom, Griffiths and Van Reenen (2002), using the stock of patents, instead of R&D capital, as a measure of innovation.

- Jona-Lasinio et al. (2011) estimate the contribution of innovative property (which is wider than R&D) on labour productivity growth and illustrate that for the United Kingdom, the contribution stands at **0.11%** (corresponding to **3.5%** of total labour productivity growth), with the specific impact of R&D standing at just **0.01%** (compared to 'architectural and engineering design' standing at **0.08%** and 'new financial products' standing at **0.04%**).

There is relatively limited information relating to investments in **computerised information and ICT** and their direct impact on productivity, and in reality, it is possible that a sizeable proportion of the impact of ICT and software has been subsumed into R&D.

- In a UK-specific study, Giorgio-Marrano et al. (2006) find that between 1996 and 2003, ICT capital contributed between **0.18%** to annual labour productivity growth during that period, with values of **0.14%** for innovative property and **0.26%** for economic competencies, respectively (corresponding to approximately **5.8%**, **4.5%** and **8.4%** of labour productivity growth respectively).

- In a more recent analysis, Jona-Lasinio et al. (2011) provide an estimate of the contribution of ICT to labour productivity growth of **0.15%** (corresponding to **4.8%** of total labour productivity growth).

Empirical research - key findings on the spillover effects of investments in intangible assets

Focusing on **spillover** effects that arise from investments in **economic competencies**, by definition, the results are difficult to compare given the different levels of analysis, the different sources of data and the different spillovers that are being identified. However, most of the evidence that we have been able to identify and assess does suggest that human capital spillovers do exist, and may be reasonably significant. In terms of reliability, in general, we believe that the analyses undertaken at the firm level probably provide the most robust results from a methodological point of view. Summary information is presented in Table 16.

- The **intra-firm** analyses incorporate the impact of average levels of human capital within the firm on individual workers' wages and productivity. The majority of evidence appears to point to a **positive** impact of co-worker education on individual wages or productivity within companies (Battu et al (2003), Metcalfe and Sloane (2007), Mas and Moretti (2006))

- Compared to the impact of an additional year of a worker's education on their own earnings (c. **6-7%**), in an average sized firm, the impact of all co-workers' receiving and additional year of education can add up to **9-12%** to a worker's earnings (Battu et al (2003), Metcalfe and Sloane (2007)). These analyses also demonstrate that unlike the diminishing earnings returns to a worker's own education, there is **no saturation point** in relation to the spillover effect associated with other workers' education.

- Other analyses merge local-level or industry-level information to firm-level data in order to investigate the potential impact of local labour market or industry characteristics on firm-level productivity or individual earnings. Here, again, it seems that there exist **positive** and **significant** spillovers. For example, at individual level, following a 1 percentage point increase in the share of graduates in the local labour market, Moretti (2004) reports estimates of enhanced wages of between **0.4-1.9%** for the US; Muravyev (2008) estimates spillovers of around 1-2% for Russia; Bauer and Vorell (2010) find a spillover effect at regional level of around **0.2%** and **0.6%** for high-skilled and low-skilled workers respectively; and Bratti and Leombruni (2009) find a spillover effect between **0.7%-1.4%** and **0.4%-1.0%** on white-collar and blue-collar workers respectively.

- At firm level, even though there are some difficulties in interpreting the relative magnitudes, estimates of the size of the regional spillover effects relative to the direct effects range from 0.5:1 to 4.5:1.

- Finally, a number of the studies demonstrate that, although higher levels of human capital increase the extent of spillovers, it is also the case that higher levels of human capital increase the rate at which other forms of investment in intangible assets are absorbed within firms (i.e. a double spillover), thereby augmenting the extent to which spillovers occur (e.g. O'Mahony and Vecchi (2009), Mason et al. (2007), Simões and Duarte (2007)).

In relation to the main findings concerning the extent to which spillovers of **scientific and creative property** occur at different levels of the economy.

- The first strand of literature analyses the effect of knowledge spillovers at an international level. The classic approach employed inserts a measure of foreign R&D directly into a country's production function, while controlling for domestic R&D and other factors. Despite criticisms of the methodology of the original approaches (e.g. Coe and Helpman, 1995)), recent literature, using superior methodological approaches, **do find evidence of international R&D spillovers**. For instance, a 1% increase in foreign R&D expenditure results in a **0.06%-0.20%** increase in total factor productivity (Engelbrecht (1997)), Lumenga-Neso (2005), Coe et al (2009)). Using an alternative measure of foreign R&D, Madsen (2008) finds that a 1% increase in international patent stock results in an increase in **0.09%-0.22%**

increase in total factor productivity). In terms of the strength of the evidence, we consider these results to be comparatively robust.

- A relevant factor which influences spillovers arising from scientific and creative property is technological proximity. In particular, the degree of technological proximity between the innovator and the firms benefiting from spillovers of the newly-developed knowledge determines the nature and extent of the spillovers of knowledge occurring between them (e.g. imitative). In addition, countries, industries and firms further away from the technological frontier can potentially benefit the most from R&D spillovers, providing some basis for convergence between them (Griffith et al. (2004)).

- Evidence of spillovers at the cross-regional level in the EU is found by Fischer et al. (2007) using the patent stock as a proxy for knowledge. Regarding spillovers within regions affecting firm-level productivity, the evidence exhibits significant variation. Piekkola (2011) and Riley and Robinson (2011a) observe **no** regional spillovers associated with R&D, but **positive** spillovers from IT (a 10% increase in ICT capital intensity at regional level results in a **0.12-0.23%** in firm level productivity). However, Geppert and Neumann (2011) discover a **positive** effect of regional R&D intensity on firm-level productivity (a 10% increase in regional R&D capital intensity results in a **0.17%** in firm level productivity), while Aiello and Cardamone (2007) indirectly confirm this result by emphasising the importance of geographical proximity capturing R&D spillovers.

- At the firm level, there is robust evidence signalling the importance of R&D spillovers on firm level productivity, even if the effect can vary across R&D and non-R&D firms or across technologically similar and dissimilar firms (see Ejermo, 2004 and Cincera, 2005).

Comparing direct vs. spillover effects from the investment in intangible assets

Table 24 of the main report provides a summary of the main studies simultaneously estimating **both** the direct and external effects of the different types of intangible assets, from which several conclusions regarding the relative size of spillover effects can be drawn.

- The evidence seems to indicate that externalities derived from increases in regional **ICT capital** on firm-level productivity are **larger** than the direct effects on firm productivity of raising that firm's own investment in computerised information (Riley and Robinson (2011a) estimate the ratio of the spillover to direct effect to be **1.5:1**, while Geppert and Neumann (2011) estimate the ratio to be closer to **3:1**).

- Considering spillovers from investment in **R&D**, the evidence suggests that these are strongest at an international level, where the spillover effects are **larger** than the direct effect, with some additional evidence indicating relatively strong R&D externalities within regions. In particular, as emphasised by the results of Engelbrecht (1997), Coe and Helpman (1995), Coe et al. (2009), Madsen (2008) and Lumenga-Neso (2005), a country benefits **at least as much** from an increase in international R&D investment in terms of increased domestic total factor productivity, compared to an equivalent increase in its own national R&D expenditures.

- In addition to this international perspective, Geppert and Neumann (2011) show that the externality effect of raising a region's investment in R&D on the labour productivity of firms in that region is **larger** than the direct effect on productivity of a firm's own R&D activities. The work of Aiello and Cardamone (2008) reaches the same conclusions for intra-regional spillovers within industries.

While the evidence regarding the relative size of spillovers from **economic competencies** (i.e. education and training) varies across studies, some main points can be established.

- There is some evidence that there is a **high ratio** of indirect to direct effects (approximately 2:1) from regional human capital to firm-level productivity (Riley and Robinson (2011a)). Focusing on the manufacturing sector, Galindo-Rueda and Haskel (2005) confirm that a service sector firm benefits more from an increase in aggregate education levels in the region it operates in than from raising the share of highly educated workers in its own workforce (in a ratio of approximately of **4:1**).

- The spillover effects of increasing regional education levels on the wages of individuals are substantial (see Moretti (2004a), Muravyev (2008) and Rauch (1993)).

- Some of the evidence indicates that a worker's individual wage gains from an increase in industry-level human capital (training) are of a **similar magnitude** than the wage effects of increasing their own level of training by an additional year (see Dearden et al., 2005).

- Within-firm human capital externalities also appear to be relatively large when compared to the direct effects. Battu et al. (2003) and Metcalfe and Sloane (2007) analyse the spillover effect on individual wages stemming from an increase in an individual co-worker's education, as well as the effect of raising a firm's entire workforce education. The authors find that increasing the education of level of all co-workers by approximately one year results in **larger** wage increases for a worker (**9-12%** effect) than if the latter raised his own education by one year (**6-7%** effect).

Policy conclusions

The weight of the evidence suggests that spillovers from the investment in intangible assets exist at many levels. Despite some measurement issues, the analysis also suggests that where these spillovers are estimated alongside the direct effect of the investment in intangible assets, the relative effect of these spillovers is large and often exceeds the direct effects (up to a factor of 4).

The evidence reviewed indicates that the threat of labour poaching significantly decreases firms' incentives to provide training for their workers, leading to sub-optimal levels of firm investment in training. The evidence reviewed suggests that as a result of poaching externalities, the level of training is at least 4% lower than the average[6] level of training. The existence of other spillover effects suggests that the gap between current training levels and the optimal level of training may be even greater. Given this, if spillovers are significant and/or there is evidence of poaching externalities, then there is a clear case for government intervention to exploit these spillovers.

Depending on the specific nature of the market failure and externality identified, there are different types of government intervention that might take place. For instance, because of information failures, it might be the case that employers are unaware of and thus do not take into account the intra-firm spillovers that might result from investment, with a subsequent under-investment in training. In these circumstances, the primary scope for government intervention might be to address these information failures by raising awareness about the extent of spillovers amongst employers, disseminating information, facilitating coordination between firms and tackling potential credit constraints faced by firms.

At the other end of the spectrum, due to the normal functioning of the labour market and the ability of employees to move between firms, it may be the case that positive externalities spill over to rival firms and limit an individual employer's incentives to invest in the education and training of their workers. Specifically, employers may face reduced incentives to train their employees if there is a risk that these employees can move to another firm and appropriate the productivity benefits associated with their enhanced training. If it is the case, then to maintain the incentives to employers, there may be a rationale for government intervention through the direct funding of training, employer subsidy or some other form of incentive.

Between these two extremes, there may be a role for government to alleviate the potential market failure through a combination of policy interventions.

Clearly, irrespective of the source or level within the economy at which the externality arises, the potential cost of capturing these externalities should be sufficiently low to ensure that the economic benefits outweigh the costs. However, the crucial point is that any intervention should not simply compare the potential costs of intervention with the potential benefits derived from the *indirect* spillover effects, but rather the costs of intervention should be compared with *both* the *direct* and *indirect* benefits associated with the investment intangible assets. In other words, if the economic incentives facing the potential investor (i.e. the employer) to invest are insufficient so that this potential investment is lost, the direct economic benefit will not be generated. In consequence, any potential spillovers will also fail to materialise. Given the link between the initial investment and the subsequent direct and indirect effects, this provides a more powerful rationale for government intervention to ensure that the incentives facing the investor are *sufficient* to encourage firms to undertake the investment, thereby capturing *both* the direct effect and indirect effect.

[6] In theory, this would be assessed as the level where the marginal social benefit associated with training equals with the marginal social cost of training (see Figure 2).

1 Introduction

London Economics were commissioned by the Department for Business Innovation and Skills to undertake a literature review of the main evidence relating to the impact of the investment in intangible assets on productivity spillovers. The report is set out as follows. In Section 2 of the report, we provide a relatively short summary of the theoretical literature relating to economic growth theory and growth accounting. We also introduce the concept of a spillover and how they are incorporated into existing growth theories. In section 3 of the report, we provide a summary of the means and methods by which spillovers may actually occur (i.e. spillover channels), as well as some of the empirical evidence in the area. Section 4 contains a significant volume of information and analysis on the methods that have been adopted for the measurement of the investment intangible assets and associated metrics, alongside some recent evidence demonstrating the role of intangible capital in economies internationally.

Section 5 of the report is the first substantive empirical chapter, where we provide an assessment of the evidence associated with the *direct* impact of the investment in intangible assets broken down according to whether the form of intangible asset relate to economic competencies, scientific and creative property or computerised information and IT. This analysis is further disaggregated according to the level at which the impact occurred (i.e. individual, firm, region, industry, national). Section 6 is another assessment of the empirical literature with the focus of attention being a review of the indirect or spillover effects associated with the investment in intangible assets. A number of papers in the area either consider the *direct* effect associated with investments in intangible assets or the *indirect* effect, making comparison less straightforward. Therefore, at the end of section 6, we also present an assessment of the impact of the spillover effect relative to the impact of the direct effect, where both these effects have been considered simultaneously. Section 7 provides our review of the literature relating to knowledge spillovers, while Section 8 provides some initial thoughts on options for future research.

2 Economic Growth Theory

2.1 An introduction to economic growth and growth accounting

The importance of accurately taking account of and measuring investment is underlined by their contribution to economic growth, the analysis of which necessitates an initial discussion of the basic economic growth theory and accounting framework, as developed by Solow (1956). The model is based on an aggregate production function relating aggregate output (Q) to tangible capital, such as machinery and equipment (K), and labour (L). In addition, output is assumed to depend on a technology variable (A), so-called total factor productivity, which captures the advances in technological development that result in a more efficient use of inputs in the production of output. Solow's aggregate production function thus reads

$$Q = A(t)F(K(t), L(t)),$$

where F(.) constitutes an unspecified function of capital and labour (Corrado *et al*., 2005)

Under the assumption that both capital and labour is required for production, (i.e. F(.) is truly a function of both inputs, and that labour and technology grow at constant and exogenously given rates (gL and gA, respectively)), Solow shows that the economy is moving towards a steady state, implying that capital and output grow at the same rate (gL+gA), which in turn implies that output per worker grows at the rate of technological progress (gA). Furthermore, Solow derives a neo-classical growth accounting framework, which distinguishes the individual contribution of each of the above factors to aggregate economic growth. In particular, in this framework, the growth of economic output is decomposed into the growth rates of labour and tangible capital, weighted by their respective shares of total input[7], as well as the growth rate of technological change (Sianesi and Van Reenen, 2000). The basic growth accounting equation is given below (from Corrado et al., 2006)

$$g_Q = s_L(t)g_L(t) + s_K(t)g_K(t) + g_A(t)$$

A difficulty with the neo-classical growth model is the treatment of technological progress, or total factor productivity (A). Technological change is exogenous in the model, i.e. no assumptions are made concerning the origin of and mechanisms behind technological progress, leaving it as an unexplained and automatic process. As a consequence, while total factor productivity constitutes one of the main sources of economic growth, output growth accounting exercises cannot accurately explain or understand it, and technological change remains a residual in the above equation (Sianesi and Van Reenen, 2000).

2.1.1 Endogenous growth theory

Various extensions of this basic model have been developed in order to diminish the empirical size and importance of this residual and to explain the mechanisms behind technological advances, with strong implications for growth accounting results. A model

[7] $S_L(t)$, and $S_K(t)$ for labour and tangible capital, respectively.

extension developed by Mankiw et al. (1992) constitutes one of the more important contributions, emphasising the role of education for growth. In particular, the authors add human capital (i.e. skilled labour, and specifications about its accumulation process) to the basic Solow model. Additionally, the "new growth theories" endogenise technological progress, providing explanations for the development of technological advances. Lucas (1988) relaxes the exogeneity assumption on technological progress, and includes human capital, which is determined by the model. He concludes that the wage rate of labour at a given skill level will increase with the wealth of a country only if human capital is not internal (i.e. there is some spillover effect embedded in human capital). Another model relaxing the exogeneity assumption was developed by Romer (1990), who describes innovation as a commercially oriented process conducted by firms seeking to increase their profits, and extends the Solow model accordingly. Grossman and Helpmann (1994) focus on the rate of technological progress as the driver for sustained economic growth and the importance of understanding the determinants underpinning technological developments and industrial innovation in different countries.

2.1.2 Extensions to endogenous growth theory

Abdih and Joutz's paper (2006) focuses on R&D-based endogenous growth models that identify technological progress as the primary driver of growth. These models are characterised by the existence of a knowledge/technology production function that takes account of the number of researchers within a firm and the existing stock of knowledge available to them. The paper examines how new knowledge depends on the existing stock of knowledge, which is what the authors call the "inter-temporal spillover of knowledge". They use data on patent filings to discover a long-run (co-integrating) relationship that supports the idea of the knowledge production function.

In Lloyd-Ellis and Roberts' (2002) endogenous growth model, neither skills nor technology alone can drive growth. Instead, the human capital accumulated by households and the technological knowledge generated by firms act as complements to one another. The incentives for development of both are linked to the extent that new technology requires the development of new skills, and skill acquisition creates an incentive for technological development. The authors identify that the two factors are "bounded complements in growth" in that the marginal productivity of one is constrained by the other. In addition, the authors identify "dynamic complements in productivity" in the sense that the rate of return of one depends on the growth rate of the other. One of the predictions of the model is that if human capital lags behind technology growth, this will cause wages to diverge, which allows human capital to grow more quickly and catch up with technological development. The model also has implications for the effectiveness of policy instruments designed to promote growth by encouraging the accumulation of human capital or technological progress.

2.1.3 Combining neo-classical and endogenous growth theories

Barro and Sala-i-Martin (1995, 1997) combine elements of endogenous growth theory with elements of the neoclassical growth model in an attempt to overcome the shortcomings of both models. The neoclassical growth model predicts conditional convergence[8], which is

[8] Conditional convergence is sometimes referred to as β convergence, and means that the growth rate of an economy is inversely related to its starting point, i.e. poor countries grow faster than rich countries.

supported empirically, however, treats technological progress as an exogenous element. By contrast, endogenous growth theory recognises technological progress as a driver of long-run growth within the model, but fails to predict convergence. Barro and Sala-i-Martin (1997) suggest that the preference within some economies to copy innovation, rather than to invent for themselves, allows for conditional convergence within the endogenous model. The imitating country will grow relatively quickly as it catches up with the innovative leader, but growth rates will then begin to converge, since the cost of imitation rises as the stock of copy-able material is used up. The cross-country dynamic that results from this type of technological diffusion is similar to that of the neo-classical model. One further consequence of this relationship between innovator and imitator is that it diminishes the incentive to invent, and the authors suggest that this could be amended by strengthening international property rights. Davidson and Segerstrom (1998) also distinguish between innovative and imitative R&D, but argue that subsidies to innovative R&D lead to faster economic growth whereas subsidies to imitative R&D decelerate economic growth. This means that R&D subsidies can have an overall negative effect on global economic growth in developing countries where R&D is mostly imitative.

2.2 What is a spillover?

In order to provide a detailed discussion of the theoretical considerations and empirical results regarding productivity and knowledge spillovers, it is necessary to first pay attention to the general theory of externalities, of which R&D and productivity spillovers constitute a specific type. **Externalities** or **spillovers** refer to situations in which the activities of one agent in the market induce **external** effects (either positive or negative) on other agents in that market, or put differently, '*an externality is present whenever the well-being of a consumer or the production possibilities of a firm are directly affected by the actions of another agent in the economy*' (Mas-Collell *et al*., 1995).

An important assertion of the theory is that any external effects that are mediated, reflected or accounted for through price mechanisms do not constitute true externalities or spillovers.

The crucial distinction regarding the impact of intangible assets on productivity is between the **direct** and **indirect** effect, and not how the benefits are distributed or allocated between individuals, organisations, regions or countries. Taking an example, suppose that a firm trains an employee (at a cost £5,000 for instance). Suppose the enhanced productivity or value-added as a result of that worker's enhanced training and skills acquisition is £10,000. This productivity gain exceeds the cost of training (otherwise, no training would take place). Suppose that the trained worker's wages are augmented by £1,000 as a result of their increased productivity. Suppose also that other co-workers become more productive as a result of interaction with the trained worker (which generates value added of £2,000). In this example, we would say that the direct effect of the training is £5,000, which is equal to the difference in the total productivity gain minus the cost of training. The **direct** effect of £5,000 is split between the employer and the employee in the ratio of 4:1 (and this ratio reflects the relative bargaining strength of the employer and employee, which in turn reflects the nature of the training received (firm specific or transferable), as well as the functioning of the local labour market).

Although the £1,000 enhanced earnings to the trained worker is a benefit (to the individual) – and needs to be acknowledged – it is a direct effect and not a spillover or an externality.

In this example, the indirect effect, or externality, is the £2,000 value added associated with the enhanced productivity of the co-workers (which in this case is completely appropriated by the employer). The economic literature consistently treats externalities in this manner.

Categorisation of spillovers

Spillovers can be sub-categorised into two main types:

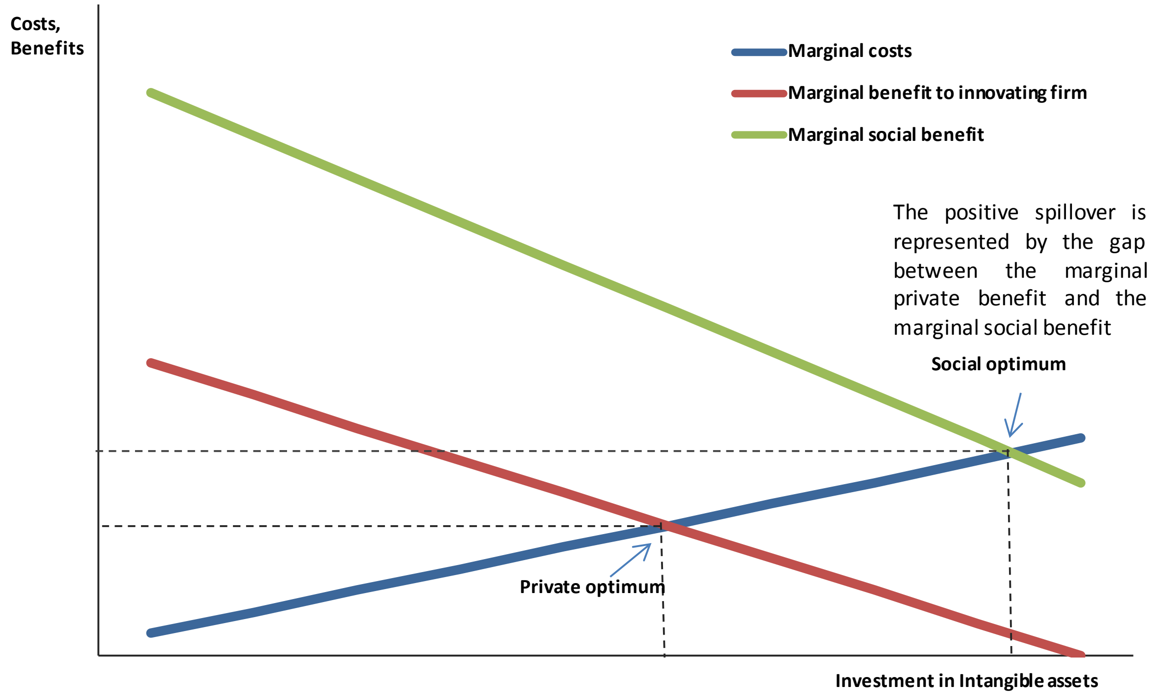
1. *Negative spillovers* involve situations where the effects of one agent's actions are detrimental to the well-being of other agents. For example, along a river, if an upstream oil refinery pollutes the water with its emissions, it negatively affects downstream fisheries, whose profitability crucially hinges on the river's water quality.

2. *Positive spillovers* involve situations in which one agent directly benefits from the activities of another. A popular example refers to the immunisation or vaccination of an individual against a certain disease, which he or she hence cannot spread to other individuals.

Productivity and knowledge spillovers constitute additional examples of positive externalities, where knowledge developed with the help of R&D efforts by one firm spills over to other firms' stocks of knowledge and productivity levels, without the beneficiary firms contributing to the expenses the innovating firm made in acquiring the scientific results. The innovating company does not take into account the benefits it provides to other firms, since it does not reap the full returns to its own investment. In other words, the private benefit an active R&D company achieves through innovation is smaller than the level of social benefit, which includes both the private benefit to the innovating firm and the productivity benefits achieved for other companies resulting from the spillovers of knowledge across firms.

We illustrate the implications of these differences between the private and social returns for the case of an individual firm's investment in R&D activities in Figure 3. In order to maximise profits, the innovating company chooses a level of investment in R&D so that the marginal private benefits from that investment equal the marginal costs of conducting R&D (the private optimum). However, due to knowledge spilling over from this company to other firms, benefiting their stock of knowledge and consequently increasing their productivity levels, at every level of investment, the marginal social benefits to the innovating firm's investment are larger than the private benefits to the company conducting the original research. The social optimum is provided by the level of investment for which marginal costs equal marginal social benefits. Since the innovating firm cannot capture the entire returns to its investment, this social optimum of investment in R&D by the firm is larger than the investment the company chooses for itself, resulting in an under-investment in R&D.

Figure 3: Illustration of a positive externality



Source: London Economics

2.2.1 Do externalities result in sub-optimal outcomes and how big is the problem?

Since the 1990s, various studies have attempted to explain the observation that firms are willing to invest in their workers' general training, which contrasts the predictions of classical human capital theory. The standard model developed by Becker (1964) illustrates circumstances in which firms have no incentives to invest in the training of their workforce. This model distinguishes between general training, which increases a worker's productivity equally in many firms, and specific training, which is only of value to the firm investing in the training. It is argued that in a perfectly competitive labour market, firms will only invest in the specific (and not general training) of their workforce, since workers are able to reap the entire return to their general training in the form of higher wages, and thus bear the costs of receiving it. More recent studies (e.g. Acemoglu and Pischke (1998)) emphasise how, in reality, frictions in the labour market (such as search costs or factors adversely affecting the mobility of labour across firms) drive a wedge between the productivity and wage gains from general training. As a result, firms will have an incentive to invest in the general training of their workforce, since they can earn rents on their trained workers by paying wages that do not fully compensate them for their increased post-training productivity.

However, even though firms do invest in the training of their workforce when the labour market is not perfectly competitive, the level of investment will be sub-optimal (Muehlemann and Wolter (2011)). This results from labour **poaching externalities**, which occur when firms poach each other's employees after these have received training, in order to benefit from their increased productivity without sharing the costs of training. As a result, the firm providing the training is unable to reap the full benefits to its initial investment in human capital. Hence, if the firm anticipates that its competitors may poach their trainees after the completion of their training, it will spend relatively less on increasing the education of its workforce than if poaching is not a credible threat. The papers presented below investigate the strength of labour poaching externalities for different countries by estimating the effect of regional labour market density on firm investment in training[9].

Muehlemann and Wolter (2011) hypothesise that the density of regional labour markets might adversely affect firms' training decision and the number of trainees hired by firms in that market, since density implies an increased threat of competitors' poaching of employees after they have received training. To define local labour markets, they use travelling times, rather than distances or political borders. Using data from administrative surveys of Swiss apprenticeship training, the authors discover that a 1% increase in regional labour market density (i.e. the local number companies per hectare in the same industry) results in a **0.2%** decrease in the probability of firm-provided training. In addition, their findings suggest that, if training is financed by companies and not the apprentices themselves, a 1% increase in local labour market density results in a **0.15% decrease** in the number of apprentices trained by those firms offering training (i.e. the extent of the training provided by firms). However, the authors also find evidence of a virtually **zero effect** of labour market density on the number of apprenticeships offered by firms if firms generate a net benefit (or a negative net cost) from training[10],[11].

Brunello and De Paola (2006)[12] and Brunello and Gambarotto (2007) examine the effect of local labour market density on training participation in Italy and the UK, respectively.

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[9] Due to differences regarding the measurement of labour market density and the probability and extent of training, the estimates vary significantly across studies.

[10] Firms' net costs are calculated comparing costs (apprentice pay, cost of training personnel, administrative and recruitment costs etc.) and benefits (value of the productive work of an apprentice) associated with training. The analysis suggests that increased labour market density appears to have a minimal effect on the employer decision to offer apprenticeships as long as the employer achieves some net benefit from training. This implies that if apprentices contributed to a greater extent in the funding of apprenticeships then a greater number of apprenticeships might be offered. Although this is the case in theory, in practice, there may be some limits to the extent that this holds. For instance, it may be possible to move the burden to apprenticeships by reducing apprenticeship wages (for instance), although it may be more unlikely that the other firm costs (such as line management, on the job training, use of equipment while not producing viable output) could be passed over to apprentices.

[11] The authors present the following policy implication. Specifically, "the threat of poaching is relevant for a firm only if apprenticeship training constitutes a net investment. Thus it is important that training regulations allow firms to cost-effectively train apprentices. The potential poaching behaviour of nearby firms will not affect the provision of apprenticeship positions as long as training results in a net benefit from the firm's perspective. Thus, political initiatives aimed at mitigating any effects of poaching would need to be targeted only at industries where training is found to be employer-financed. However, any such policy would be first of all expensive, but secondly also ineffective, as training subsidies would induce firms to change their behaviour, with the aim to receive training subsidies in future periods".

[12] Brunello and De Paola's results refer to off-the-job training provided by specialised external organisations, paid for or organised by firms. However, the authors argue that their results should not change significantly if applied to on-the-job training.

Brunello and De Paola (2006) measure labour market density as the number of employees per square kilometre, and employ firm data from the Survey of Italian Manufacturing of 2001 to achieve their estimates. Their results suggest that a 1% increase in local labour market density reduces the percentage of trained employees across firms by **0.146%**[13]. Brunello and Gambarotto (2007), using individual data from the British Household Panel Survey between 1994 and 2000, and defining density as regional employment per square kilometre, find that a 1% increase in local labour market density implies a **0.014** decrease in the probability of employer-provided training[14]. This constitutes a decrease equal to approximately 4% of the average share of individuals who have received employer-provided training in the period considered[15].

Supporting the findings of these previous analyses, Harhoff and Kane (1997) test the effects of poaching by analysing data from a survey commissioned by the Ministry of Research and Technology for Germany in 1992. First, they find that the probability of firms' training of apprentices and the number of apprentices trained per firm were significantly smaller for firms in urban or suburban areas than in other regions. Second, their results imply that the size of the workforce in the county in which a firm operates, or in counties within commuting distance to a firm, is negatively related to the probability and extent of apprenticeship training provided by companies. Finally, the number of other firms in the same industry and county has a marginally significant negative effect on the extent of apprenticeship training which firms offer.

Relative magnitude of poaching externalities and agglomeration effects

However, increased labour market density might also produce a positive impact on firms' incentive to invest in training for their workers. Dense labour markets might benefit from improved matching between employers and potential employees (Helsley and Strange (1990), as cited in Muehlemann and Wolter (2011)). More significantly, spatial proximity increases the degree to which positive spillovers of knowledge occur between individuals and firms. Since trained workers are more capable of exploiting these spillovers, firms in dense labour markets might invest greater amounts in the training of their workforce in order to increase their absorptive capacity and productivity (Brunello and Gambarotti (2007), Brunello and De Paola (2006)). Given these potentially conflicting outcomes, these studies analyse the net effect of agglomeration on training, and find that it is negative, implying that poaching externalities are strong enough to outweigh any positive effects of agglomeration on firm incentives to invest in training. The evidence presented thus indicates that the threat of labour poaching significantly decreases firms' incentives to provide training for their workers, leading to sub-optimal levels of firm investments in training.

2.3 Spillovers and endogenous growth

A series of contributions on the mechanisms of economic growth published in the early 1990s remarked that technology driven growth may not be efficient from a market

[13] When evaluating at the sample mean percentage of trained employees in firms with up to 500 employees.

[14] When evaluating at the average firm size.

[15] The authors find an average incidence of employer-provided raining in the UK of 32% in the sample

perspective: in fact market efficiency requires that price equals the marginal cost and that the returns to investment are fully appropriable (i.e. the investor can internalise all the benefits from a given investment). However, neither mechanism is fully compatible with technological change and innovation: on the one hand, innovative activities require the price to be monopolistic (and therefore above the marginal cost), at least for a period to appropriately reward and incentivise innovation (e.g. patents), while on the other hand, returns to investment in knowledge are unlikely to be fully internalised, since they are generally not fully excludible.

Two distinct mechanisms explain the emergence of R&D spillovers sustaining long-run endogenous growth. In the first theory, developed by Romer (1990) and sometimes defined the ‘love of variety approach’, productivity increases with an expansion of the range of available production inputs. Here, knowledge enters the aggregate production function in two ways: directly, given that a new design (for example) enables the production of an intermediate good with new embodied knowledge, but also indirectly, since the new design will also contribute to the public stock of knowledge available. While the direct commercial effects of the innovative design can be fully internalised (via patents etc.), the benefits arising from the indirect effects are non-excludable, given that other inventors may learn from the original design and build on it.

The second spillover mechanism, as outlined by Grossman and Helpmann (1991) and Aghion and Howitt (1992), refers to the ‘quality ladder approach’. According to this theory, increases in productivity are mainly driven by improvements in the quality of inputs, resulting in an upward movement of the product on the quality ladder. An improvement of the product through current R&D efforts implies that future researchers can start subsequent improvements from a higher level on the quality ladder, pointing to the existence of inter-temporal R&D spillovers. Stein (1997) describes a process that is similar to the latter, where the introduction of a new product by a market entrant leads to knowledge spillovers to future innovators, who can learn from the new product and improve upon it.

Both mechanisms underline that human capital productivity will increase over time, even if the stock of human capital remains constant (however, increases in education levels are crucial for enhancing the capacity to innovate and to benefit from external knowledge). If the public stock of knowledge available is rising over time (derived from innovative activities taking place), product developers can access the additional knowledge accumulated. Clearly, firms only consider their private returns when deciding on R&D activities and therefore knowledge investment is likely to be sub-optimal from a social perspective.

2.4 Human capital spillovers

Similar arguments can be made for human capital spillovers and knowledge transfers: if raising one’s education has a positive effects not only on own productivity, but also on co-workers’ productivity, increasing education levels will have both a direct (through enhanced own productivity) and an indirect effect (by increasing productivity of co-workers) on total productivity.

In particular, the theory has identified three different positive externalities at local level (city or county) stemming from a better educated population and workforce:

1. A positive effect on workers' productivity, thanks to the proximity to better educated co-workers;

2. A positive effect due to the reduction in the propensity to engage in activities generating negative outcomes (such as crime); and

3. A positive effect on public policy, due to a more informed choice of political representatives made by a better-educated electorate.

While the latter two externalities can have an indirect effect on productivity, we focus on the direct effect caused by a better-educated workforce on productivity spillovers. As outlined by Moretti (2004b), there are a number of possible reasons explaining how externalities[16] may arise:

- Technological externalities: as in the model outlined by Lucas (1988), the average human capital level of the workforce has a positive effect on the productivity of all production factors (in this sense the effect is built into the production function). Knowledge and skills are shared across workers through formal and informal interactions.

- Negative externalities: in this case education does not increase productivity per se, but only has a signalling effect. Individuals decide to stay in education for longer to signal their innate ability and the (positive) private returns to education exceed social returns.

The importance of human interactions as a channel for human capital externalities across workers is also recognised by Duranton (2004). However, realising that this standard theory is not the only positive externality of human capital, he adds a 'thick' local labour market argument to the discussion. Here, assuming that an increase in the amount of skilled labour in a particular labour market will attract more specialised suppliers to that market, the marginal product of labour in the market will be significantly increased as a consequence of increased worker specialisation. Thus, while this latter type of educational externality does not involve knowledge spillovers per se, it considers the direct implications of external human capital on worker productivity.

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[16] Note that Moretti (2004b) does also discuss **pecuniary externalities. In particular,** because of the complementarity between human and physical capital (but also technology, see Acemoglu, 1996 and 1998), individuals will choose the optimal amount of education based on an expectation of the local availability of physical capital, while firms will invest in physical capital based on their expectations of the education of the workforce. An increase in investment in education by a group of workers will induce firms to invest more in physical capital. Given that search is costly, some of the workers who have not increased their education will benefit from the increased physical capital, and hence benefit from a positive externality. In this case market interactions explain the positive spillovers. However, these pecuniary externalities appear to be reflected through the price mechanism and this are not considered spillovers in the strict sense.

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3 Spillover channels

The exact mechanism through which spillovers occur are manifold [sic], but still ill-understood. For example, knowledge may be 'embodied' in people, who, if they change jobs, carry the knowledge to their new employer, or it may be embodied in products like investment or intermediary goods. Knowledge may be exchanged at conferences and meetings, or through the (specialised) press. Other, more controversial processes through which spillovers may occur are reverse engineering or industrial espionage. The sources of the relevant technological knowledge are also manifold [sic]. Knowledge may stem from universities, public research institutes, other firms or private inventors. Within the group of other firms, knowledge may either stem from direct competitors who are in the same line of business, or from firms producing completely different products, but with 'relevant' technologies underlying their production process. (Verspagen, B. (1997) p. 228)

In this section we explore how productivity spillovers may arise, through which mechanisms they diffuse, and how they can affect economic and productivity growth. We review the main theoretical approaches and empirical applications employed in the literature. All mechanisms reviewed explain how knowledge investment by firms or individuals can affect the available knowledge and productivity of other firms (i.e. inter-firm) or individuals. In Table 1, we summarise the levels at which spillovers may potentially occur and the stylised mechanisms through which they are generated and diffused.

3.1.1 Summary

One of the most commonly cited channels through which spillovers of knowledge and productivity may occur refers to the **mobility of skilled and experienced labour**. Various papers assert that knowledge regarding production processes, organisational structures, new technologies etc. is embodied in individual workers through training and work experience with their employers. When a worker leaves his current employer for a new job at a different firm, his accumulated knowledge will be diffused throughout the new firm through interactions with his new colleagues, increasing overall productivity levels for the new employer. A limitation to this theory is that these spillovers of knowledge will only constitute true externalities if the labour market does not internalise them via wage effects. Nevertheless, various authors consider the mobility and turnover of labour as one of the most significant mechanisms behind knowledge spillovers within and between industries, between foreign multinational enterprises and firms operating in their host countries, and between regions and countries, with the latter effect being caused by the mobility of university students.

Focusing on international knowledge externalities, the literature identifies three main channels through which these might occur. First, knowledge might be diffused through **international trade** in intermediate inputs, where domestic companies purchasing the input will benefit from the technology embodied in the latter. Regarding this mechanism, different authors disagree concerning the question whether domestic firms will benefit only from the knowledge that is produced in the countries they trade with, or whether it is the stock of knowledge available in the trading countries (more generally) that matters, undermining the relevance of bilateral trade relationships. Secondly, it has been asserted that knowledge spillovers might be caused by **foreign direct investment** (FDI), where domestic firms achieve productivity increases via purchases from foreign-owned multinational subsidiaries, or multinationals deliberately initiate operations abroad in order to benefit from local knowledge in their host countries. Finally, international knowledge spillovers might also result from **direct learning about foreign technologies** by domestic companies, through the exchange of blueprints at prices that are lower than the costs originally incurred by the innovator.

In the studies focusing on intra-industry spillovers, **interactions between workers** are considered as the primary channel through which these inter-firm externalities are diffused. The literature emphasises how formal knowledge exchange, e.g. through conferences attendance and patents, as well as informal contacts and knowledge sharing between workers, will lead to intra-industry spillovers. Furthermore, several studies analyse how certain spillover channels can be considered as part of a firm's deliberate strategy to benefit from knowledge externalities. For example, spillovers might occur if firms decided to enter into R&D collaborations with rival companies or universities, in an attempt to internalise the externalities arising from each other's research efforts. In addition, companies might strategically poach their rivals' R&D labour to reap benefits from their competitors' R&D activities.

A large number of studies analyses how **geographical proximity** influences the effectiveness of the identified knowledge spillover channels, and the size of the resulting spillovers. The widely-used approach of trailing patent citations to identify the impact of proximity on the size of knowledge externalities demonstrates that knowledge externalities remain mostly localised, which is in respects similar to the case for human capital above. However, several criticisms and extensions to this methodology have been advanced. An additional factor influencing the size of knowledge spillovers and the effectiveness of spillover channels, which will be subject of the analysis in following sections, is the extent to which a company's R&D activities and human capital enhance its ability to absorb any existing external knowledge; a notion referred to as 'absorptive capacity'.

A significant strand of the literature investigates the extent to which human capital externalities, as a particular type of knowledge externalities, are similarly prone to **agglomeration effects**. It is argued that working alongside highly educated and experienced workers will induce knowledge spillover effects through interactions between employees (such as imitation, learning- by-doing, social pressure or leading-by-example). Arguing that these interactions are facilitated through geographical proximity of workers, it is asserted that the size of human capital spillovers is significantly influenced by agglomeration effects, facilitating spillovers between workers within the same region, city, or firm.

Table 1: Spillovers: stylised mechanisms		
Level	**Mechanisms**	**Potential limitations**
Intra-firm	Working alongside better educated co-workers may increase own productivity in the absence of any increase in own human capital. A positive effect on own productivity may occur through imitation, social pressure, leading-by-example or learning-by-doing. Firms can stimulate spillover diffusion by training employees or hiring better educated employees. Firms may also encourage internal knowledge transfer through appropriate policies facilitating knowledge exchange.	Firms may experience higher returns compared to the employee's returns. However, firms will take into account both direct and indirect (but still internal to firms) benefits of education when funding training. Also, better educated individuals may be able to obtain a higher wage, reflecting the higher embodied knowledge and potential positive externalities.
Intra-industry (inter-firm)	Formal/informal mechanisms of contacts and knowledge exchange between employees working for firms in the same industry. Labour mobility and knowledge embodied in skilled/highly experienced workers.	Some of the benefits may be internalised through formal or informal market mechanisms (e.g. contractual arrangements). Sector-wide corporations at industry level may sponsor training if that raises productivity in the sector. More able/experienced workers may be able to extract a higher wage premium.
City/Regional	Knowledge flows and human capital spillovers (beyond industry level) may happen at city or regional level. For example, local inventors may have more occasions (or may be more willing) to share knowledge with each other. Research conducted at university level can have a positive effect on firms' productivity. Knowledge transfers may also occur more easily across firms in different industries (for example through labour mobility or formal/informal contacts) but located in different geographical areas.	At least part of the positive knowledge transfers may be already incorporated in economic mechanisms; for example universities and firms may transfer knowledge to local firms through the labour market, through consultancy and training services or through local co-operation agreements (with firms sponsoring university research projects). Positive externalities may be explained by social connections, rather than simply geographical proximity.
International	Knowledge transfer may occur through knowledge embodied in intermediate goods exchanged through international trade and through purchases from foreign-owned multinational subsidiaries (FDI).	Other economic mechanisms may be occurring simultaneously, influencing what we observe as a positive knowledge transfer. It might be difficult to measure precisely the extent to which exporting firms are able to extract a return to knowledge embodied in intermediate goods.

Source: London Economics

3.2 Classical empirical approaches relating to R&D externalities

Two of the earliest papers concerning knowledge spillovers were authored by Griliches (1979) and Jaffe (1986). While Griliches (1979) focuses on the theory of R&D externalities, Jaffe (1986) provides one of the first empirical applications to estimate their impact on total factor productivity.

Griliches (1979) was one of the first authors to study the conduits, nature and effects of R&D spillovers. Asserting that the level of productivity and knowledge achieved by a firm or industry not only depends on its own research effort but also on innovations and knowledge developed by other firms or industries it has access to, he discusses two channels of potential R&D spillovers mentioned in the literature. The first one of these concerns a firm's **purchase of knowledge-intensive inputs** from other industries, a mechanism that has been widely discussed in the literature, especially in relation to the international trade of these inputs. While the author acknowledges that the buyer benefits from prices that do not reflect the input's true value to the buying firm, and which are thus less than the 'full quality' price, he states that these do not represent true knowledge spillovers, but mere consequences of measurement problems. In contrast, according to his view, R&D spillovers consist of the ideas and knowledge that a firm derives from the R&D developed by another firm, and provides an example where a firm in the photographic equipment industry and another in the scientific instruments industry work on similar projects and consequently gain from each others' R&D outcomes.

An important assertion of Griliches' model of R&D spillovers is that the size of knowledge externalities between companies depends on the technological similarities between the industries they operate in, which is further emphasised and analysed by Jaffe (1986). He recognises that research efforts by other firms might significantly reduce the resources needed by a company to achieve its own R&D successes, but only if the companies are technologically related, i.e. they comprise neighbouring firms in 'technology space'. Throughout his empirical assessment, he employs the distribution of firm patents over specified patent classes in order to characterise the relative technological position of firms and to estimate the impact of R&D spillover effects on productivity.

3.3 Labour mobility

Several of the studies reviewed emphasise the importance of **labour mobility** as a channel for knowledge spillovers. The general theory behind the link between labour mobility (i.e. the assertion that the movement of a skilled worker from one firm to another might benefit the new employer), is relatively straightforward. By training and employing individuals, companies transfer information concerning new technologies and materials, production methods, or organisational structures to these workers. Hence, companies embody knowledge through the labour they employ. When these workers leave their companies to offer their services to other businesses, the hiring organisation will not only benefit from receiving a more productive worker, but the new employee's knowledge is likely to be shared with other workers, which will lead to the diffusion of that knowledge throughout the firm, and result in higher productivity levels for the entire company. These knowledge transfers constitute spillovers from one company to the other, but only if the worker's wage premium received from his new employer understates the productivity increases he provides to this firm, i.e. the labour market does not internalise the entire knowledge spillover effect.

To assess this hypothesis, Görg and Strobl (2002) and Balsvik (2011) examine the question whether labour mobility constitutes a channel for knowledge spillovers from multinational enterprises (MNEs) to domestic firms operating in a particular country. The main presumption in both studies is that multinational firms have access to a firm-specific asset, such as a superior knowledge base, production technology, or better marketing and management techniques, which they accumulate from their operations in various countries. The authors then investigate the existence of spillovers of this firm-specific knowledge from MNEs to domestic firms, which occur when workers formerly employed in multinational enterprises leave their companies to work for domestic firms in the same country.

The work conducted by Görg and Strobl (2002) constitutes one of the first contributions to the literature concerning the impact of labour mobility on spillovers between multinational enterprises and domestic firms. They examine 240 companies in Ghana's manufacturing sector between 1991 and 1997. Focusing on firm ownership, they estimate the difference in productivity growth between domestic firms and firms run by owners who previously worked for an MNE in the same industry. They employ a growth accounting model in their methodology, and regress the growth rate of firm-level total factor productivity on variables indicating whether each firm's owner had previously been employed with, or received training from, a multinational firm in the same or a different industry. The empirical results exhibit that firms that were managed by an owner who worked for an MNE in the same industry prior to opening up their own firm witnessed significantly higher productivity growth than other domestic firms. In contrast, and supporting the concept of technological or industrial proximity as a spillover channel, the positive effect on productivity growth was neither found for managers who worked for multinationals in different industries, nor was it found for managers who received training by MNEs without actually having been employed with them.

Foster and Pöschl (2009) focus on inter-industry knowledge spillovers, and hypothesise that technology is transmitted across industries through the movement of skilled workers, who will share the knowledge they acquired from their former employers with their new co-workers, resulting in the diffusion of knowledge within the entire firm. Using data for ten EU member states in the period between 1995 and 2004, they estimate how a particular sector's productivity is influenced, among other factors, by the R&D investment made in other sectors, weighted by the share of workers who have left other sectors for employment in another. The authors' evidence confirms the importance of labour mobility as a channel for knowledge spillovers, with R&D disseminating across industries in the case at hand.

In a slightly different focus, other studies investigate the extent to which the mobility of university graduates induces spillovers between countries and regions. For example, Le (2009) assesses how students from developing countries who study or work in a foreign country contribute to their home countries' total factor productivity. In particular, the technical knowledge that these students acquire abroad can be transferred to their home countries upon the students' return, or if they stay in frequent and close contact with individuals from home. Le's empirical results prove that student mobility can be an effective conduit of technological transfer between developed and developing nations. A further study, conducted by Faggian and McCann (2006), also stresses the role of university students as carriers of knowledge, and analyses how students who stay in the geographical vicinity of their universities for employment after graduation impact the respective region's growth in the local stock of knowledge.

Are externalities reflected in earnings?

As outlined in the general theory of externalities (section 2.2), external effects that are reflected through the price mechanism do not constitute true spillovers. Møen (2005) considers this notion, and criticises the results of the above papers by questioning whether the transfers of knowledge through the movement of skilled labour between companies constitute actual externalities, or whether the labour market internalises the potential spillover effects through wages. The author describes knowledge spillovers through labour mobility as a situation in which a researcher who has accumulated valuable knowledge by working in one firm changes employers without compensating his former employer for the full knowledge he has accumulated and taken with him. A human capital framework to investigate knowledge transfers through labour mobility is tested using information from Norway. The findings suggest that at the start of their career, technical workers in R&D-intensive firms effectively pay for the knowledge they gain on the job by receiving lower wages. In contrast, the evidence points to a later increase in researchers' wages, implying that they receive a return on their accumulated knowledge in the future. As a consequence, the author asserts that the described potential knowledge spillovers resulting from labour mobility are, at least to some extent, internalised by the labour market. Since the spillover effects are reflected in the price of labour (i.e. wages of researchers), the transfers of R&D knowledge between firms resulting from the movement of labour might not constitute true knowledge externalities.

To test this hypothesis, Balsvik (2011) conducts a study for Norway's manufacturing sector involving labour flows from MNEs to firms operating only in Norway, through the incorporation of data for 14,400 workers during the 1990s. Employing a growth accounting framework, the effect of the domestic firm's share of employees with recent work experience in multinationals on productivity is estimated. The evidence reveals a robust and significantly positive relationship between the two variables, again implying that the mobility of workers from multinational enterprises acts as an important channel for knowledge spillovers between MNEs and domestic firms in the same industry. In particular, the author finds that workers with MNE experience contributed 20% more to the productivity of their plant than labour without prior employment in multinationals. Since the wage premium of workers with experience at MNEs was found to be only 5%, the analysis demonstrated that new employers benefited more from their labour mobility than the employee did themselves and supports the hypothesis that the human capital spillovers generated through labour mobility exist over and above those internalised by the firm in the form of higher employee compensation.

3.4 Intra-industry knowledge spillovers

Appleyard (1996) focuses on spillovers of knowledge among companies within the same industries, and identifies two categories of technological spillover channels. The author draws a distinction between *private* and *public* channels of technological spillovers, and compares their usage within the semi-conductor and steel industries of the United States and Japan. The author discovers significant differences concerning the channels through which inter-firm knowledge spillovers occur in the two countries that stem from institutional differences. While employees in the US semi-conductor industry rely on private channels, such as face-to-face interaction or consortia to gain external knowledge, information flows in the Japanese sector rather occur through public channels, e.g. journals, conferences, and patents. Regarding differences between industries, private knowledge sharing appears less likely in industries with rapid technological change (due to the significant uncertainty regarding the payoff of sharing knowledge with rivals via private channels.

Intra-industry spillovers and firm strategy

However, it is important to note that spillovers occur only when they have not been priced into the cost function of the beneficiary firm. In particular, some firms attempt to deliberately appropriate the knowledge generated by other firms and internalise these spillovers. For instance, Levin (1988) refers to some of these channels for knowledge spillovers between competitors (without the distinction between private and public mechanisms) and emphasises that different spillover mechanisms entail different levels of costs of acquisition of the external knowledge. He considers technology licensing and reverse engineering of products as the more costly ways for firms to benefit from their competitors' R&D efforts, while the acquisition of technical details through patent disclosures and interpersonal communication (technical meetings, publications and conversations with rivals' employees) appear relatively cheap. Further, he discusses the hiring of competitors' employees as an additional mechanism through which firms can achieve 'spillovers' of R&D from their competitors to the benefit of their own stock of knowledge; however, it is debatable whether this knowledge capture can still be considered a spillover given the fact that the wages paid to the employee moving from the R&D producing firm to the hiring firm will incorporate some degree of remuneration associated with the knowledge embodied in the workers prior experience.

A second study considering the induction of spillovers as a deliberate strategic choice by firms is authored by Gersbach and Schmutzler (1999). They hypothesis is that labour occupied in R&D activities is one of the main drivers of knowledge externalities, which are caused by companies poaching each other firms' R&D employees in order to benefit from knowledge developed by rivals. They develop a three-stage duopoly model with endogenous knowledge spillovers (i.e. companies have the ability to strategically prevent or encourage the flow of R&D spillovers). In the first stage of the game-theoretical model, two companies choose a cost-reducing level of innovation. The second stage then consists of the companies' competition for each other's R&D employees, where each firm attempts to *poach the others' R&D employees* (with the aim of achieving knowledge spillovers and the associated cost reductions). In the third stage, the two companies enter product market competition, where each firms' competitive position crucially depends on the cost structure as determined by innovation and knowledge spillovers in the previous stages. The authors use the results of the game to compare the innovation incentives between *Cournot* models, where firms compete in quantities, and *Bertrand* models, where competition revolves around the prices set by each of the competing companies. They show that the existence of endogenous spillovers increases innovation incentives in *Bertrand* games relative to *Cournot* competition, with the opposite outcome in the case of exogenous spillovers.

Aharonson *et al*. (2007) similarly focus on the importance of employees for technological spillovers, asserting that knowledge is diffused through *interactions among employees of companies involved in R&D*. They examine how entrants into knowledge-intensive industries may strategically choose to locate in close proximity to incumbents active in R&D of technologies similar to their own, with the intention of achieving significant spillovers of incumbents' knowledge. According to the authors, externalities, especially from knowledge at its early stage, occur through face-to-face contacts, professional relationships, social and professional networks, norms of information exchange and trust among employees, all of which are significantly supported by close proximity among companies active in related R&D. It is also emphasised that knowledge spillovers are not uni-directional, but that entrants typically fear appropriation of their own ideas when establishing facilities close to their competitors. The authors suggest two factors that may moderate fears of appropriation: increasing returns to knowledge externalities and the development of entrepreneurial and open environments that facilitate sharing, both of which are supported in small geographic clusters of technologically-related companies.

A final strategy-related theory of spillovers stems from Lambertini *et al*. (2004), who examine *strategic R&D co-operation between companies*, rather than industry-science collaborations, and underline how these can lead to increased knowledge externalities between the companies involved. Applying game-theoretical models to a number of industries, they find that R&D co-operation between firms leads to significantly larger research efforts of the companies involved, and that cooperation among them results in increased information exchange and, subsequently, enhanced knowledge spillovers within the collaborative agreement. However, the empirical results also reveal that the actual extent to which firms can control knowledge externalities is relatively low, thus undermining the importance of firms' strategies and decision-making processes on technological knowledge spillovers.

Finally, Czarnitzki (2009) focuses on *collaborative R&D agreements between industry and science*, (e.g. between private businesses and universities), as a means for companies to internalise knowledge spillovers. He describes the free-riding problem associated with spillovers, which implies that companies investing in R&D cannot fully appropriate the returns to this investment, since some of the newly developed knowledge is involuntarily transferred to other firms, which then free-ride on others' R&D efforts without incurring any costs. Companies wishing to increase the appropriability of their knowledge investments may decide to enter into strategic R&D consortia with science-related institutions, since these collaborative agreements allow firms to internalise the spillovers related to their research.

3.5 International knowledge spillovers

A significant amount of research has focused on the reasons why, and the extent to which, knowledge spillovers cross national borders, and thus how R&D in other countries affect domestic total factor productivity. Here, we review the theoretical reasoning behind these international knowledge flows as provided by the literature.

Empirically, the effect of international technology diffusion has traditionally been estimated using a production function relating domestic total factor productivity for country c at time t to domestic (R) and foreign R&D (S):

$$lnTFP_{ct} = \alpha_c + \alpha_t + \beta_r lnR_{ct} + \beta_s lnS_{ct} + \varepsilon_{ct}$$

The term capturing foreign R&D (S) is generally defined as a weighted sum of other countries R&D activities, with a bilateral weight (ω_{cht}) capturing the relative importance of R&D undertaken in country h for productivity in country c

$$lnS_{ct} = \sum_{h \neq c} \omega_{cht} S_{ht}$$

Earlier literature tried to proxy the ω using input-output shares, while the R&D spillovers literature related to the Coe and Helpman (1995) approach, discussed below, has typically used import shares as weights[17].

Keller (2001) has reviewed the literature on international spillovers and summarises the potential channels through which international spillovers are found to occur. Theories of endogenous technological change and growth have highlighted the following characteristics related to technology diffusion[18]:

- **Technology is non-rival:** the marginal costs for an additional firm or individual to use the technology are negligible and do not have an impact on the costs sustained by the original users.

- **The presence of knowledge spillovers:** the return to investment in new technology is partly private (benefiting the inventor or developer) and partly public (not all benefits are captured by the inventor, but a fraction will contribute to the pool of publicly available knowledge).

The author underlines the two basic mechanisms through which spillovers are diffused internationally:

- **Active spillovers - direct learning about foreign technological knowledge:** technological knowledge constitutes a distinguished design or blueprint. International spillovers occur if a foreign blueprint becomes available to domestic firms at less than the original cost incurred by the inventor or developer. If the creation of a new product is easier, the larger the available stock of knowledge, which implies that international spillovers can raise the productivity of domestic research. Spillovers generated in this way can be defined as active spillovers, given that foreign knowledge becomes part of the domestic knowledge available for further innovation.

- **Passive spillovers - international trade and Foreign Direct Investment (FDI):** technology diffuses internationally through the employment of specialised and advanced intermediate products that have been invented abroad. If the intermediate good costs less than its opportunity cost (i.e. the cost of producing the good domestically, including the cost related to R&D activities), there is a gain for domestic firms associated with having access to foreign intermediate goods. These

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[17] Keller points out that, while these approaches follow a partial-equilibrium model and both the R&D expenditures and the weights used are typically endogenous. Other studies (such as Eaton and Kortum (1997, 1999) and Eaton, Gutierrez, and Kortum (1998)) tried to use general equilibrium models under strong assumptions, while Keller (2001) uses a single equation in a partial equilibrium model estimating the TFP effect of foreign R&D jointly with the importance of one or more channels of diffusion for foreign R&D (which could be interpreted as estimating the weights ω of the foreign R&D variable together with the parameter β that measures the TFP elasticity).

[18] For theories of endogenous technological change see Aghion and Howitt (1992), Grossman and Helpman (1991), Romer (1990), and Segerstrom, Anant, and Dinopoulos (1990). An overview of endogenous growth theories and knowledge diffusion is contained in Grossman and Helpman (1995) and Aghion and Howitt (1998).

international knowledge flows can be defined *passive* spillovers: so far as the technology is embodied in the product, it will become available to domestic producers through the intermediate output; however, the technology will not contribute to the domestic stock of knowledge and to domestic invention. The channels through which these passive spillovers occur are normally identified in international trade (import of intermediate goods) and FDI (purchases from foreign-owned multinational subsidiaries).

A more recent paper by Keller (2009) discusses the exact mechanisms behind the *passive* spillovers from FDI in more detail. He considers three ways in which FDI can act as a channel for technology spillovers between foreign affiliates of multinational enterprises and host-country firms. The author emphasises the existence of both *inward* FDI spillovers, where host country firms benefit from multinational affiliates' technology through the three channels specified, as well as *outward* FDI externalities, where a multinational company decides to go abroad to acquire technological knowledge from local firms.

Reiterating the importance of labour mobility discussed in section 3.2, the first mechanism again emphasises *labour mobility* and *turnover*, and assumes that multinational affiliates in host countries commonly hire local labour and teach those workers about their technology through formal or on-the-job training. When these employees leave the affiliate to work for host country firms, the knowledge they have acquired will thus be transmitted to the latter, resulting in technology spillovers. Secondly, the author illustrates how the affiliate might generate R&D spillovers to firms in the same country through its *business operations* (providing an example of Walmex in Mexico, whose competitors copied its system of cold chain operations shortly after its introduction). Finally, the author points to *vertical spillovers* that can occur if the affiliate buys inputs from local suppliers or sells them to local downstream companies at a price below these inputs' market value, in which case the company buying the input benefits from the R&D associated with the input without incurring the cost of these efforts[19].

Coe and Helpman (1995) consider only international trade in production inputs as the main conduit of technological spillovers. As similarly stressed by Coe *et al*. (2009), both the inter-temporal spillovers characterised by the '*love of variety approach*' and the 'quality ladder approach' (detailed explicitly in section 2.3) can cross national borders, implying that total factor productivity of a country not only depends on the domestic stock of knowledge, but also on foreign R&D capital produced by its trading partners. Coe and Helpman consider the 'quality ladder approach' and the 'love of variety approach' as the two main channels through which knowledge spillovers occur, and assert that international trade leads these knowledge spillovers across international borders. Since a majority of production inputs are traded internationally, firms employ inputs manufactured and developed by foreign firms in their production process, the technological content of which then spills over to the domestic stock of knowledge and productivity. Coe and Helpman develop the model (presented above) to estimate the impact of the R&D capital produced

[19] Lee (2006) acknowledges inward and outward FDI technology spillovers and imports of intermediate goods (identified by Keller (2001; 2009)) as potential channels, and adds a different mechanism through which knowledge externalities might disseminate internationally. In particular, he describes a *direct channel for spillovers*, where knowledge circulates across borders directly, without being embodied in specific transactions of goods or investments. He also examines the comparative significance of the different spillover channels (see section 5.2 for a more detailed discussion of his results).

by foreign trade partners on domestic total factor productivity, and test their theory for a number of countries. Coe *et al*. (1997) similarly stress international trade in inputs as a channel for spillovers, but emphasise that trade doesn't only lead to spillovers by making foreign intermediate inputs available to a country, but that international trade also entails important direct learning effects between the trading partners, since they make useful but otherwise costly information available to each other.

Lumenga-Neso *et al*. (2005) (see also section 6.2) augment Coe's and Helpman's argument. Whereas the latter stress the existence of direct spillovers through bilateral trade relationships, where a country benefits from the R&D produced by its trading partners, Lumenga-Neso et al.(2005) concentrate on indirect knowledge spillovers between countries, which take place even if the countries in question do not directly engage in trade with each other. In their argument, it is rather the level of knowledge *available* in foreign countries that diffuses across national borders and adds to domestic technology and productivity. For example, if country A trades with country B (but not with country C) and country B trades also with country C, country A can still benefit from the R&D developed in country C through the R&D available in country B. In other words, international R&D spillovers can occur even if two countries are not trading with each other directly, and focusing on bilateral trade would not capture R&D spillovers occurring through international trade[20].

3.6 The geographical dimension

One of the most important sources of knowledge spillovers involves the geographic or technical proximity of firms and their workers. Tracking knowledge flows and assessing the extent to which they are diffused internationally or remain local can be a daunting exercise. Applications in the empirical literature have mainly used three different approaches to identify the positive effects generated by knowledge externalities locally and internationally:

1) Looking at the cross-country or cross-industry growth rate in total factor productivity: the fundamental idea is that countries and firms *further* away from the technological frontier will benefit the most from knowledge transfers (see Griffith et al., 2004). Evidence of convergence across countries and industries provides a signal that knowledge transfer is occurring; however the association is only indirect and many other factors may influence TFP growth rates, and it is difficult to isolate the effect of knowledge flows from other mechanisms.

2) The production function approach (as in Coe and Helpman, 1995), where foreign R&D is directly controlled for in the estimation of a country's productivity growth, along with domestic R&D and other variables. The mechanisms through which foreign R&D affects domestic productivity are normally identified in *international trade* and FDI. As also described in Section 6.2.2, there is an issue with appropriately weighting the contribution of each foreign country's R&D on

[20] To capture these indirect international technology spillovers, the authors transform the term S_{ct} in the model equation $lnTFP_{ct} = \alpha_c + \alpha_t + \beta_r lnR_{ct} + \beta_s lnS_{ct} + \varepsilon_{ct}$ to include both the sum of R&D produced in foreign trading partner countries as well as the import-weighted sum of foreign R&D available in each of these countries.

domestic productivity, the nature of the evidence is still indirect, and there may be other economic mechanisms taking place at the same time.

3) Knowledge flows do leave a paper trail in terms of patent citations: starting from Jaffe et al. (1993), researchers have investigated whether knowledge flows are localised or diffuse across regions and countries. However, there are some limitations to this approach. As patent citations are only an imperfect (and noisy[21]) measure for knowledge flows, the identification of the correct counterfactual is difficult and a fraction of the knowledge flow is accounted for by other economic (market or non-market) mechanisms and do not indicate the presence of positive spillovers.

The first approach is described in detail in Section 6.2, while below we review some of the mechanisms underpinning the approaches outlined in 2) and 3), along with other evidence. For a detailed review of relevant articles see the later empirical sections.

3.6.1 Geographical proximity and agglomeration

Introduction

The importance of geographical proximity and industrial concentration was already acknowledged by Marshall (1920). The Marshallian factors favouring geographic concentration of industries are normally listed as[22]: (1) the pooling of demands for specialised labour (labour market economies); (2) the development of specialised intermediate goods industries (economies of specialisation) and (3) intra-industry knowledge spillovers, thanks to the sharing of knowledge through social linkages and personal contacts. Krugman (1991) observed that economists should focus on the first two of these, given that "*knowledge flows, by contrast, are invisible; they leave no paper trail by which they may be measured and tracked, and there is nothing to prevent the theorist from assuming anything about them that she likes*".

How to identify the knowledge flows and assess the spatial extent of the effects has been an extensively investigated issue in literature. The classic approach by Jaffe et al. (1993) uses patent citations to assess whether knowledge spillovers are mostly localised or extend beyond borders and their findings indicate significant effects of localised knowledge spillovers. While the approach has been widely replicated and extended in literature, two main critiques have been put forward concerning the approach used to identify how spillovers can arise (see Breschi and Lissoni, 2001), and the identification of the appropriate counterfactual (see Thomson and Fox-Kean, 2005).

Trailing patent citations has been widely used in the empirical literature as a signal of knowledge flows and the evidence mainly points towards the existence of *localised knowledge effects*. However, attention should be paid to assess the robustness of the identification strategy and to evaluate whether the estimated effects are purely spillovers

[21] Jaffe et al. (2000) conducted a survey of both citing and cited inventors, investigating the extent to which cited and citing inventors communicate with each other and the influence of the cited on the citing patent. Patent citations were found to provide a signal of knowledge spillovers, but a noisy one (with around one half of citations not reflecting knowledge spillovers).

[22] See Krugman (1991), Jaffe et al. (1993) and Breschi and Lissoni (2001)

or may also cover effects explained by other economic mechanisms. Below we present the classic papers in the area, the main critiques and integrations to the original approach. Empirical evidence is also presented in the sections 6 and 7.

Using patent citations as a proxy for knowledge flows

The classic approach

Jaffe et al. (1993) use patent citations as the 'paper trail' to measure knowledge flows. Specifically, they try to assess the extent to which spillovers are geographically localised using patent citations as a measure of knowledge flow. They test whether knowledge spillovers are geographically localised using two samples of US patents (one for 1975 and one for 1980), and look at the number of citations the examined patents have received by 1989 (excluding self-citations). Citations are seen as a form of knowledge flow from the original patent inventors to the citing inventors. They build three patent groups: one formed of originating patents, one formed of citing patents with a reference to the original patent, and the control group formed of patents similar to the citing patent (in terms of patent class and year), but with no reference to the original patent. Comparing the geographical distribution of the citing patent and its matched control patent with the geographical distribution of the originating patents, they find strong evidence in favour of the hypothesis of the existence of localised knowledge spillovers, at country (US versus foreign), state (US state) and metropolitan area level, with this last effect being particularly strong[23],[24].

Extensions of the classic approach

Subsequent literature extends and re-examines the original approaches proposed by Jaffe (1989) and Jaffe et al. (1993). For example, Anselin et al. (1997) extend the original Jaffe (1989) model using a dataset with information on innovation count[25] and R&D activities at both the state and metropolitan statistical area level (using R&D laboratory employment as a proxy for industrial research activities in the latter case). They try to capture local spatial interactions between academic and industry research at both state and metropolitan area level using a wider range of variables (at metropolitan area level, these variables are referred to as spatially lagged variables, capturing the effect of *university research* and

[23] Citing patents are twice as likely to come from the same state as the control patents, and between two and six times more likely to come from the same metropolitan area. At country level they are up to 1.2 times as likely to be localised (the difference is around 2-4 percentage points for 1975 patents, and bigger (up to 10 percentage points) for 1980 patents (possibly due to the shorter time span available and the fact that earlier citations are more likely to be localised than later citations)).

[24] In earlier work by the same author, Jaffe (1989) explores the existence of geographical spillovers stemming from university research and positively affecting commercial innovation. The author focuses on US state-level data on corporate patents, corporate R&D, and university research and found evidence of geographical spillovers of university research on corporate patents in the areas of Drugs, Chemicals, and Electronics, Optics and Nuclear Technology. Jaffe accounts for state-level industrial R&D activities by constructing an index of *geographic coincidence* of industry R&D and university research at state level, but only finds weak evidence that the geographic co-location (at state level) of universities and research laboratories positively affects the diffusion of spillovers.

[25] Innovation count is defined as the number on innovations introduced to the US market in 1982, based on an extensive review of new product announcements in trade and technical publications.

private research undertaken in counties within a given distance band from the geographic centre of the metropolitan spatial area). Their main findings suggest that university research generates positive spillovers on innovation activities, both directly and indirectly (through the interaction between university research and private R&D), and that these effects extend to the state level.

Maurseth and Verspagen (2002) also use data on patent citations from the European Patent Office. Since the data is not at firm level, they conduct their analysis at EU regional level. An indication of localised knowledge effects would suggest that geographical distance, national borders and linguistic differences may act as a barrier to knowledge flows across EU regions having different characteristics. Their findings highlight that knowledge flows are industry-specific, and that they are higher in regions within the same country, and also in regions belonging to different countries, but sharing the same language. Thus, industrial specialisation and geographical differences may act as a significant barrier towards the cross-country diffusion of spillovers.

Critiques of the classic approach

Breschi and Lissoni (2001) critically review the literature related to geographical spillovers (and localised knowledge spillovers in particular). Their critique covers both the logical steps identifying geographical proximity as a facilitator for knowledge flow and the empirical methodologies applied. According to the authors, the standard approach justifying the existence of geographical knowledge spillovers relies on academic and private research being a *public good* (non-rival and non-excludible) that freely spills over to other users; however, being tacit (i.e. highly contextual and difficult to codify), some degree of personal contact and geographical proximity is still required to exploit the spillover. In other words, the author suggests that knowledge "**is a public good, but a local one**".

This view ignores the existence of economic (market and non-market) mechanisms underlying knowledge transfer. Specifically, knowledge transfer may occur through the labour market (for example students being hired by local firms after completing their university course), through consultancy and training services offered to local firms, or through local co-operation agreements (e.g. firms sponsoring university research projects). The classic view does not consider that technical and scientific knowledge is tacit, in the sense that it is highly specific and only accessible to a restricted group. Knowledge sharing is therefore likely to happen between members of the same network (academic or other), rather than with local actors outside the network (i.e. technological proximity rather than simply geographic proximity). The authors also point to the general lack of robust evidence and the appropriateness of the data and unit of analysis used[26].

The same authors (Breschi and Lissoni (2003)) revisit the Jaffe et al. (1993) methodology, highlighting that the original paper implicitly assumes that knowledge externalities are the result of oral communications between patent inventors[27]. However, it is not entirely clear

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[26] For example, the Jaffe (1989) paper used state-level data and wide industry aggregation

[27] The authors argue that Jaffe et al. identified pure spillovers (i.e. cases where no pecuniary transfers are involved at all), which can occur in the case of non-trade related personal communication exchange or through some form of reverse engineering (studying both manufactured goods and technical documents).

why inventors should share information without being adequately compensated: the answer normally put forward is the existence of social obligations between researchers or universities and firms. However, spatial proximity is only one factor explaining social connections (members of a community can be scattered around the world) and the attention should be shifted, in the authors' view, from geographical proximity to *social proximity* to explain knowledge flows and the existence of pure spillovers. Starting from these considerations, Breschi and Lissoni propose a measure of social proximity looking at social networks of inventors (i.e. if inventors A and B have worked together in the past, A might be willing to share future information (at no cost) to B (direct linkage), but also to C, who inventor A does not directly know, but who is known by B (indirect linkage)). Moreover they also look at the number of patents coming from inventors who have moved across companies and location[28]. Their results, using data on Italian patents, show that network relationships are crucial for knowledge flows, and localisation effects only occur when labour mobility and network linkages are also localised. The authors also find that labour mobility (hiring workers with technical knowledge from competitors) is an effective way to access a network of knowledge exchanges.

Thomson and Fox-Kean (2005) reassess the original Jaffe et al. (1993) experiment, scrutinising the methodology used to construct the control group. In particular the authors present two criticisms on how the control group of patents was constructed: firstly, the *aggregation problem* (i.e. the level of industrial aggregation used) and, secondly, the fact that the selection process used to identify the control group does not ensure the existence of any industrial link between the originating and control patents. The aggregation problem relates to the level of aggregation of the industrial classification used, which is very wide and heterogeneous (three-digit level in the U.S. classification system (USCS)): hence, while the citing patent belonging to the same three-digit level classification is also likely to fall in the same detailed subclass, patents in the control group belong to the same 3-digit class, but are less likely to fall in the same detailed subclass. In other words, the patent in the control group is less likely to be cited simply because it might be more relevant to a different industry.

The second criticism relates to patent classification. It is possible that a citing patent is assigned to both technological classes A (primary class) and B (secondary class) and the control patent shares the same primary class A, but not the secondary class. Assuming that the originating patent was only assigned to the primary class B, this would imply that while the originating and citing patent share a technological class and the citing and control patent share a technological class, the originating and control patent are in fact unrelated. The authors conduct an analysis similar to that carried out by Jaffe et al. (1993), correcting for these potential biases in the selection of the control group. Their findings suggest that *much of the localised knowledge spillovers* found by Jaffe et al. (1993) at state and metropolitan area level *disappear,* although there are still significant localisation effects at country level; however, they also acknowledge the limitations of the testing exercise using an imperfect classification and non-experimental settings.

The mechanism outlined by Jaffe et al. requires personal communication, given that studying a patent or a manufactured good is not enough to fully capture its intrinsic characteristics, unless the inventor adds explanations or practical demonstrations.

[28] Inventors' "mobility" is a signal that technical knowledge embodied in inventions can be appropriated by the inventor to some extent (there are no *pure spillovers*) and employers are willing to pay for it.

The evidence available on the effect of co-location on knowledge spillovers is far from conclusive. In fact, the direction of the relationship between knowledge flows and co-location is unclear, given that “knowledge spillovers provide incentives to co-locate and, conversely, the existence of co-location to begin with may encourage ‘cross-pollination’“. In general, as also pointed out by Thomson and Fox-Kean (2005), it is not just the robustness of the findings in Jaffe et al. (1993) that should be questioned, but the validity of obtaining meaningful results using standard patent classifications in the matching process[29].

Starting from these considerations, Thomson (2006) uses the relative geographic frequencies of patent citations as a measure of localised spillovers, but employs an alternative matching scheme. The identification strategy used compares, for each patent, the geographic distribution of citations added by the inventor to those added by the examiner, with the former being an indication of localised knowledge spillovers[30]. The author investigates localisation effects at country, US state and metropolitan area level, and finds evidence supporting the existence of localised spillovers at both international and intra-national level: inventor citations are approximately 20% more likely to match the country of the originating patent compared to examiner citations, and around 25% more likely to match the same intra-national location (state and metropolitan area). However, intra-national but not international localisation spillovers are found to be declining over time.

Other evidence of agglomeration spillovers

Greenstone et al. (2010) use data on large plant openings at US county level to assess the existence of localised *spillovers* on productivity. In the presence of positive spillovers, they argue that the opening of a new plant 1) should increase the TFP of existing plants; 2) the increase may be larger for similar plants; 3) if spillovers are large enough, firms located outside the county have an incentive to relocate in the county and as a result economic density should increase; 4) finally, the prices of local inputs should increase, as new entrants bid for the inputs.

To construct treatment and counterfactual groups, they use information on the decision process underpinning the choice of where to locate large manufacturing plants. Specifically, they use as a counterfactual the group of existing plants in the ‘losing’ counties (the one or two closest alternatives that were shortlisted but not selected) compared to the group of existing plants in the winning (selected) county. Using data on 47 plant openings between 1973 and 1998 and controlling for differences in pre-existing trends and fixed effects at plant level (and other control variables), they find that TFP of existing plants in ‘winning’ counties is 12% higher than the counterfactual group five years after the opening of the new plant. Moreover, they find that the spillovers are larger for plants sharing similar technologies and a labour pool with the new plant. This finding is

[29] “We remain convinced that the best way forward is to devise identification systems that avoid entirely technology classification systems that were devised for the sole purpose of helping examiners locate prior art”

[30] More specifically, the identification strategy rests on two assumptions: “the first is that examiners (…) cannot be learning about prior art because of geographic proximity to related technological activities. The second is that an inventor citation is more likely to represent a true knowledge flow than is an examiner citation”.

consistent with the presence of intellectual externalities, as far as these occur among firms using similar sets of knowledge or are embodied in workers moving across firms. The finding is also consistent with the presence of a better worker-firm match in the labour market reflected in higher TFP.

Irwin and Klenow (1994) study whether benefits from learning-by-doing arise in the semiconductor industry and whether these are completely internalised by firms or also generate national and international spillovers. This sector was of particular interest, given the strategic importance, the technological component involved, and the fierce international competition. Their main findings show that learning rates are around 20% and that the positive benefits mostly remain within the firm ("*firms learn three times more from an additional unit of their own cumulative production than from an additional unit of another firm's cumulative production*"). However, considering the relative size of own and external production, the magnitude of learning-by-doing spillovers is substantial, with no significant difference in the effect at national and international level.

Orlando (2004) also examines intra-industry R&D spillovers occurring within a specific industry (the Industrial and Commercial Machinery and Computer Equipment, identified by the class SIC 35) using both three-digit and four-digit industry codes. He finds that R&D spillovers are substantial and insensitive to geographical distance within the same narrowly defined industry (four-digit code); are smaller but significant (and declining with distance) outside the 4-digit class but within the 3-digit class; and negligible outside the 3-digit class.

In a final paper tying together some of the previous work on knowledge spillovers, by considering the relative effect of alternative routes of knowledge spillovers, Levin (1988) presents results from a survey of 650 R&D executives on the nature of appropriability and technological opportunity in 130 industries. Seven methods of learning are identified as important: licensing technology, reverse engineering of a product, acquiring technical details through patent disclosures, publications or interpersonal communication comprising technical meetings, informal conversations with employees of an innovative firm, hiring employees of an innovative firms, and conducting internal R&D. The survey demonstrated that *independent R&D* was indicated as the most effective method of learning, followed by licensing technology and reverse engineering of a product.

3.6.2 Agglomeration effects and human capital spillovers

Empirical approaches

In section 2.4 we introduced the theory behind human capital spillovers. Here we briefly review the main empirical approaches used in literature to identify and measure human capital spillovers. Detailed empirical evidence is presented in Section 6.1 estimating the effect of geographical concentration of human capital on productivity of fellow workers. As pointed out by Mas and Moretti (2006), working alongside with more productive co-workers can generate either a positive or a negative externality: the former case occurs if working with more skilled and productive co-workers results in a higher and more productive effort due to imitation, social pressure, leading-by-example or learning-by-doing. However, the message is not clear cut in the sense that negative externalities may also arise if it is not possible to accurately measure individual effort, and the presence of more productive workers provides less productive workers with a potential to free-ride. Moreover, as remarked by Rosenthal and Strange (2008), higher spatial concentration may also produce negative externalities if public infrastructures and facilities are not able to cope with the increased population density and therefore agglomeration increases congestion, travelling times and, as a result, negatively affects wages and productivity.

A further point of interest is whether working with highly educated co-workers affects differently the productivity of different groups of workers with different levels of education. Positive spillovers can be higher for individuals with a similar level of education (highly educated) if there is complementarity within skill level rather than across skill levels. On the other hand, less educated workers might benefit more from the presence of highly educated co-workers, given that their productivity level is lower and the impact potentially greater. However, in the presence of imperfect substitution between high-skilled and low-skilled workers, a positive shift in the labour supply of high-skilled workers may have a positive effect on the wages of low-skilled workers even in the absence of positive externalities, simply because the supply of low-skilled workers have become relatively scarce. On the other hand, observing a positive impact of external human capital level on the wages of high-skilled workers is a clear indication of the existence of spillovers, also outweighing any potential negative effect due to an increased supply of high-skilled workers.

Finally, positive externalities may arise only in concentrated geographical areas or also extend, to some degree, to nearby areas. Controlling for different spatial distances can provide an indication on the spatial extent of human capital spillovers and on how this erodes as we move further away from the original place of work.

These issues have been investigated extensively in the empirical literature. The model typically being estimated is an extended Mincer model of the following form (see Moretti, 2004b)

$$\ln(w_{ict}) = X_{it}\beta_{ct} + \gamma A_{ct} + \alpha Z_{ct} + \mathbf{d_c} + \mathbf{d_t} + \varepsilon_{ict}$$

where w is the wage of individual i in city (or region) c at time t, X_{it} is a vector of personal characteristics, including the individual level of human capital A_{ct} represents the level of human capital in city c at time t, Z_{ct} is a vector of city (or regional) characteristics potentially correlated with A_{ct} and $\mathbf{d_c}$ and $\mathbf{d_t}$ identify city and time fixed effects respectively. The parameter of interest is γ, which represents the effect of the city (or regional) level of human capital on average wages after controlling for private returns to education. Typically the level of human capital in cities or regions has been proxied by average years of schooling or the percentage of the population holding a degree level qualification. Some authors have also estimated an augmented model controlling for the presence of both regional and firm human capital spillovers[31].

One of the main challenges in empirical applications is the likely presence of endogeneity in the relationship between human capital agglomeration and productivity. For example, talented workers may be drawn to agglomerated areas in search of higher wages or better amenities. In this case, it is necessary to control for the potential reverse causal effect: do

[31] See for example Bauer and Vorell (2010)

skilled workers move to more productive areas, or do more agglomerated areas make workers more productive? The empirical literature has used various approaches to tackle this and other endogeneity issues (for example using the lagged presence of universities as an instrument for the presence of college educated workers (Moretti (2004b)) or exploiting local geological characteristics as in Rosenthal and Strange (2008)). This is discussed in greater detail in Section 6.1[32].

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4 Measurement of investment in intangible assets and spillovers

4.1 Intangible assets and growth accounting

“You see the computer revolution everywhere except in the productivity data” (Solow (1987) cited in Corrado *et al*., 2005).

As Solow (1987) pointed out, intangible assets have traditionally been subject to measurement problems, resulting in recent doubts as to whether the conventional growth accounting frameworks are accurate. The recent revolution of information technology has expressed itself in the introduction of the Internet, advanced telecommunications, and the continuous launch of technological products. However, while their significant impact on economic growth is undisputed, investments in intangible assets, in contrast to tangible asset expenditures, have traditionally been expensed as intermediate inputs in firm-level and national accounts, effectively deducting them from rather than adding their contribution to economic growth (Van Ark *et al*., 2009). Corrado *et al*. (2006) emphasise that the failure to appropriately take account of intangible investments has led to a bias in traditional growth accounting.

In their 2005 paper, Corrado *et al*. provide arguments for a capitalisation of outlays in intangible assets and for the necessity to include them in economic growth accounting procedures. Using an inter-temporal model of consumer choice, they indicate that investment can be defined as any use of resources that reduces current consumption in order to increase it in the future. As this criterion applies to expenditures on tangible as well as intangible assets, they argue that investments in either of the two should be treated symmetrically. Corrado *et al*. (2006) provide similar arguments from a standpoint of production, in addition to consumption. As a consequence, the role of both investments in tangible, as well as intangible assets should be accounted for in growth models and empirical studies on economic growth.

An analysis of the changes to traditional accounting procedures with respect to the treatment of intangible assets necessitates a comparison of both traditional and new accounting methods. Both approaches consider a world of three goods: consumption (**C**), tangible investment goods (**I**) and intangible assets (**N**). However, the traditional growth accounting model only considers two inputs in the production function: tangible capital (**K**) and labour (**L**). As a consequence, in the traditional approach, intangible assets are regarded as an intermediate good (i.e. they are produced using capital and labour, and constitute an input in the production of consumption goods and tangible assets). Since intangible goods thus act as both an output and an input to production, they net out in the aggregate gross domestic product (GDP) identity[33] (see Corrado *et al*., 2006).

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[33] $P^Q(t)\ Q(t) = P^C(t)\ C(t) + P^I(t)\ I(t) = P^L(t)\ L(t) + P^K(t)\ K(t)$ where P^X denotes respective prices of each output / input (Corrado *et al.*, 2006).

The conventional growth accounting framework[34] allocates the aggregate growth rate of economic output to the growth rates of each input capital and labour, weighted by their respective shares of total input, as well as a residual (Corrado et al., 2005). The latter indicates the growth rate of total factor productivity, measuring the change in output that cannot be explained by changes in inputs, and includes factors such as the introduction of new technologies or an improvement in organisational structure, for example. Thus, intangible assets are not explicitly factored in standard economic growth accounting and are only captured by the conventional residual, which understates their role for economic growth.

Treating intangible assets as capital induces a change to both the GDP identity and the economic growth accounting framework. The former now includes intangible capital on the input side and intangible investment goods on the output side.

$$P^Q(t)Q(t) = P^C(t)C(t) + P^I(t)I(t) + P^N(t)N(t) = P^L(t)L(t) + P^K(t)K(t) + P^R(t)R(t)$$

where **N** and **R** denote intangible capital and investment goods, respectively (Corrado et al., 2006). The augmented growth accounting framework then reads

$$g_Q(t) = s_L(t)g_L(t) + s_K(t)g_K(t) + s_R(t)g_R(t) + g_A(t)$$

where $\mathbf{s_R}$ and $\mathbf{g_R}$ refer to the share of intangible investment goods of total inputs and the growth rate in intangible investments, respectively (Corrado *et al*, 2006).

Thus, the standard growth accounting framework is expanded to explicitly take into account the contribution of the growth in intangible assets, weighted by its share of total inputs, to the aggregate growth in economic output. This new approach to the treatment of intangible investment goods in national and firm-level accounting allows for an explicit and more accurate assessment of intangibles' contribution to economic growth.

4.2 Measuring intangible assets

Clearly, using investment in intangible assets as an input in the production function poses the question of how to identify and measure expenditures on intangible goods, and what share of the overall expenditure should be considered as investment. In order to aid the measurement of investment in intangible assets, Corrado et al. (2005) developed a framework which identifies and classifies various types of intangible investments according to three broad categories.

1. **Computerised information** refers to outlays on knowledge included in computer software developed for a businesses' own use, and in computerised databases.

[34] $g_Q(t) = s_L(t)\, g_L(t) + s_K(t)\, g_K(t) + g_A(t)$ where g_X and s_X denote growth rates and shares, respectively (Corrado *et al.*, 2006).

2. **Innovative property** takes account of both spending on scientific R&D and on the exploration of new mineral reserves, as well as expenditures on research in less scientific but more creative research. The latter include investments in copyrights in patents, as well as in the development of other products related to the financial industry, architectural and engineering designs, and social sciences and humanities research.

3. **Economic competencies** take into account the value of firm-specific human capital, the costs of firms' organisational structure, with both the expenses on external consulting and own-account structural change from within the company, and outlays on advertising and market research related to a company's brand equity.

The usefulness of this framework has been widely recognised, and numerous studies have employed the scheme in order to estimate investment on intangible assets in various countries (cross-country comparison reported in Table 2). All studies use a combination of sources, mainly from national accounts and firm-level surveys (with estimates grossed up to the national level). In Table 3 we describe in detail the sources used in the Corrado *et al*. (2005) and Giorgio-Marrano and Haskel (2006) studies.

Table 2: Intangible investment as a percentage of GDP, cross-country comparison – estimates

Author	**UK: Giorgio-Marrano and Haskel (2006), AUS: Barnes and McClure (2009), JAPAN: Fukao *et al.* (2008), US: Corrado *et al.* (2005), NL: Van Rooijen-Horsten *et al.* (2008), CAN: Belhocine (2009), GERMANY: Hao *et al.* (2009), FRANCE: Hao *et al.* (2009), ITALY: Hao *et al.* (2009), SPAIN: Hao *et al.* (2009), FIN: Jalava *et al.* (2007), SWE: Edquist (2008)**															
Country	**UK**	**AUS**	**JAPAN**	**US**	**NL**	**CAN**	**GERMANY**		**FRANCE**		**ITALY**		**SPAIN**		**FIN**	**SWE**
Data	**2004**	**2005/6**	**2000-05**	**1998-2000**	**2005**	**2005**	**2004**	**2006**	**2004**	**2006**	**2004**	**2006**	**2004**	**2006**	**2005**	**2004**
Computerised Information	**1.70**	**0.80**	**2.20**	**1.65**	**1.40**	**1.03**	**0.71**	**0.73**	**1.31**	**1.42**	**0.66**	**0.64**	**0.74**	**0.79**	**1.02**	**1.83**
Computer software	1.70	0.80	2.10	1.61	1.40	0.83	0.69	0.71	1.27	1.37	0.66	0.63	0.71	0.76	.	.
Computerised databases	.	.	0.20	0.03	.	0.2	0.02	0.02	0.04	0.05	0.01	0.01	0.03	0.03	.	.
Innovative property	**3.23**	**2.20**	**5.90**	**4.53**	**1.80**	**4.97**	**3.47**	**3.59**	**3.12**	**3.18**	**2.26**	**2.21**	**2.51**	**2.78**	**4.01**	**5.39**
Scientific R&D	1.06	0.80	2.80	1.96	1.00	1.9	1.69	1.72	1.32	1.30	0.52	0.58	0.55	0.63	2.73	2.59
Mineral exploration	0.04	0.30	0	0.19	0	1.11	0	0.01	0.02	0.04	0.04	0.09	0.04	0.04	0.04	0.01
Copyright and license cost	0.21	0.10	1.10	0.80	0.20	0.11	0.20	0.21	0.32	0.31	0.10	0.10	0.19	0.18	0.14	0.11
Other product development (PD)	1.92	1.10	2.00	1.59	0.60	1.85	1.57	1.65	1.46	1.53	1.59	1.44	1.73	1.93	1.10	2.68
New PD in the financial industry	0.69	.	.	0.79		0.03	0.70	0.75	0.58	0.60	0.79	0.58	0.35	0.52	.	0.25
New architectural/eng. designs	1.20	.	.	0.72	0.60	1.82	0.87	0.9	0.88	0.93	0.80	0.86	1.38	1.41	1.10	2.42
R&D in social science and humanities	0.03	.	.	0.07	.	.	.	.	.	.	.	.	.	.	.	0.01
Economic competencies	**5.95**	**2.90**	**3.40**	**6.82**	**5.20**	**3.79**	**3.27**	**2.84**	**5.22**	**3.3**	**2.67**	**2.19**	**2.19**	**1.90**	**4.07**	**3.32**
Brand equity	*1.59*	*0.90*	*1.10*	*2.51*	*2.30*	*0.5*	*0.84*	*0.56*	*1.51*	*0.99*	*1.19*	*0.71*	*0.58*	*0.42*	*1.74*	*1.61*
Advertising expenditure	1.20	.	.	2.31	2.10	0.41	0.69	0.41	1.24	0.73	0.91	0.47	0.33	0.19	.	1.43
Market research	0.39	.	.	0.20	0.30	0.09	0.15	0.15	0.27	0.26	0.28	0.24	0.25	0.23	.	0.18
Firm-specific human capital	*2.45*	*0.40*	*0.50*	*1.24*	*1.20*	*2.16*	*1.34*	*1.29*	*1.51*	*1.51*	*1.00*	*1.02*	*0.83*	*0.81*	*1.18*	*1.05*
Organisational structure	*1.92*	*1.60*	*0.50*	*3.10*	*1.80*	*1.13*	*1.09*	*1.00*	*2.21*	*0.81*	*0.48*	*0.45*	*0.78*	*0.68*	*1.15*	*0.66*
Purchased	0.60	.	.	0.86	1.30	0.71	0.5	0.54	0.31	0.32	0.11	0.15	0.25	0.27	0.41	0.20
Own account	1.31	.	.	2.24	0.40	0.42	0.59	0.46	1.90	0.49	0.37	0.3	0.53	0.41	0.73	0.47
Total (as a % of GDP)	**10.88**	**5.90**	**11.50**	**13.10**	**8.40**	**9.78**	**7.05**	**7.16**	**8.77**	**7.9**	**5.15**	**5.04**	**5.20**	**5.47**	**9.10**	**10.55**

Source: London Economics; analysis based on different authors

Table 3: Abbreviated classification and methods of intangibles in the UK and the US		
Item	**Method and data sources**	
Computerised Information	**United Kingdom**	**United States**
Computer software	Estimate developed by the ONS using three different surveys: the **Business Spending on Capital Items Survey**, the **Quarterly Inquiry into Capital Expenditure** and the **Annual Business Inquiry**. Expenditure is measured using spending on software purchases and own-account spending.	Covers expenses of software developed for a firm's own use; based on **NIPA** data that include three components: own use, purchased, and custom software.
Computerised databases	Spending on database activities and data processing is mainly covered in expenditure on software	Own use likely is captured in **NIPA** software measures. Data from the **Services Annual Survey** (SAS) suggest that the purchased component is small.
Innovative property		
Scientific R&D	R&D expenditure data in the UK is collected by the **Business Enterprise R&D** survey (BERD). Spending in the "computer and related activities" industry was subtracted from the overall R&D spending	R&D in manufacturing, software publishing, and telecom industries. The **census** collects data on behalf of the National Science Foundation (NSF). Industrial R&D data are available from the early 1950s and cover work in the physical sciences, the biological sciences, and engineering and computer science (excl. geophysical, geological, artificial intelligence, and expert systems research).
Mineral exploration	Spending associated to perspectives of future returns is measured using **national accounts** data	Mineral exploration from **Census of Mineral Industries** and **NIPA**s. Other geophysical and geological exploration R&D in mining industries is estimated from **census** data and the **Census of Mineral Industries**
Copyright and license costs	**UK National Accounts** relative to TV and radio, publishing and music industries	R&D in information-sector industries (excl. software publishing) proxied by: Development costs in the motion picture industry extrapolated from the cost per release for **Motion Picture Association of America** members and development costs in the radio and television, sound recording and book publishing industries which are crudely estimated to be double the new product development costs for motion pictures.
Other product development (PD)		
New PD in the financial industry	Measured as a proportion of total intermediate spending by the financial services industry	New product development costs in the financial services industries estimated as 20% of intermediate purchases from a **Bureau of Economic Analysis** data set.
New architectural/eng. designs	Use data for the relevant sector (**SIC742**) and consider 50% of total turnover for the sector	New architectural and engineering designs, estimated as half of industry purchased services. **Census Bureau&SAS**
R&D in social science and humanities	Estimated as twice the turnover of R&D in the **SIC732** "Social Sciences and Humanities"	R&D in social sciences and humanities estimated as twice industry purchases services. Source: **SAS**
Economic competencies		
Brand equity		
Advertising expenditure	Data from 3 different sources: two are derived from the **ABI**, the third from the **Advertising Association**.	Purchases of advertising services; advertising expenditures. Data comes from Bob Coen's **Insider's Report**.
Market research	Use turnover of firms in the 'market research' industry (SIC74.13) and double it to include own-account spending	Outlays on market research, estimated as twice industry purchased services. Source: **SAS**
Firm-specific human capital	Direct and indirect measures of on-the-job and off-the-job training costs are mainly based on data from the **NESS** (2005), and also use the **Learning and Training at Work Survey** (2000) and the **Community Vocational Training Survey**. Off-the-job training are estimated using data on the number of employees attending external courses, the direct cost of the courses and the opportunity cost of employee's time	Includes direct costs of training as well as cost of worker's time. Surveys of employer-provided training were conducted by the **Bureau of Labor Statistics** (BLS) in 1994 and 1995. Estimates for other years derived from the industry detail on per employee costs reported in **Bureau of Labor Statistics surveys** and trends in aggregate educational costs, industry employment, and industry employment costs.
Organisational structure		
Purchased	Estimate is based on data from the annual survey of firms in the UK consulting industry by the **UK Management Consulting Association**, cross-checked with **ABI** data	Estimated using **SAS** data on the revenues of the management consulting industry.
Own account	Based on data from the **Annual Survey of Hours and Earnings**. The estimate is derived from the wage bill of senior managers	Estimated as value of executive time using **BLS** data on employment and wages in executive occupations.

Source: London Economics adaptation of Haskel and Marrano (2006) and Corrado et al. (2005)

4.2.1 The INNODRIVE project and methodology

Given the increasing awareness of the importance of appropriately measuring and taking account of intangible capital, the European Union funded the INNODRIVE (“Intangible Capital and Innovation: Drivers of Growth and Location in the EU project”) which ended in February 2011. The methodology developed by the researchers involved in the project builds on the classification of intangible assets developed by Corrado et al. (2005). Crucially, the INNODRIVE provides two databases on intangibles, at national and firm level[35]:

- Macro level - the INNODRIVE National Intangibles Database provides time series of gross fixed capital formation for different intangible components. The series covers the EU-27 and Norway[36] and data are currently available for the years between 1995 and 2005.

- Micro level – the INNODRIVE Company Intangibles Database provides the share and wages of labour in occupations related to three main types of intangible capital, as well as aggregated firm-level data for intangible capital components (for Finland, Germany, the United Kingdom, Slovenia and the Czech Republic). The time coverage of the Company Intangibles Database varies from country to country (for the UK, it currently covers the period 1998-2006).

At the macro level, the following sources are used:

[35] For a thorough review of the INNODRIVE database and methodology see (Görzig *et al.*, 2011), Piekkola (2011) and the "INNODRIVE Intangibles Database, http://www.innodrive.org/"

[36] Capital stocks and modified National Accounts series (consistent with New Intangible GFCF) are available only for a subgroup of countries.

Table 4: INNODRIVE national intangibles database - sources

Item	Data sources
Computerised Information	
Computer software	EU KLEMS database
Computerised databases	Based on software estimates
Innovative property	
Scientific R&D	Business Expenditure on Research and Development (BERD) surveys
Mineral exploration	National accounts
Copyright and license costs	National accounts
Other product development (PD)	
New PD in the financial industry	National accounts
New architectural/eng. designs	National accounts
R&D in social science and humanities	Not used
Economic competencies	
Brand equity	
Advertising expenditure	Structural Business Statistics (SBS)
Market research	Structural Business Statistics (SBS)
Firm-specific human capital	OECD and Eurostat Continuing Vocational Training Survey
Organisational structure	
Purchased	Structural Business Statistics (SBS)
Own account	Structure of Earnings surveys and Labor Force Surveys

Source: Jona-Lasinio et al. (2009)

The micro subset focuses on linked employer-employee firm-level data (when possible) and attempts to measure firm-specific intangible capital, thus excluding the intangible components firms purchase externally. The three main categories of intangibles include:

- **Organisational capital** (OC), taking account of management, marketing and skilled administration personnel;
- **R&D**, including technicians, engineers and similarly technologically educated labour; and
- **Information and Communications Technology** (ICT) and expert labour related to this particular field.

The intangible capital stock series is constructed using the following steps and assumptions (see Görzig et al, (2011) and Robinson and Riley (2011b)):

1. A share of the labour costs for ICT, R&D and Organisational Capital is considered as investment in intangibles (with a service life of more than one year), while the rest is dedicated to current production of goods and services (service life with less than a year);

2. A *factor multiplier* is generated to take into account that capital services and materials complement labour in the production of intangible assets[37].

[37] Thus, the approach is in line with Lloyd-Ellis and Roberts' (2002) "complements of growth" idea discussed in Section 2.1.2

Consequently, the share of labour costs in 1) is scaled by the ratio of total production to labour costs (factor multipliers) in the IT, R&D and Business services sectors[38];

3. A *combined multiplier* is determined by the product of this factor multiplier and the investment share of each intangible, which is the scaling factor applied to firms' expenditures on intangible workers.

4. Investment is then capitalised using the *Perpetual Inventory Method*, applying different depreciation rates to ICT, R&D and Organisational Capital.

Table 5: INNODRIVE Assumptions

	ICT	R&D	Organisational capital
Share of labour cost dedicated to the production of intangible capital goods (service life more than a year)	0.50	0.70	0.20
Factor multiplier	1.48	1.55	1.76
Combined multiplier	0.70	1.10	0.35
Depreciation rates	0.33	0.20	0.25

Source: Görzig et al., (2011)

Table 5 shows the assumed values of the shares applied for calculating investment in the stock of intangible capital. The first row shows that the share of labour costs assumed to contribute to intangible capital varies across types of capital. Organisational capital is the least effective means of investment, because a large share of the labour cost goes to daily operations; however, as the second row demonstrates, the amount that is invested contributes greatly. Row 3 is the combined (multiplicative) effect of rows 1 and 2, and row 4 shows the assumed depreciation rates of the capital stocks.

In Table 6, a detailed list of the occupations whose labour costs are used in the construction of intangible measures is presented (see Görzig *et al*., (2011)). Table 5 above shows the share of labour costs assigned to investment in intangible capital for each type of intangible.

[38] SIC 72, 73 and 74 respectively.

Table 6: Detailed ISCO88 codes for INNODRIVE intangible occupations

Intangible	ISCO 88	Professionals	Higher tertiary quals.
ICT	1236	Computing services department managers	
ICT	213	Computing professionals	
ICT	312	Computer associate professionals	
R&D	1237	R&D managers	
R&D	211	Physicists, chemists and related professionals	
R&D	212	Mathematicians, statisticians and related professionals	
R&D	214	Architects, engineers and related professionals	
R&D	221	Life science professionals	
R&D	222	Health professionals (except nursing)	
R&D	223	Nursing and midwifery professionals	
R&D	311	Physical and engineering science technicians	
R&D	321	Life science technicians and related associate professionals	
OC	1221	Prod. operat. dep managers in agriculture, hunting and forestry	
OC	1222	Prod. operat. dep managers in manufacturing	
OC	1223	Prod. operat. dep managers in construction	
OC	1227	General managers in manufacturing	
OC	1229	Prod. operat. dep managers not elsewhere classified	
OC	1233	Sales and marketing department managers	
OC	1234	Advertising and public relations department managers	
OC	1231	Finance and administration department managers	Yes
OC	2441	Economists	Yes
OC	3411	Securities and finance dealers and brokers	Yes
OC	342	Business services agents and trade brokers	Yes
OC	241	Business professionals	Yes
OC	242	Legal professionals	Yes
OC	343	Administrative associate professionals	Yes
OC	3416	Buyers (production sector)	
OC	347	Artistic, entertainment and sports associates (production sector)	
OC	3416	Buyers (service sector)	Yes
OC	347	Artistic, entertainment and sports associates (service sector)	Yes

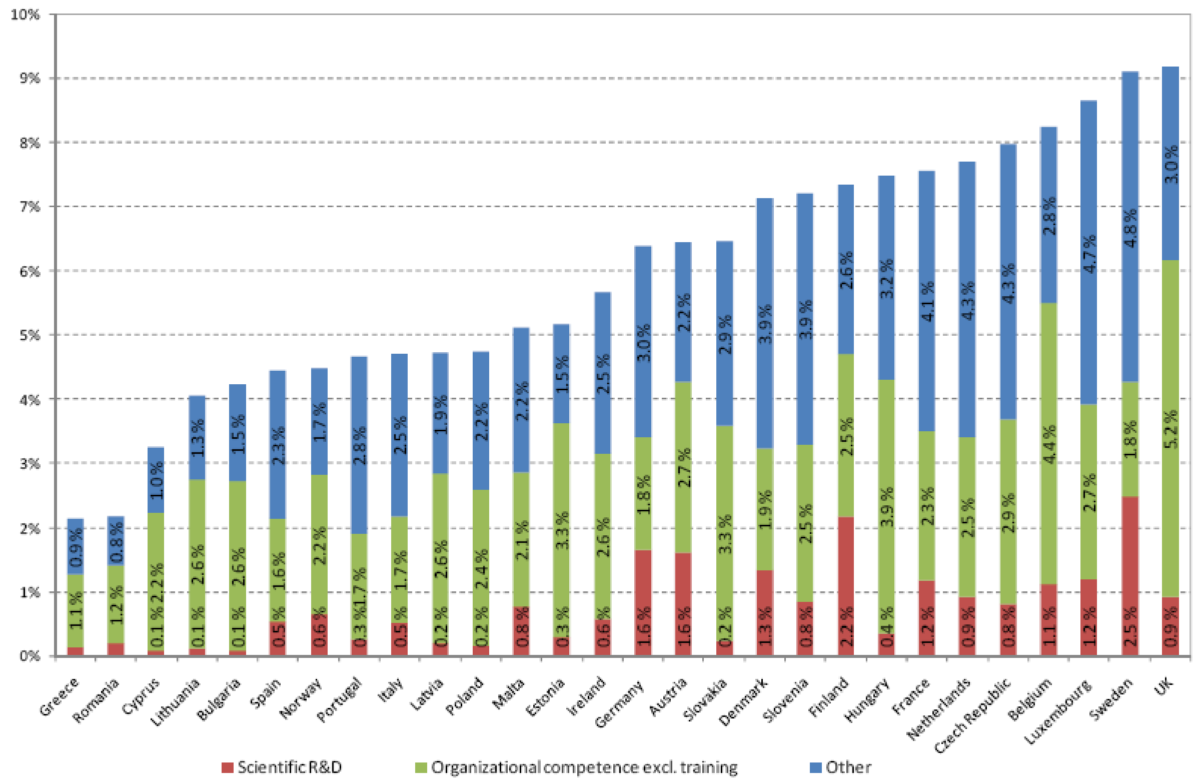
Source: Görzig et al., 2011

4.2.2 Evidence using the INNODRIVE macro database and data

A series of studies used the INNODRIVE methodology to analyse the impact of intangibles at a country level. All relevant literature at firm level is reviewed in section 5 and section 6 of this report. In Figure 4, we show a chart from Majcen et al. (2011) using the INNODRIVE macro database[39]. The value of intangible capital as a percentage of GDP varies from around 2% to more than 9% in the United Kingdom and Sweden. Also, the United Kingdom has the highest value (in terms of GDP) for organisational capital (which excludes training), with more than 5% of GDP. The value for scientific R&D is around 1% and the 'Other' category around 3%.

[39] Estimates at national level are constructed using a slightly different methodology (Jona-Lasinio *et al* (2011), Roth and Thum, 2010))

Figure 4: Intangibles as a percentage of GDP using the INNODRIVE macro database



Source: Majcen et al. (2011) based on INNODRIVE macro database and Jona-Lasinio (2011)

4.2.3 The NESTA Innovation Index

A significant (and very recent) contribution to the measurement of national expenditures on intangible assets, and their contribution to economic growth in the United Kingdom, is the Innovation Index developed and implemented by Haskel et al. (2009) and Haskel et al. (2011) for NESTA (National Endowment for Science, Technology and the Arts). The project quantifies:

1) Spending on intangible assets in the United Kingdom, both on aggregate and industry levels, and

2) How much the growth in intangible capital contributes to national economic growth, which builds upon growth accounting theory

The measurement of UK investment in intangible assets closely corresponds to the approach outlined by Corrado et al. (2006). In particular, intangible assets are again categorised into the above three main categories, and most of the sources employed in the estimates correspond to the databases used by Corrado et al (2006), with a majority of the data originating from the Office of National Statistics, the BERD, the UK National Accounts, the Annual Survey of Hours and Earnings and the Annual Business Inquiry (see Table 7).

The NESTA Innovation Index reflects the growth in economic output in excess of the contributions of tangible capital and labour, and its measurement approach entirely follows the growth accounting framework established by Corrado *et al*. (2006), outlined previously. The index attempts to capture what would happen to the growth in output if the growth in tangible capital and labour were zero, and can be derived by rewriting the augmented growth accounting identity

$$g_Q(t) = s_L(t)g_L(t) + s_K(t)g_K(t) + s_R(t)g_R(t) + g_A(t)$$

into an algebraic expression of the index:

$$Nesta\ Innovation\ Index = \ g_Q - [s_L(t)g_L(t) + s_K(t)g_K(t)] = s_R(t)g_R(t) + g_A(t)$$

Hence, the index illustrates the joint contribution of total factor productivity growth (**g_A**) and changes in the stock of knowledge capital, weighted by its share of total inputs (**$s_R(t)g_R(t)$**)

Table 7: NESTA Innovation Index: intangible investment data sources

Type of intangible investment	Current source	Period availability
Computerized Information		
Computer software	Office of National Statistics (ONS) using ASHE and the ABI	1970-2007
Computerised databases	ONS	1970-2007
Innovative property		
Scientific R&D	Business Enterprise R&D survey (BERD) and ONS	1980-2007
Mineral exploration	National Accounts	1948-2008
Copyright and license costs	National Accounts	1970-2008
Other product development		
New PD in the financial industry	Own-account: software methodology using Annual Survey of Hours and Earnings (ASHE) wage bills and interviews. Purchased: assumed zero	1970-2006
New architectural/engineering designs	Own-account: software methodology using ASHE wage bills and interviews. Purchased: input-output tables	1992-2006
R&D in social science and humanities	Turnover data from Annual Business Inquiry (ABI) and methodology employed by Marrano, G., Haskel, J. and Wallis, G. (2007)	.
Economic competencies		
Brand equity		
Advertising expenditure	Input-output tables	1992-2004
Market research	Input-output tables and ABI	1992-2004
Firm-specific human capital	National Employer Skills Survey 2005	1970-2004
Organisational structure		
Purchased	Survey by UK Management Consulting Association	1997-2005
Own account	ASHE	1997-2006

Source: London Economics adaptation of Haskel et al. (2011)

Based on the above data sources, Haskel *et al*. (2011) estimate intangible investment in the United Kingdom between 1990 and 2008, providing absolute values per category, as well as intangible investment for each type of intangible as a share of total investment in intangible capital. These estimates are displayed in Table 8.

Table 8: Intangible investment in the UK per category as a share of total intangible investment

	1990		1995		2000		2008	
	£	%	£bn.	%	£bn.	%	£bn.	%
Software development	£6bn	*11%*	£10bn	*14%*	£16bn	*17%*	£22bn	*16%*
R&D	£8bn	*14%*	£9bn	*13%*	£12bn	*13%*	£16bn	*12%*
Design	£13bn	*23%*	£13bn	*19%*	£15bn	*16%*	£23bn	*17%*
Mineral exploration/copyrights	£3bn	*5%*	£3bn	*4%*	£2bn	*2%*	£4bn	*3%*
Branding	£5bn	*9%*	£7bn	*10%*	£12bn	*13%*	£15bn	*11%*
Training	£12bn	*21%*	£15bn	*22%*	£21bn	*22%*	£27bn	*20%*
Organisational capital	£9bn	*16%*	£12bn	*17%*	£17bn	*18%*	£31bn	*22%*
All intangibles	**£56bn**		**£69bn**		**£95bn**		**£138bn**	
All tangibles	**£67bn**		**£62bn**		**£87bn**		**£104bn**	

Source: London Economics' adaptation of Haskel et al. (2011)

An additional study focusing explicitly on recent data for the United Kingdom was conducted by Haskel and Pesole (2011). Closely following the Corrado framework for their categorisation of intangible assets, they estimate intangible investment in the financial industry in the UK and compare this sector to the manufacturing industry. Their sources, and resulting estimates, are exhibited in Table 9.

Table 9: Share of intangible investment in the UK by industry and asset

Year	2000		2006		
Intangible asset	**M**	**FS**	**M**	**FS**	**Source**
Software	0.19	0.21	0.15	0.22	National Accounts
Total R&D	0.78	0.06	0.78	0.06	Business Enterprise R&D survey (BERD)
Design	0.32	0.08	0.26	0.07	*Purchased*: input-output tables; *Own-account*: architect and designer occupations
Brand equity	0.21	0.20	0.17	0.17	Input-output tables
Firm-specific human capital	0.21	0.07	0.13	0.05	National Employer Skills Survey (NESS) and one-off survey 1998
Organisational capital	0.25	0.19	0.25	0.19	*Purchased*: Management Consultancy Association; *Own account*: ONS Pilot Intangible Investment Survey and Warwick / Aston Survey

Notes:
1. Each cell provides investment in the particular asset in the particular industry as a share of total investment of the same asset in the total market sector; e.g. in 2000, the manufacturing industry accounted for 19% of investment in software.
2. Total R&D is defined as the sum of scientific R&D, new product development in the financial industry, and R&D in science and humanities.
3. M = Manufacturing; FS = Financial sector

Source: London Economics adaptation of Haskel and Pesole (2011)

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5 Direct impact of investment in intangible assets on productivity

5.1 Economic Competencies

In this section of the review, we explore some of the empirical evidence demonstrating the direct effect of investment in intangible assets on productivity. It is important to note that the analysis is not simply assessing the determinants of economic growth or productivity, as this contains a very sizeable volume of material and has been reviewed extensively elsewhere in the academic literature (see Table 28 in Annex 1 for some earlier contributions), but rather a more precise review of the specific investment in intangible assets on productivity, and follows on from the evidence collected on measurement and metrics in Section 4.1.

We consider the role of investments in intangible assets on productivity growth along three broad categories, namely economic competencies, scientific and creative property, and computerised information and information technology. However, we do not provide a review of the evidence relating to the earnings and employment outcomes associated with education, training, qualifications and skills attainment accruing to the individual (general human capital literature relating to the economic benefits captured by those in receipt of training and skills).

The review at this stage reflects the most relevant empirical work undertaken in the area, and is predominantly international in perspective (and covers a range of levels, including national, regional, employer and employee); however, we focus on evidence for the United Kingdom in the first instance across all categories. We describe and synthesise the information below.

5.1.1 Summary of findings

In terms of the **direct** impact of investments in intangible assets on productivity, the analyses reviewed consistently demonstrate the positive impact of the various elements of intangible assets on productivity, but particularly stress the role of **economic competencies** (incorporating human capital and skills) in explaining productivity growth and levels. Some summary information is presented in Table 10 of the main report. The literature assessing the impact of investments in intangible assets on firm-level productivity in the United Kingdom consist of two primary strands of literature:

Studies from the first of these strands involve growth accounting exercises, and show that economic competencies account for approximately **0.1-0.2** percentage points of **labour productivity growth** at firm-level (e.g. Riley and Robinson (2011b), Riley and Robinson (2011c))). This corresponds to between **3.2%** and **6.4%** of total labour productivity growth.

Economic competencies make a comparatively greater contribution to productivity growth than other forms of intangible capital. According to Jona-Lasinio et al. (2011), economic competencies account for **0.30%** of productivity growth, compared to **0.15%** for ICT and

0.11% for R&D (corresponding to **9.7%**, **4.8%** and **3.5%** of total labour productivity growth respectively).

In the second stream of literature, which considers the impact of human capital on firm or industry **productivity levels**, the analyses generally indicate that an increase in the level or structure of human capital within industries increases industry-level productivity (by **0.1-0.3%** following a 1 percentage point increase in human capital (e.g. Gailndo-Rueda and Haskel (2005), Mason et al. (2007)), or by as much as 0.6% for labour productivity following a 1 percentage point increase in the volume of training (Dearden et al. (2005)). These results are summarised in Table 10.

Table 10: Estimates of direct effects – economic competencies

Author	Year	Country	Level	Source of intangible asset	Outcome measure	Impact
Dearden *et al.*	2005	UK	Industry level	1 pp ↑ training (see note 1)	Labour productivity	↑0.6% labour productivity; ↑0.3% wages
Disney *et al*	2003	UK	Industry level	Within-establishment change (structure, technology)	Industry productivity growth	Accounts for 5%-18% of productivity growth
Galindo-Rueda and Haskel	2005	UK	Firm level	1 pp ↑ share of Level 4 qualified employees	Firm-level productivity	0.303% ↑ in manufacturing 0.218% ↑ in services
Mason *et al.*	2007	International	Industry	1 pp ↑ share of human capital	Industry productivity	0.07% to 0.216% ↑ industry productivity
Haskel, Hawkes and Pereira	2005	UK	Firm	Difference in skill levels between 1st and 9th decile	Firm-level productivity	3-10% of productivity differences explained
Haltiwanger *et al*	1999	US	Firm	Human capital	Firm-level productivity	Positive effect
Rauch	1993	US	National	1 year ↑ education and work experience	Total factor productivity	2.8% ↑ total factor productivity
Barrett and O'Connell	1999	Ireland	Firm	Human capital (academic/vocational)	Firm-level productivity growth	Positive effect/ No effect
Barnes and McClure	2009	Australia	National	Human capital	Multi factor productivity	Accounts for 5-8% of MFP growth
Carriou and Jeger	1997	France	Firm	1 pp ↑ training expenditure	Value added	↑ 2% value added
Jona-Lasinio *et al.*	2011	International	UK	IIA (Economic competencies (skills)) IIA (Innovative Property) IIA (ICT/Software)	Labour productivity growth	Accounts for 0.30% (0.06%) Accounts for 0.15% Accounts for 0.11%
Riley and Robinson	2011b	UK	Firm	IIA (Organisational capital) IIA (Innovative Property) IIA (ICT/Software)	Labour productivity growth	Accounts for 0.10% to 0.20% Accounts for 0.10% Accounts for 0.10%
Riley and Robinson	2011c	UK	Firm	IIA (Organisational capital) IIA (R&D capital) IIA (ICT/Software)	Labour productivity growth	Accounts for 0.12% to 0.17% Accounts for 0.13% to 0.17% Accounts for 0.08% to 0.13%

Source: London Economics (2011)
Notes:
(1) pp – percentage point

5.1.2 Productivity versus productivity growth

It is exceptionally difficult to make a simple comparison of the effect of investment in intangible assets across all the papers presented, not just because of the different sources of potential spillover, but also because of the different outcome measures under consideration. In particular, a number of studies focus on the impact of changes in intangible assets on productivity, while other attempt to identify the role of investment in intangible assets on the productivity growth rates. Taking an example illustrates this point more fully. **Labour productivity** is normally defined using some measure of output or value added per worker. If we assume this to be £30,000, then the identification of a 0.5% increase in labour productivity from investment in intangible assets, labour productivity might be expected to be £30,150 (0.5% of £30,000), corresponding to a change of £150. Suppose that **labour productivity growth** is 3.0% per annum (between 1950 and 2010, labour productivity growth in the United Kingdom has averaged 3.1%), using the above example would imply that labour productivity would be expected to increase from £30,000 to £30,900 over the course of a year. If another analysis determined that 10% of *labour productivity growth* is accounted for by investment in intangible assets using a growth accounting framework, this would imply that approximately £90 of the change in labour productivity is as a result of the investment in intangible assets. Clearly, some care needs to be taken when considering the impact of the investment in intangible assets on whichever outcome measure is being addressed as part of the analysis.

5.1.3 Research specific to the United Kingdom

In one of the first empirical analyses considering the impact of training on productivity in the United Kingdom[40],[41], Dearden et al (2005)[42] examine the effects of work-related training on direct measures of productivity using industry-level data. The traditional approach to considering the impact of education and training on productivity is to consider the effect of skills acquisition on wages (which are assumed to be an exact reflection of productivity and are based on the most straightforward neoclassical view of the labour market, where the market is perfectly competitive and wages will equal the value of marginal product[43]). However, there are reasons why the relationship between training and wages may not be perfectly aligned (such as imperfect competition in the labour market or the acquisition of firm-specific skills as opposed to general transferable skills (see Stevens

[40] In earlier work predating this empirical analysis (Blundell *et al*, 1999), the authors refer to evidence on the links between the skill composition of the work force of a firm and labour productivity. A sample of UK manufacturing firms were matched with continental firms producing similar products, allowing for a comparison between productivity to be undertaken across manufacturing plants (see Daly, Hitchens and Wagner, (1985) Mason and van Ark (1994); Steedman and Wagner (1987); Steedman and Wagner (1989); Mason, van Ark and Wagner (1994); Prais, Jarvis and Wagner (1989). These studies found that the higher average levels of labour productivity in non-UK manufacturing plants were closely related to the higher skills and knowledge base of the non-UK organisations' work-forces. In the UK, the lower level of skills was found to negatively affect labour productivity (and the introduction of new technology).

[41] Blundell, R., Dearden, L., Meghir, C., and Sianesi, B., (1999), "Human Capital Investment: The Returns from Education and Training to the Individual, the Firm and the Economy", Institute for Fiscal Studies

[42] Dearden, L, Reed, H, and Van Reenen, J (2005), "Estimated Effect of Training on Earnings and Productivity, 1983-99", CEP Discussion Papers 674, Centre for Economic Performance, LSE, February 2005

[43] See Chevalier *et al.* (2004) for a test of the opposite hypothesis

(1994)). For these reasons, observed wages may not provide an exact measure of productivity at firm level (but are more likely to provide an underestimate).

Using a longitudinal panel of British industries between 1983 and 1996, and combining this information with individual-level UK Labour Force Survey and the Annual Census of Production for industries in the manufacturing, mining and utilities sectors, Dearden et al.(2005) find that (tangible) capital per worker is strongly correlated with productivity. In addition, they find that worker turnover has a significantly negative association with productivity; investment in R&D has a significantly positive correlation; and younger workers (aged between 16 and 24) are significantly less productive compared to older age groups (35 to 44-year-olds). The most pertinent results indicate that training has a statistically and economically significant effect on industry-level productivity. Although the magnitude of the coefficient falls as more rigorous model specifications are implemented (i.e. controlling for fixed effects), the change is not dramatic. In particular, a one percentage point increase in training is associated with an increase in value added per hour of about 0.6% and an increase in hourly wages of about 0.3%[44],[45],[46].

In another paper focusing on the United Kingdom using firm-level information, Disney et al. (2003) analyse productivity growth in the UK manufacturing industry from 1980 to 1992. As with Dearden et al. (2005), they utilise the Annual Census of Production Respondents Database, which allows the authors to group manufacturing establishments as 'survivors', 'new entrants' or 'exitors' on the basis of the number of times an establishment is observed over the period of analysis. They identify two channels that contribute to productivity growth, namely changes occurring *within* the establishment (such as the adoption of new technology and organisational improvements, but wider than straightforward human capital accumulation); and *external* restructuring relating to market shares and firms entering or exiting the market. The effect on productivity growth from changes *within* the establishment is estimated using two different econometric methods. The alternative

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[44] Blundell *et al.* (1999) also refer to a number of international empirical studies quantifying the direct contribution of training to firm productivity and indicate that training has a positive impact on productivity; however, there is a huge degree of variation between the results, which are also somewhat dated. The authors refer to studies demonstrating large impacts of training on productivity (Bartel, 1991 and 1995, Barron, Black and Loewenstein, 1989); to relatively small effects (de Koning, 1993) or no effect (Black and Lynch, 1996 and 1997). However, the majority of these studies suffer from relatively small samples (with the exception of Black and Lynch (1996). There is also some mention of the impact on productivity of training undertaken with a *previous* employer. Specifically Bishop (1994) shows that previous on-the-job training increases a worker's initial productivity by almost 10% but has no lasting effect, while *previous* off-the-job training has more long-lasting benefits and increases current productivity by 16%.

[45] To investigate the externality issue, the authors also estimated some individual level wage using the Labour Force Survey and suggest that 'taken literally' about half of the impact of training on wages at the industry level is attributable to externalities.

[46] With a similar approach to Dearden et al. (2005), but using firm level-data Colombo and Stanca (2008) use a panel of Italian firms and find that a one percentage point increase in training intensity boosts firms' productivity by about 0.074 per cent. Moreover, the effect is even bigger when they control for training duration. Training has also a positive effect on wages, but this is found to be significantly smaller than the effect on productivity (around 0.045). The impact of training by occupational groups is varied, with high returns found for blue-collar workers and negligible returns for executives and clerks. In a more recent paper, Konings and Vanormelingen (2010) use longitudinal data on Belgian firms and find that the productivity effect of training is on average 23%, while the wage effect is around 12% (i.e. a one percentage point increase in training raises productivity by approximately 0.23% and wages by 0.12%).

econometric approaches demonstrate that changes within establishments account for between 5% and 18% of productivity growth. Both modelling methods find that *external* effects account for approximately half of the productivity growth (49% and 53%)[47].

In more recent work, Galindo-Rueda and Haskel (2005) construct a firm-level data set with matched productivity and qualification data by linking the Annual Business Inquiry and National Employer Skills Survey for England. The authors examine the effect of workplace skills and other characteristics (such as part-time status and gender) on both productivity and wages in firms. The authors also investigate how productivity-implied returns to worker characteristics compare with wage-implied returns, therefore providing information on how rents are distributed between employers and employees.

The results of the analysis indicate that firms with a higher share of college-educated, full-time and male workers also tend to be more productive[48], although there are considerable variations across sectors (manufacturing versus service firms). Specifically, in terms of firm-level productivity, the aggregate analysis suggests that there is a positive and declining impact of qualification levels on gross value added (down to level 1 qualifications), although only the coefficients relating to level 4 skills (and higher) are statistically significant. In contrast, the ‘wage equations’ appear to suggest that the return to training is concentrated amongst workers in the form of higher wages. However, the authors note that the result hides differences between manufacturing and services sectors. The detailed results (presented in Table 11) indicate that the productivity gains to employers in manufacturing sector firms from higher level skills are greater than in for service sector firms, while the productivity gains from lower level skills are lower in manufacturing sector firms than those achieved by employers in service sector firms (although in both sectors, lower level skills do not seem to be associated with significantly higher levels of firm-level productivity in absolute terms). The only robust difference in implied returns relates to part-timers, who tend to work for firms that pay wages that are too low for the observed productivity differences (see also Haltiwanger *et al*. (1999)).

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[47] In addition, initial descriptive statistics of the external effects show that ‘entering’ establishments average total factor productivity of 103.9% of that of ‘surviving’ establishments (i.e. firms that were observed the previous year). Furthermore, the total factor productivity of ‘exiting’ establishments is only 94.5% of that of establishments that are observed the following year. This indicates a degree of self-selection into and out of the market, and means that productivity for the industry as a whole increases as a result of market entry and exit. This explains why external factors partly determine productivity growth (but also that care should be taken when longitudinal analyses do not incorporate the possibility that firms enter and leave the marketplace)

[48] Galindo-Rueda, Fernando and Haskel, Jonathan (2005), “Skills, Workforce Characteristics and Firm-level Productivity: Evidence from the Matched ABI/Employer Skills Survey” *SSRN eLibrary*.

Table 11:	**Estimates of impact of training on firm-level productivity**					
	All firms		**Manufacturing**		**Services**	
	Productivity	Wage	Productivity	Wage	Productivity	Wage
Share Level 4+	0.155 (0.091)	0.423 (0.049)	0.497 (0.208)	0.343 (0,053)	0.127 (0.094)	0.478 (0.065)
Share Level 3	0.020 (0.044)	0.120 (0.033)	0.139 (0.130)	0.188 (0.051)	0.025 (0.046)	0.109 (0.042)
Share Level 2	0.014 (0.033)	0.051 (0.025)	-0.021 (0.081)	0.060 (0.035)	0.037 (0.035)	0.055 (0.032)
Share Level 1	0.037 (0.046)	0.044 (0.038)	-0.153 (0.107)	0.032 (0.048)	0.110 (0.058)	0.057 (0.051)

Source: Galindo-Rueda and Haskel (2005)

Note: Joint maximum likelihood estimation of production function (log gross output) with labour quality term and wage equation (log wage bill per employee), with standard errors (in parentheses) adjusted for clustering at the reporting unit level. Observations are ESS establishments matched to ABI reporting units (single and multi-plant reporting units). Coefficients on qualification shares in productivity column denote relative productivity (implied wage returns) with respect to baseline of male full-time workforce with no qualifications

The results presented here relate to the model specification presented in Table 10 of the Galindo-Rueda and Haskel (2005) article where both firm level and regional skills levels are incorporated in model specifications (column 3) and thus do not correspond directly with the results presented in Table 10.

Undertaking a complex cross-country analysis, Mason (2007)[49] demonstrates that human capital levels are *strongly* related to average labour productivity levels across a wide range of industrial sectors (and that human capital is negatively related to inefficiency and thus contributes indirectly as well as directly to labour productivity performance, by helping to improve the way that all resources are utilised). There are a range of elasticity estimates produced (which reflect the responsiveness of productivity to changes in skill levels). The estimated human capital coefficient ranges in size between 0.071 and 0.216 (implying that a 1 percentage point increase in human capital results in an increase of productivity of between **0.07%** and **0.216%**); however, the results vary significantly across country. For instance, some model specifications suggest that the impact of human capital on productivity in the UK is not much more than half the US effect[50]. In addition, the author

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[49] Mason, G. et al (2007), *Cross-country Analysis of Productivity and Skills at Sector Level*, NIESR, Sector Skills Development Agency report. Using a pooled ordinary least squares approach they find that the different countries react to human capital increases in different ways; the US enjoys a 0.17% increase in output if the share of graduates increases by 1%, whereas output only increases by 0.09% in the UK. Using a battery of econometric methods, they find positive and significant effects of human capital on productivity for most methods.

[50] For a wider assessment of the impact of investment in intangible assets on productivity, Corrado, Hulten and Sichel (2005) developed expenditure based measures of a larger range of intangibles for the United States. They calculated that previously unmeasured intangible capital contributed 0.24 of a percentage point (18%) to conventionally-measured multifactor productivity (MFP) growth in the United States between the mid-1990s and early 2000s. This methodology has been applied in a number of other country studies — with

finds that there is little evidence of the *growth* in human capital having a short-term impact on productivity growth.

In more recent evidence in the field using firm-level information, Riley and Robinson (2011b) use details of UK firms' employees, their occupations, earnings and hours worked sourced from the Annual Survey of Hours and Earnings (ASHE). These employee data are linked via the ONS Inter-Departmental Business Register (IDBR) to firms in the Annual Business Inquiry (ABI), which holds information on firms' labour costs, output, capital investment, intermediate expenditures, and employment[51]. Using the growth accounting methodology, and by aggregating firm-level data to national estimates, the authors demonstrate that investment in intangibles (across all three categories of intangible assets) contributes **0.4%** to average annual labour productivity growth (significantly higher than the impact of tangible investment). The intangible asset that has the biggest contribution to labour productivity is organisational capital (between **0.1%** and **0.2%**). The authors also find that there is a tendency for firms to bundle intangible assets (particularly ICT and organisational capital (see also Bloom (2010)).

The most recent evidence regarding the direct impact of investment in intangible assets on productivity in the United Kingdom has been developed by Riley and Robinson (2011c). Following the methodology developed in INNODRIVE described in section 4.2, they slightly extend the firm-level measurements of intangible investment used in the paper previously referred to (Riley and Robinson (2011b)), and combine individual occupation and wage data from the Annual Survey of Hours and Earnings and the Labour Force Survey with data from the Business Structure Database and the Annual Business Inquiry. Employing growth accounting to estimate the contribution of intangibles to labour productivity growth in the period of observation (1998-2006), their findings indicate that investment in intangibles, across all three categories, accounted for **0.46%** and **0.33%** of the growth in labour productivity in the total market economy[52] for the periods 1998-2001 and 2003-2006, respectively. Focusing on each specific type of intangible asset, ICT capital exhibited the lowest contribution to the growth in labour productivity in each of the two sub-periods. Between 1998 and 2001, organisational capital and investments in R&D contributed an equal share of **0.17%** to productivity growth, while between 2003 and 2006,

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estimates of the contribution of previously unmeasured intangible capital to MFP growth of 14% (United Kingdom (Marrano, Haskel and Wallis (2007)), 3% in Finland (Jalava, Aulin-Ahmavaara and Alanen (2007)) and 0% in the Netherlands (van Rooijen-Horsten *et al.* 2008)), over a similar period. Other country studies estimated only the contribution of all intangibles to MFP growth: -19% in Japan (Fukao *et al.* (2008)), 19% in France, 18% in Germany, 9% in Spain and 0% in Italy (Hao, Manole and van Ark (2008)). Additional details of these studies can be found in Jona-Lasinio *et al.* (2011). Note also that these last authors demonstrate in primary research that intangible capital is a relevant source of growth in the advanced EU member states (and, looking at the contribution of each intangible asset as a source of growth, R&D appears most significant for Sweden and Finland, while for UK, organisational capital is the main driver of growth). Intangible capital appears only to play a minor function in slow-growing countries. These studies are discussed in Section 4.

[51] However, because the ASHE is a 1% sample of employees in UK businesses, the authors were only able to construct adequate occupational measures for the small sample of (very large) UK businesses that have sufficient employees included in the ASHE.

[52] In their calculations, agriculture, financial services, education and health are excluded from the total market economy.

investment in R&D accounted for the largest contribution (**0.13%**) to productivity increases across the three categories.

5.1.4 Alternative approaches

Haskel, Hawkes and Pereira (2005) use plant-level data from the United Kingdom to investigate whether more productive plants employ more skilled workers, and also, which share of the variation in productivity can be attributed to differences in skills. The data underlying the analysis come from three sources: first, business level data is derived from accounting or official Census data; secondly, formal workforce skills are generated using the National Employer Skills Survey; and thirdly, the measure of informal skills (such as time-keeping, motivation, and so on are derived from worker-level information on wages, occupation, age, etc.) are gathered from the New Earnings Survey. The authors find that, in 2000, plants in the top decile of total factor productivity hired new employees with an average of 4 months more schooling than plants in the bottom decile. However, there are some methodological issues associated with this paper, as the sample size contains only 292 plants in total, which implies that the results relating to each decile contain only 30 plants, and further indicates that the estimate is not overly robust. They also find that hard skills, as measured by qualifications, as well as soft skills are significantly associated with plant-level productivity. About **3-10%** of the *productivity gap* between plants in the top decile and plants in the bottom decile is explained by differences in skills.

Turning to an analysis based on individual level data for the United Kingdom, Chevalier *et al*. (2004) test the education signalling hypothesis to assess the extent to which skills contribute to productivity. In standard education economics, the idea that education reflects innate productivity (or ability) rather than increasing skills is known as signalling (Spence, 1974). The degree of education signalling in the labour market suggests that there is a deadweight loss associated with qualification acquisition, and that the societal benefits associated with qualification attainment are less than the estimated economic benefits (as represented by an assessment of the net present value associated with qualification attainment (resulting from enhanced earnings or a likelihood of being employed)). Chevalier *et al*. (2004) utilise a change in compulsory schooling laws in the United Kingdom to test whether the signalling hypothesis has any support (and, if refuted, implies that educational attainment does contribute to productivity). The idea is that if education attainment is a signal of innate productivity, then a reform of compulsory schooling laws (such as an increase in minimum school leaving age from 15 to 16) should cause already more productive individuals, who would otherwise have left school at 16 to acquire additional schooling in order to differentiate themselves from those less productive individuals now forced to stay in school until 16 as a consequence of the policy reform. If signalling is the only reason to undertake additional schooling, then the same effect carries through the entire educational system, meaning there should be an increase in educational attainment at all subsequent levels. The result of the analysis by Chevalier *et al*. (2004), however, finds that the support for the signalling hypothesis on UK data is negligible, which, in turn, means that education raises human capital and thus improves the productivity at an individual level. This supports the finding of the analyses presented earlier in the section.

5.1.5 International country-specific evidence

In terms of international evidence of the direct effect of the investment in intangible assets on productivity, Haltiwanger *et al* (1999) use employer-employee data from the United

States (State of Maryland) to investigate how firm characteristics (including the number of employees, average age, and human capital) affect a firm's productivity. In this paper, productivity is defined as firm sales divided by number of employees. The firm-level characteristics included in this analysis include variables denoting the share of employees in three different age groups, the share of employees in three different education bandings, the share of female workers, and the share of workers who were born in a foreign country. The authors restrict the sample to those firms with more than 10 employees, and only firms that were active for the entire period of 1985-97 (note that this selection of firm-level data may *underestimate* productivity growth given the fact that more productive firms are likely to be 'born' and coincide with the demise of less productive firms (see Disney et al. (2003)). The results indicate that higher labour productivity occurs in firms if their workforce is younger, they have a higher proportion of non foreign-born workers, and have higher proportions of male workers. In addition, and most pertinent to this review, a more highly educated workforce is associated with higher levels of productivity at the firm level. However, it is important to note that there are some limitations to this study, specifically the fact that the actual number of hours worked is unavailable. As such, some of the differences in the levels of labour productivity may be driven by a disproportionately high level of part-time employment that may be more prevalent among some industries traditionally associated with lower levels of productivity.

In another US study, Rauch (1993) estimates the effect on total factor productivity arising from one extra year of average schooling in American metropolitan areas (see also Moretti (2004a)). The model includes measures of average schooling and average work experience. The total effect from an extra year of education is estimated to be a 2.8% increase in total factor productivity.

A study by Barrett and O'Connell (1999) examined the effect of training on productivity growth using a nationally representative sample of 1,000 Irish enterprises that were randomly selected (and for which there were 654 useable observations). In general terms, it was found that training had a positive effect on the productivity growth over the period of the analysis. The authors also distinguished empirically between general and specific training and showed that while general training had a positive influence on enterprise productivity growth, firm-specific training did not.

Using data from the Nordic countries[53], Herbertsson (2003) attributes the importance of capital, labour, and total factor productivity to output growth over the period 1970-92. His introduction of human capital to the regression results in a drop of the estimate for the share of output growth arising from total factor productivity growth by 19 percentage points to 74% across the countries. This implies that improved human capital forms a large part of the explanation of the output growth experienced in the Nordic countries in the 1970s and 80s.

Alternative measure of organisational competencies

In a number of papers more focused on the organisational structure of firms (as opposed to the more narrow focus on workforce training and skills), Black and Lynch (2001) investigate the effect of workplace practices and information technology on productivity using business survey data. They find that firms in which employees have more say in the

[53] Denmark, Finland, Iceland, Norway and Sweden.

decision-making process or in which there is a profit-sharing system covering non-managerial employees, enjoy higher productivity. Similarly, Black and Lynch (2000), use a nationally representative sample of US establishments surveyed in 1993 and 1996 to examine the relationship between workplace innovation and establishment productivity and wages. Matching plant level practices with plant level productivity and wage outcomes, and estimating production functions and wage equations using both cross-sectional and longitudinal data, the authors find that there is a positive and significant relationship between the proportion of non-managers using computers and the productivity of establishments; and firms that re-engineer their workplaces to incorporate more high-performance practices experience higher productivity. In addition, profit sharing and/or stock options are also associated with increased productivity. Re-iterating the previous paper, Black and Lynch (2000) also find that "employee voice" has a larger positive effect on productivity when undertaken in the context of unionised establishments.

5.1.6 Cross- country comparisons

In the only research found demonstrating the different contributions of investment in intangible assets to productivity, Jona-Lasinio et al. (2011) decompose investment in intangible assets into three components (and sub-components): software, innovative property and economic competencies. Economic competencies is further disaggregated into the impact of 'advertising and marketing research', 'organisational capacity' and 'skills', using a combination of data sets including National Accounts data, Labour Force Surveys, Structure of Earnings surveys, Structural Business Statistics and a range of Eurostat data (and some other sources to fill in data gaps).

Table 12 summarises the contribution of tangible and intangible assets to labour productivity growth in the business sector of the sample countries. Intangible capital deepening (ICD) contributes more to labour productivity than tangible capital deepening (TCD) in France (**0.43%** to **0.25%**), Denmark (**0.38%** to **0.37%**), and Finland (**0.40%** to **0.19%**). In the United Kingdom, the contribution of intangible assets to labour productivity growth is **0.57%** (corresponding to slightly more than one fifth of total labour productivity growth in the period considered) compared to a **0.74%** contribution from investment in tangible assets. However, it is more interesting to understand the relative contribution of software, innovative property and economic competencies to the aggregate impact of IIA on labour productivity growth, and to understand how this varies across countries.

Specifically, of the **0.57%** contribution of all investment in intangible assets to labour productivity growth in the United Kingdom, *more than half of this is accounted for by economic competencies* (**0.30%**), compared with **0.15%** associated with software/ICT and the remaining **0.11%** attributable to innovative property. Further disaggregating the economic competencies, investment in skills in the UK accounts for **0.06%** of labour productivity growth.

Although these estimates may not appear very significant, the contribution of economic competencies generally (and skills specifically) in the UK appear to be the largest across any of the countries included in this analysis. Specifically, in Germany, the aggregate investment in intangible assets contributes approximately **0.38%** to labour productivity growth (**0.43%** in France), with the economic competencies component being responsible for **0.14%** (**0.16%** in France) and the 'skills' component specifically contributing **0.04%** in both Germany and France. In some countries, the contribution of economic competencies to labour productivity growth is close to zero or negative (Italy and Spain), with the contribution of skills being even more negative. The results of the findings of this analysis appear to be qualitatively equivalent to the cross-country analysis presented by Mason (2007).

In one other cross-country comparison (and feeding into the section of this report relating to spillover channels), the paper by Krueger and Kumar (2004) distinguishes between spending on vocational education and general education (university education), and investigates whether differences in spending between the United States and Europe explain why US growth has exceeded European growth. They find that general education makes the take-up of advanced technological innovations (such as information and communication technologies) more likely, and therefore that the United States, which has comparatively higher spending on general education, has had a productivity growth advantage over Europe (see also Barrett and O' Connell (1999)).

Table 12: Intangible assets as new sources of labour productivity growth

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	LPG	TCD	ICD	SW	IP	R&D	ARCH	NFP	Other	Econ Comp	ADV	Org Cap	FSHC	TFPG
Austria	2.05	0.62	0.47	0.10	0.22	0.13	0.05	0.03	0.00	0.15	0.06	0.07	0.02	0.95
Denmark	1.61	0.37	0.38	0.17	0.17	0.11	0.05	0.01	0.00	0.04	0.03	0.03	-0.01	0.84
Finland	3.07	0.18	0.40	0.09	0.27	0.23	0.06	-0.01	0.00	0.04	0.03	0.08	-0.08	2.48
France	2.07	0.25	0.43	0.14	0.13	0.03	0.07	0.02	0.01	0.16	0.02	0.10	0.04	1.38
Germany	1.69	0.60	0.38	0.05	0.18	0.08	0.05	0.05	0.01	0.14	0.03	0.08	0.04	0.71
Italy	0.26	0.46	0.13	0.03	0.06	-0.01	0.03	0.03	0.01	0.04	0.03	0.04	-0.03	-0.34
Netherlands	2.25	0.50	0.47	0.12	0.15	0.03	0.06	0.06	0.00	0.19	0.05	0.15	-0.01	1.27
Portugal	1.94	1.61	0.37	0.09	0.12	0.03	0.02	0.05	0.01	0.16	0.07	0.10	0.00	-0.05
Spain	0.24	0.43	0.10	0.06	0.04	0.02	0.02	-0.01	0.00	-0.01	0.00	0.01	-0.02	-0.29
Sweden	3.69	0.78	0.66	0.18	0.28	0.19	0.08	0.00	0.01	0.20	0.03	0.13	0.03	2.21
United Kingdom	2.71	0.74	0.57	0.15	0.11	0.01	0.08	0.04	-0.01	0.30	0.06	0.19	0.06	1.38

Source: Jona-Lasinio et al. (2011)

Notes: LPG Labour Productivity Growth; TCD is tangible capital, ICD is intangible capital, SW is software, IP is innovative property, R&D is Research and development, ARCH stands for architectural and engineering design, NFP is new financial products; ADV is advertising, FSHC is training, Org Cap is Organisational Capital

5.1.7 Variation in the impact of investment in intangible assets on productivity

As with the research undertaken by Mason (2007), some of the evidence of the impact of investment in intangible assets is not fully conclusive, or requires additional inspection of the sectors and periods for which the analysis is undertaken. According to Barnes and Kennard (2002), Australia experienced a productivity surge in the mid- to late-1990s. The aim of their paper is to identify the share of this productivity increase that could be directly attributed to a *more highly skilled workforce*. The skill level of the workforce is represented by an index based on groups along three parameters; educational attainment, work experience[54] and gender. The index was created by aggregating the groups using the relative wages of the different groups as weights. The authors suggest that of total annual productivity growth rates of 0.2%, 0.9%, 1.3%, and 2.1% (over four different periods), improvements in skills levels directly account for **0.2%**, **0.7%**, **-0.3%**, and **0.3%**, respectively. Therefore, although skill improvements have had an effect, Australia's productivity surge cannot be attributed entirely to changes in the skill composition of the workforce.

To reinforce this analysis, additional work undertaken by the Australian Productivity Commission (Barnes and McClure (2009)) demonstrates that adjusting for intangible investment not currently included in the national accounts does *not* have a large direct effect on the level or pattern of conventionally-measured (multi-factor) productivity growth. In particular, the contribution of these intangibles was **8%** of conventionally-measured (multi-factor) productivity growth (0.09 of a percentage point) over the last productivity cycle (1998-99 to 2003-04), and **5%** (0.13 of a percentage point) in the period of the productivity surge (1993-94 to 1998-99). This contrasts with the United States, where intangibles accounted for a large share of the productivity acceleration from the mid-1990s. Note that the results presented here for Australia are similar in magnitude to those undertaken for Canada by Belhocine (2008).

In some research relating to French manufacturing firms, Carriou and Jeger (1997) use repeated cross-sectional data for 10,000 companies with more than 50 employees during the period 1986 to 1992. Given the existence of a training levy in France, the authors were able to make use of information relating to the actual number of hours of training received[55]. They impute a cost to these, based on the figures used by the French training authorities, and estimate the effect of training volumes on value-added. Controlling for a number of workers at different qualification levels, capital stock and industrial sector, they find that a 1% increase in expenditure on training yields a 2% increase in value added. In addition, using four years of panel data for the larger companies (100+ employees), they establish that the returns to training are independent of prior levels of training expenditure. In other words, there is no evidence of training 'saturation' (i.e. the effects of additional training continue year on year). However, Delame and Kramarz (1997) assert that there is no simple relationship between training provision and value added, and in particular, the impact of training depends in many respects on the training ethos within the firm. In

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[54] Due to data limitations, the work experience parameter is really a potential work experience measure, which is a function of age, years of schooling and, for women, number of children.

[55] Data are combined from firms' returns to the Treasury, which include training-levy related material plus an annual company survey by INSEE

particular, training seems to raise value added only among the ‘committed’, high-expenditure firms, and does so largely via an interaction with the numbers of highly qualified personnel. In other words, training appears to raise their productivity, and have its main impact on value added in this way (indirectly). There is no direct link established between training expenditures and profit.

5.1.8 Different skills impacting different channels of productivity

Vandenbussche et al. (2004) suggest two channels through which human capital affects productivity growth and analyse how the composition of human capital affects the importance of either channel. The two channels suggested are innovation and imitation; innovation is the research and development carried out by domestic workers, while imitation arises when foreign ideas are incorporated in domestic production processes. Using OECD data for 19 countries in the period 1960-2000 for the analysis, human capital is measured using a ‘total schooling measure, and the composition of human capital is measured based on the share of workers who have completed primary or secondary, and tertiary level education. They find that the contribution to total factor productivity growth from low-skilled workers decreases when a country closes in on the technological frontier. This indicates that low-skilled workers are more suited for taking advantage of imitation of foreign developments than own innovation.[56]

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[56] See Section 2.1.2 for theoretical reasons to distinguish between innovative and imitative R&D.

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5.2 Scientific and creative property

5.2.1 General evidence

The literature on R&D and productivity is very rich and covers both macro and micro evidence. In all studies considered by the authors, R&D is invariably found to have a significant and positive effect on output growth. However, the range of estimates of the elasticity of output with respect to R&D does vary across studies to some extent, depending on the approach adopted, the data considered and the extent of disaggregation.

Looking at firm-level evidence (presented in Table 13), in one of the first studies to address the issue, Griliches (1979) found that the elasticity of output to R&D in US manufacturing was around **0.07** on average (implying a 10% increase in R&D increases output by 0.7%). Schankerman (1981) presents estimates of the output elasticity to R&D for the US which range between **0.10** and **0.16** (using information from 110 U.S. firms (chemical and oil industries) in a 1963 cross-section)[57]. Griliches and Mairesse (1983) provide estimates of up to 0.19 (using data on 77 U.S. firms (scientific sectors) between 1966 and 1977), while Jaffe (1986) estimates an impact of **0.20** (using information on 432 US firms between 1973 and 1979). In France, the elasticity of output with respect to R&D is higher than in the US, ranging between **0.09** and **0.33** (Cuneo and Mairesse (1983), who make use of information on 182 French manufacturing firms between 1972 and 1977).

The evidence relating to the United Kingdom indicates that the direct effect of R&D is lower than the estimates generated internationally. In an earlier study relating to the United Kingdom, Griffith *et al*. (2006) provide evidence for a sample of UK manufacturing firms listed on the LSE. Their estimated output elasticities to R&D are lower than those estimates for the United States, and approximate **0.029** (implying that a 10% increase in the firm-level stock of R&D would increase output by approximately 0.29%[58]. Similar results for the United Kingdom (approximately 0.03) are presented in Bloom, Griffiths and Van Reenen (2002), using the stock of patents, instead of R&D capital, as a measure of innovation.

Jona-Lasinio *et al*. (2011) estimate the contribution of innovative property (which is wider than R&D) on labour productivity growth and illustrate that for the United Kingdom, the contribution stands at 0.11% (corresponding to **3.5%** of total labour productivity growth), with the specific impact of R&D standing at just **0.01%** (compared to 'architectural and engineering design' standing at **0.08%** and 'new financial products' standing at **0.04%**).

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[57] Implying that a 10% increase in the volume of research and development would increase productivity by between 1.0 and 1.6%

[58] The authors also note that UK firms' total factor productivity would have been at least 5% lower in 2000 in the absence of the US R&D growth in the 1990s (see also next section in spillovers)

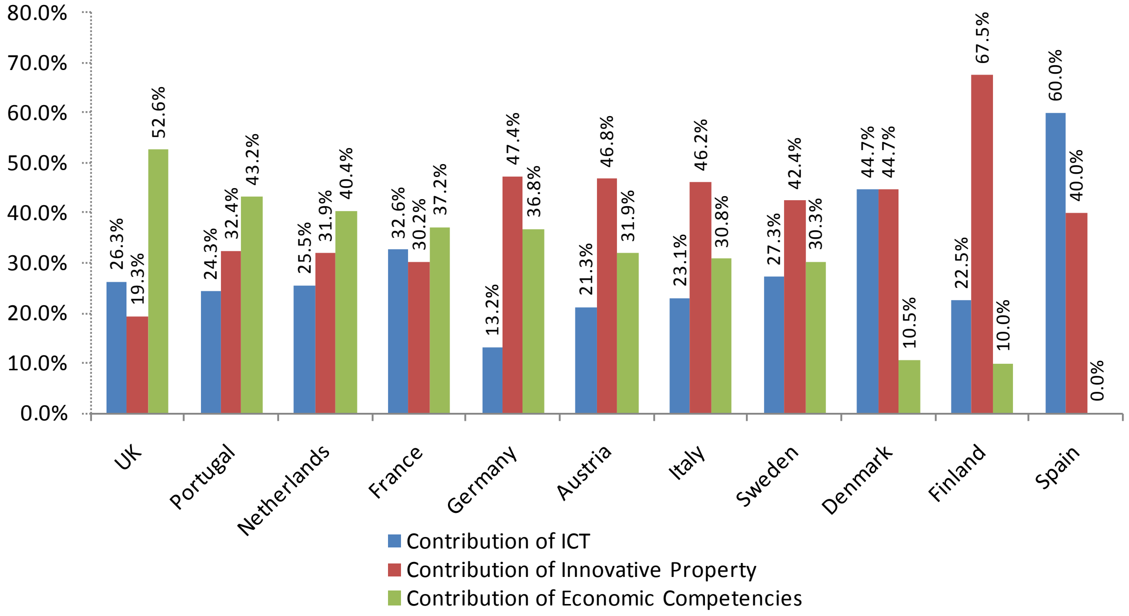
Table 13: Estimates of impact of the elasticity of private R&D		
	Productivity	**Study sample**
Cross-sectional studies		
Minasian (1969)	0.11 - 0.26	17 U.S. firms (chemical industry); 1948 to 1957
Griliches (1980a)	0.03-0.07	39 U.S. manufacturing industries; 1959 to 1977
Griliches (1980b)	0.07	883 U.S. firms, 1957 to 1965
Schankerman (1981)	0.10-0.16	110 U.S. firms (chemical and oil industries); 1963 cross-section
Sveikauskas and Sveikauskas (1982)	0.22-0.25	144 U.S. manufacturing industries; 1959-1969
Cuneo and Mairesse (1984)	0.20	182 French manufacturing firms; 1972 to 1977
Griliches and Mairesse (1983)	0.05 0.19	133 U.S. firms; 1966 to 1977 77 U.S. firms (scientific sectors); 1966 to 1977
Griliches (1986)	0.09-0.11	491 U.S. firms 1972-1977
Jaffe (1986)	0.20	432 U.S. firms; 1973 and 1979
Englander, Evenson, and Hanazaki (1988)	(0.16) - 0.50	16 industries across six countries; 1970-1983
Mansfield (1988)	0.42	17 Japanese manufacturing industries
Griliches and Mairesse (1990)	0.25 - 0.41 0.20 - 0.56	525 U.S. manufacturing firms; 1973 to 1980 406 Japanese manufacturing firms; 1973-1980
Hall and Mairesse (1995)	0.05 - 0.25	197 French firms; 1980 to 1987
Wang and Tsai (2003)	0.19	136 Taiwanese manufacturing firms; 1994 to 2000
Longitudinal Studies		
Minasian (1969)	0.08	17 U.S. firms (chemical industry); 1948 to 1957
Griliches (1980b)	0.08	883 U.S. firms, 1957 to 1965
Cuneo and Mairesse (1983)	0.05 (0.03-0.14)	182 French manufacturing firms; 1972 to 1977
Griliches and Lichtenberg (1984b)	-0.04	27 U.S. manufacturing industries; 1959 to 1976
Griliches and Mairesse (1984)	0.09	133 U.S. firms; 1966 to 1977
Griliches (1986)	0.12	652 U.S. firms; 1966 to 1977
Jaffe (1986)	0.10	432 U.S. firms; 1973 and 1979
Bernstein (1988)	0.12	7 Canadian manufacturing industries; 1978 to 1981
Hall and Mairesse (1995)	0.00-0.07	197 French firms; 1980 to 1987
Verspagen (1995)	-0.02 – 0.17	14 industries in 11 OECD countries; 1973 to 1988

Source: Congressional Budget Office (2005) based on Mairesse and Sassenou (1991), Mohnen (1992), and Australian Industry Commission (1995).

5.2.2 Cross-country comparisons

Returning to Table 12, the recent work undertaken by Jona-Lasinio et al. (2011) also illustrates the estimated contribution of innovative property (‘IP’, which is a wider concept than R&D; presented in column 5) on labour productivity growth. The analysis is particularly interesting, as it illustrates that for the United Kingdom, the contribution of Innovative Property stands at **0.11%,** which is approximately one third of the impact of the economic competencies category, with the specific impact of R&D standing at just **0.01%** (compared to ‘architectural and engineering design’ standing at **0.08%** and ‘new financial products’ standing at **0.04%**). Even assuming that there is some degree of blurring between the specific sub-divisions, the contribution of innovative property to UK labour productivity growth is relatively minor compared to the Nordic countries and lags Germany, France and the Netherlands. In terms of the relative contributions of the three elements of intangible assets on labour productivity growth across the countries contained in the analysis, evidence is presented in Figure 5.

Figure 5: Relative impact of intangible assets as sources of productivity growth



Source: Jona-Lasinio et al. (2011)

In another cross-country comparison, Guellec and Van Pottelsberghe (2004) explore the links between R&D activity and productivity growth, and whether institutional settings and the source of funds for R&D affect those links. They estimate a model of multifactor productivity growth for 16 OECD countries between 1980 and 1998. The findings demonstrate that technology is a significant determinant of economic growth regardless of the source of technology; that the social returns to research and development undertaken by businesses exceed the private return, because the businesses that undertake R&D are more likely to absorb technology generated outside the firm (see section 6.1 on absorptive capacity); and that public spending on R&D only increases productivity if it is non-military. In a final result, the authors note that university research, which is typically general, has a greater effect than public laboratories that perform specific research.

In the final cross-country comparison, Ulku (2007) provides an empirical analysis of the relationship between R&D intensity, the rate of innovation and the growth rate of output in four manufacturing sectors from 17 OECD countries[59]. The findings suggest that the knowledge stock (measured by patents) is the main determinant of innovation in all four manufacturing sectors selected as part of the analysis. Furthermore, R&D intensity increases the rate of innovation in the chemicals and electronics sectors (estimated

[59] Data are obtained from the following sources: patent applications made to U.S. Patent Office (NBER Patent Citation Database); sector level business enterprise R&D expenditure (BERD) (ANBERD-OECD, 2003); sector level output, investment, employment, import and export (STAN-OECD, 2003); GDP deflator and exchange rate (OECD, 2003); population (WDI, 2003); GDP in current $U.S. (WEO, 2003), imports and exports of U.S. from the partner countries (IMF-Direction of Trade, 2003).

coefficient of between 0.06 and 0.10)[60]. In addition, the rate of innovation has a positive effect on the growth rate of output in all sectors.

5.2.3 Country-level impact of R&D investment on productivity growth

In relation to other specific work in the field assessing the relationship between scientific and creative property and productivity, Aw et al. (2011) investigate the relation between R&D investment, exporting, and productivity using plant-level data from manufacturing firms in the Taiwanese electronics industry. The premise of the paper is that exporting firms have a higher productivity than non-exporters, and the authors endeavour to establish whether the premise is causal, self-selective or reflecting some other investment that may affect both exporting activity and productivity (in this paper, R&D investment is assessed in this respect). The authors find that plants that invest in R&D have almost 5% higher productivity compared to plants that do not (and also find that exporting activity increases productivity 1 year later by almost 2%)[61].

Duguet (2004) distinguishes between two types of innovation: *Incremental innovation* comprising significant improvement on an existing product; the launch of a product that is new to the firm, but not new to the market; and a significant improvement of an existing process. Radical innovation is made up of the launch of a product that is new to both the firm and the market and the implementation of a process breakthrough. The aim of the paper is to examine the contribution of incremental and radical innovation on total factor productivity growth in the French manufacturing sector. Duguet (2004) finds that ‘incremental’ innovation has no significant impact on total factor productivity growth. In contrast, ‘radical’ innovation is found to affect total factor productivity growth by 2% per annum. In addition, the data suggest that radical innovation causes discrete shifts in productivity, rather than continuous improvements.

In contrast to many of the articles described above, Comin (2004) estimates the effect of investment in R&D on US productivity growth, and finds that R&D does not explain a large part of growth in American productivity.

5.2.4 Different types of investment

Adams (1990) investigates the effect of academic research on productivity growth, and finds that it is very important in explaining productivity growth, but that it works with a lag of approximately 20 years. Similarly, academic technology and academic science spill over between firms in the same industry with a lag of 10 to 30 years. In a similar vein, Kwon (2004) investigates the contribution from university education and research to productivity growth in Japanese manufacturing. He finds that the highly educated graduates from universities played an important role in Japan’s convergence to Western productivity levels, but also that this effect has worn off. Meanwhile, in the United Kingdom, Haskel and Wallis (2010) explore the magnitude of three types of R&D (market sector level, public research councils, and civil or military defence) and how these affect productivity in the British market sector. They find that R&D conducted at the market sector level does not

[60] R&D data covers only the business enterprise R&D leaving out higher education and the government R&D that might play an important role especially in the drugs and medical and the chemicals sectors.

[61] In addition to these results, the authors demonstrate that if a plant has past exporting experience and current R&D activity, then productivity is increased by 5.6% compared to plants which do neither.

spillover to other firms; that the research conducted in public research councils filters through to the market sector at high significance; and that defence R&D stays within the defence industry and does not affect market sector productivity.

5.3 Computerised information and IT

There is relatively limited information relating to computerised information and ICT, and in reality, it is possible that a sizeable proportion of the impact of ICT and software has been subsumed into R&D.

From the more recent information that is available, referring to Table 12, the cross-country analysis undertaken by Jona-Lasinio *et al*. (2011) illustrates that there is again significant variation in the extent to which the investment in ICT/software contributes to labour productivity. In particular, the analysis indicates that the average contribution of ICT to labour productivity growth (relative to other investments in intangible assets) stands at approximately 26% (excluding Spain) with Denmark, Sweden and France seeing the greatest contributions (and the greatest contributions in absolute terms). In contrast, the contribution of intangible ICT/software assets in the United Kingdom stands at **0.15%** (out of a total of 0.57% equivalent to 27%) and compares with a 20% contribution of innovative property and approximately 53% for economic competencies.

In one important paper relating to the United Kingdom, Haskel and Pesole (2011) assess the contribution of investment in intangible assets to labour productivity growth in a number of industries (with a focus on the financial services sector). The analysis suggests that the contribution of investment in tangible assets (both ICT and non-ICT) accounts for **0.35%** of labour productivity growth in the financial services sector (out of a total of 2.89%). In contrast, the contribution of *intangible* assets stands at **0.43%** (exceeding the contribution of tangible assets). The main element of the intangible investment estimated to contribute to labour productivity growth relates to software, with a relatively even contribution among R&D, design activities, brands, human capital and organisational capacity (both in-house and purchased externally). These results are clearly sector-specific, and contrast significantly with the other industries considered as part of the exercise. In particular, investment in intangible capital appears to have a smaller role in the financial services sector compared to the contribution made by intangible assets in the manufacturing, business activities or retail, transport and hotel sectors, where the contribution to labour productivity growth from intangible capital stands at 0.92%, 0.86% and **0.49%** respectively[62] (although there is a particularly strong contribution of ICT/software within the financial services sector).

In one other paper relating to the UK, Giorgio-Marrano et al. (2006) incorporate measures of investment in information and communications technology, R&D, branding, skills, and other intangible assets to see if this changes the common belief that British productivity declined in the 1990s. They find that nominal investment in intangible assets equalled investment in tangible assets, and was around 15% of market gross value added. Of this

[62] One point that the authors make is that the residual TFP measure is more than halved once intangible assets are incorporated into the analysis implying that there is certainly scope for the ongoing analysis of IIA

intangible investment, the split across economic competencies, R&D and ICT/software was approximately 50:35:15. More significantly, by taking intangible investment into account, the growth in total factor productivity is found to accelerate rather than slow down in the 1990s. They find that (similar to the US), ICT/software contributed 31% to the annual change in labour productivity between 1995 and 2003 (compared to 24% for innovative property and 45% for economic competencies – see Table 15).

Table 14: Intangible assets as new sources of growth															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	LPG	Total CAP	ICT TAN G	Non ICT TAN G	INTA N CAP	SW	R&D	Des.	Bran d	HUM CAP	ORG CAP OWN	ORG CAP PUR	LAB QUA L	INTE R INPU T	TFP
Manufacturing	3.75	1.25	0.11	0.24	0.92	*0.08*	*0.37*	*0.16*	*0.03*	*0.11*	*0.07*	*0.07*	0.29	1.83	0.38
Retail, transport and hotel	3.07	1.11	0.35	0.27	0.49	*0.08*	*0.02*	*0.07*	*0.05*	*0.16*	*0.02*	*0.02*	0.22	1.45	0.29
Business Activities	2.21	1.41	0.40	0.15	0.86	*0.13*	*0.03*	*0.25*	*0.07*	*0.24*	*0.02*	*0.01*	0.30	0.49	0.01
Financial Services	2.89	0.77	0.43	-0.08	0.42	*0.14*	*0.02*	*0.07*	*0.00*	*0.05*	*0.04*	*0.04*	0.27	1.00	0.85

Source: Haskel and Pesole (2011)

Notes: The table reports selected industries; other industries are Agriculture, Construction, Gas, Electricity and Water. The data are average growth rates per year 2000-2005. The first column is growth in real gross output per hour. Column 2 is the total contribution of capital services per hour, namely growth in capital services per hour times share of capital in Gross Output (GO). Column 3 is growth in computer capital services times share in GO. Column 4 is growth in other tangible capital services (buildings, plant, vehicles) times share in GO. Column 5 is growth in intangible capital services times share in GO. Columns 6-12 are the breakdown contribution by asset of intangible capital services per hour; respectively the shares in gross output times growth per hour in software, R&D (including for financial services R&D derived from research occupations, as set out in the paper), Design, Brand equity (investment in marketing and branding), Firm-specific human capital (training financed by firms) and organizational capital (namely investment in management consultants for bought in spending and 20% of managerial time for own account). Column 13 is the contribution of labour services per hour, namely growth in labour services per hour times share of labour in GO. Column 14 is the contribution of intermediate inputs per hour, namely growth in intermediate inputs per hour times their nominal share in GO. Column 15 is TFP, namely column 1 minus the sum of columns 2, 13 and 14.

Table 15: Contribution of Intangible capital to annual change in labour productivity (non farm business US (UK market sector)						
	US		UK		US	UK
	1979-1995	1996-2003	1979-1995	1996-2003	(Proportion of ICD)	(Proportion of ICD)
Intangible capital deepening	0.43	0.84	0.47	0.59		
Computerised information	0.12	0.27	0.12	0.18	*32%*	*31%*
Innovative Property	0.13	0.22	0.16	0.14	*26%*	*24%*
Economic Competencies	0.17	0.35	0.19	0.26	*42%*	*45%*

Source: Giorgio Marrano, Haskel and Wallis (2006)

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6 Productivity Spillovers

In this section of the review, we concentrate on the incidence and extent of productivity spillovers associated with the investment in intangible assets. As before, we decompose the literature along the three broad categories of intangible assets: economic competencies, R&D, and computers/ ICT (though there is significantly less information in relation to the last category). We focus on those analyses relating to the United Kingdom in the first instance (when and where available), and consider the various papers according to whether the primary focus is at a national or cross-country level, regional or local level, sectoral level or firm level, although there is some overlap across the various categories given the fact that the spillovers identified may operate in either direction (for instance, higher education levels within a firm may spill over to the local labour market, or conversely, local labour market or industry skills may spill over to the firm and affect firm-level productivity).

6.1 Economic competencies

6.1.1 Summary

Before presenting the findings in detail (Table 16), we have presented the findings from a number of the studies in the field. By definition, the results are difficult to compare given the different levels of analysis, the different sources of data and the different spillovers that are being identified. However, most of the evidence that we have been able to identify and assess does suggest that human capital spillovers do exist and may be reasonably significant.

Measurement

The main strand of literature assessing human capital spillovers at local level (predominantly city and regional) uses wages (or alternatively firm-level value added) as a measure of productivity. Typically the spillover effect of local human capital is estimated controlling for the local level of human capital as well as firm-level or personal characteristics. After controlling for individual level characteristics (including skills level), the coefficient on the local human capital variable provides an estimate on the effect of human capital spillovers on productivity.

The measure of human capital used in these analyses is typically the proportion of the population with at least a degree-level qualification. However, some studies (e.g. Acemoglu and Angrist (2000)) have used average years of education to proxy for human capital levels. Focusing on the share of the population educated at degree-level or above as the source of human capital spillovers seems to be justified given that positive externalities of human capital on productivity arise from higher education attainment, rather than secondary or primary schooling levels (see for example Bauer and Vorell (2010)).

Estimation techniques

OLS estimates on the effect of localised human capital levels on wages are potentially biased if there are unobservable characteristics at local level explaining both the level of human capital and the average wage. One classic example is the endogeneity arising from labour migration where more skilled workers are attracted by cities or regions with higher wages or better amenities etc. (although the bias need not be positive (Bratti and Leombruni (2009)), In addition, the bias affecting OLS estimates could vary across different countries that are characterised by a different level of labour mobility across geographical areas.

As a result, a number of Instrumental Variables approaches have been developed to limit these biases, For example, Acemoglu and Angrist (2000) use child-labour and compulsory-schooling laws as instruments, and both variables are likely to be suitable instruments for lower schooling levels rather than higher education attainment[63]. Studies focusing on higher education attainment as a measure of human capital have exploited the characteristics of the different educational systems to identify suitable instruments: for example, Moretti (2004a) used the presence of a land-grant college in US cities; Muravyev (2008) used pre-transition levels of tertiary educational achievement in Russian cities; Bauer and Vorell use the (2010) lagged regional share of degree qualified workers for German regions; while Bratti and Leombruni (2009) use a combination of the lagged supply of degree courses and a lagged variable relating to the demographic profile in Italian provinces.

Summary of findings

Most of the evidence identified and assessed suggests that human capital spillovers do exist, and may be reasonably significant. In terms of reliability, in general, we believe that the analyses undertaken at the firm level probably provide the most robust results from a methodological point of view. Summary information is presented in Table 16.

- The **intra-firm** analyses incorporate the impact of average levels of human capital within the firm on individual workers' wages and productivity. The majority of evidence appears to point to a **positive** impact of co-worker education on individual wages or productivity within companies (Battu et al (2003), Metcalfe and Sloane (2007), Mas and Moretti (2006))

- Compared to the impact of an additional year of a worker's education on their own earnings (c **6-7%**), in an average sized firm, the impact of all co-workers' receiving and additional year of education can add up to **9-12%** to a worker's earnings (Battu et al (2003), Metcalfe and Sloane (2007)). These analyses also demonstrate that unlike the diminishing earnings returns to a worker's own education, there is **no saturation** point in relation to the spillover effect associated with other workers' education.

- Other analyses merge local-level or industry-level information to firm-level data in order to investigate the potential impact of local labour market or industry characteristics and human capital levels on firm-level productivity or individual earnings. Here, again, it seems that there exist **positive** and **significant** spillovers. For example, at individual level, following a 1 percentage point increase in the share of graduates, Moretti (2004) reports estimates of enhanced wages of between **0.4-1.9%** for the US; Muravyev (2008) reports estimates around **1-2%** for Russia; Bauer and Vorell (2010) find a spillover effect at regional level of around **0.2%** and **0.6%**

[63] Also the instruments are likely to capture the effect on the "marginal" rather than "average" learner.

for high-skilled and low-skilled workers respectively; and Bratti and Leombruni (2009) find a spillover effect between **0.7%-1.4%** and **0.4%-1.0%** on white-collar and blue-collar workers respectively.

- Evidence for the UK at regional level (Galindo-Rueda and Haskel, 2005) shows that a one percentage point increase in the proportion of graduates in the local region is associated with a **1.36%** increase in firm-level productivity (amongst manufacturing firms) in the local area. Also, Riley and Robinson (2011a) find that an increase in the level of organisational capital at regional level by 10% would be associated with an increase of **0.67%** in local labour productivity.

- Finally, a number of the studies demonstrate that, although higher levels of human capital increase the extent of spillovers, it is also the case that higher levels of human capital increase the rate at which other forms of investment in intangible assets are absorbed within firms (i.e. a double spillover), thereby augmenting the extent to which spillovers occur (e.g. O'Mahony and Vecchi (2009), Mason et al. (2007), Simões and Duarte (2007))

These results are presented in summary form in Table 16.

Table 16: Estimates of spillover effects – economic competencies

Author	Year	Country	Level	Source of spillover (Channel)	Metric	Impact
Crespi *et al*	2007	UK	National	Information flows - enterprise group, competitors, and suppliers	TFP	3.0%-4.7% of TFP determined by information spillovers [1]
Riley and Robinson	2011a	UK	National	10%↑regional capital intensity (Org; R&D;ICT)	Labour productivity	Org (+0.67%); R&D (-0.13%) ICT (+0.23%)
Mason *et al*	2007	UK	National	10% ↑ foreign patents	Patents per hour worked	+1.48% patents per hour worked
O'Mahony and Vecchi	2009	International	National	Skills intensity	TFP/ absorptive capacity	2%-5% higher productivity
Frantzen	2000	International	National	Human Capital Stock	TFP / absorptive capacity	Positive
Engelbrecht	1997	International	National	Human Capital Stock	TFP / absorptive capacity	Positive
Galindo-Rueda and Haskel	2005	UK	Regional/Firm	1pp ↑in proportion of graduates	Firm-level productivity	↑0.32% (services)[2] ↑1.36% (manufacturing)
Marrocu *et al.*	2009	International	Regional/Firm	1% ↑in proportion of graduates	Firm-level value added	0.063% to 0.363%
Moretti	2004a	US	City/ Individual	1 pp[3] ↑in proportion of graduates	Non graduate wages	1.6%/(1.9%) High School completers (non)
Croce and Ghignoni	2009	International	Region/Firm	10% ↑in regional skills (upper-secondary)	Training	1.9% ↑ in probability of firm-level training
Ramos *et al.*	2009	Spain	Inter-regional	Increases in human capital	Regional productivity	Negative
Glaeser and Maré	2001	US	City/Individual	Urban centre	Human capital absorption	↑ in human capital accumulation
Thornton and Thompson	2001	US	Sectoral	Explicit policy to promote communication	Firm-level productivity	↑1.5%-6.0%
Quella	2007	US	Sectoral	Knowledge spillovers	Industry level TFP	Valued at up to 32% of wage bill
Henderson and Cockburn	1996	US	Industry/Firm	10%↑ Industry knowledge spillovers	Firm-level productivity	↑2%
Battu et al	2003	UK	Firm to individual	across-the-workplace ↑ in education by 1 year	Own worker's wages	9.35% ↑
Metcalfe and Sloane	2007	UK	Firm to individual	across-the-workplace ↑ in education by 1 year	Own worker's wages	12% ↑
Moretti	2004c	US	Industry/Firm	1 pp[3] ↑in proportion of graduates	Firm-level productivity	↑0.8%
Mas and Moretti	2006	US	Firm	10% ↑in co-worker productivity	Own worker's productivity	↑1.7%
Backes-Gellner *et al.*	2011	Switzerland	Firm	↑in proportion of apprenticeship degrees	Salaries of graduates	Positive
Geppert and Neumann	2011	Germany	Region/Firm	10% ↑in regional intangible assets	Firm-level wages	↑0.83%
Bauer and Vorell	2010	Germany	Region/Firm	1 pp ↑ in regional share of high-skilled workers 1 pp ↑ in firm share of high-skilled workers	Firm-level wages	↑0.2% high-skilled; 0.6% low-skilled ↑3% high-skilled; no effect low-skilled
Bratti and Leombruni	2009	Italy	Regional/Firm	1 pp ↑ in regional share of college-educated among manufacturing workers	Firm-level white collar wages Firm-level blue collar wages	0.7-1.4% ↑ 0.4-1.0%↑
Rauch	1993	US	City/Individual	1 year ↑ in city-level average schooling	Individual wages	2.8-5.1% ↑
Muravyev	2008	Russia	City/Individual	1% ↑ in city share of college graduates	Individual wages	1-2% ↑
Acemoglu and Angrist	2001	US	State/Individual	1 year ↑ in state-level average schooling	Individual wages	1-2% ↑[4]

Source: London Economics based on various authors (2011)

(1) 4.7% for a firm using all sources of information relative to the average though the authors suggest that the element related to information flows from the enterprise group should be internalised, leading to a 3.0% spillover effect from other sources;
(2) Results relating to service sector firms are not statistically significant
(3) pp = 'percentage point' (4) Statistically insignificant

6.1.2 Cross-country and national level analyses

O'Mahony and Vecchi (2009) use company accounts for the United States, United Kingdom, Japan, France and Germany to analyse the relationship between intangible capital and productivity. They separate industries on the basis of skill intensity as reported in Labour Force Surveys. They find that firms in skills-intense industries enjoy between **2%** and **5%** higher productivity growth than other firms, and that this higher productivity growth is attributable to spillovers (primarily from investment in R&D and a greater *absorptive capacity*[64] in high skills industries). To test whether investment in absorption capacity is important for spillovers, the subgroup of firms who do not undertake investment in R&D are analysed separately[65]. The authors find that those firms also enjoy productivity spillovers, although they are smaller in magnitude than those experienced by the R&D intensive firms. Interestingly, in the cross-country comparison, the absorptive capacity of skills intensive industries is found to be highest in Japan (**4.9%**), followed by the United States (**2.9%**) and then Europe (**2.4%**).

In another article incorporating evidence from the United Kingdom (and bridging human capital and knowledge spillovers), Mason et al. (2007) investigate the effect of skills on productivity at the sector level for the United Kingdom, United States, France, Germany and the Netherlands. Skills are accounted for using two variables: the log of the share of unskilled workers in a country, and the log of the share of graduate workers in a country. The authors find that productivity is positively and significantly related to the predicted knowledge production measure (patents per hour worked) and to two different measures of human capital; one benchmarked on graduate-quality labour and the other benchmarked on unskilled labour. The analysis shows a strong role for human capital in contributing to R&D intensity. *Knowledge production* is positively and significantly related to proxy measures of absorptive capacity (same-country citations) and external knowledge spillover potential (foreign patents – where a 10% increase in foreign patents results in a **1.48%** increase in the number of patents per hour worked). In the output production function, the coefficients on patents and human capital are both positive and significant. Thus, human capital has a significant and positive impact on productivity, both directly (in output production) and indirectly through its positive links with R&D intensity and knowledge production.

6.1.3 Regional, cities, urbanisation and spatial spillover effects

Spillovers at regional level using firm-level data

Described in detail in the previous section when assessing the direct impact of training on firm-level productivity, Galindo-Rueda and Haskel (2005) also estimate productivity

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[64] See below or Cohen and Levinthal (1989) for an introduction to the concept of absorptive capacity.

[65] In another paper considering the absorptive capacity of skills, Griffith *et al*. (2006) map two ways research and development affect national productivity growth using a panel of OECD countries. They argue that research and development increases productivity through innovation as well as absorptive capacity. The first way is straightforward, and means that domestic firms may generate ideas for new products, which are able to capture market share. The second way should be interpreted as a way of preparing domestic firms to absorb foreign knowledge, and thereby improve production efficiency. The importance of the different ways depends on the position of the sector and country in relation to the technology leader. The further away from the technological frontier, the larger the share of the impact of research and development on total factor productivity arising from absorptive capacity, which then aids imitation of technology.

spillovers arising from local human capital on the basis of a matched dataset holding information from the Annual Business Inquiry and the Employer Skill Survey. Their sample is restricted by matching difficulties, which means that the authors prefer to cite the results of the analysis relating to enterprises with *only one plant* (although the results relating to *multi-plant manufacturing* enterprises are essentially the same as the estimates for *single-plant manufacturing* firms, there are some differences in the estimates for single-site and multi-site service firms). Focusing on single-plant firms, the authors find that the productivity of a manufacturing firm that is located in an area[66] with 40% of the resident population holding a degree will be **13.6%** greater than if the manufacturing firm located in an area with only 30% of the resident population holding a degree (the equivalent estimates for single-site service firms stand at **14.8%** (though statistically insignificant)). Importantly, as they cannot identify the reason the firm is located in a given area, there is a risk of spurious correlation between the determinants of firm location and productivity. In the authors' words, the estimate of the potential increase in productivity should be considered an upper bound for the effect. Comparing the results relating to the spillover effect of an increase in the proportion of the regional adult population in possession of undergraduate degree level qualifications to the proportion of workers within the firm with undergraduate degree level qualifications, the analysis suggests that the indirect effect is approximately 4½ times the direct effect for manufacturing firms[67].

In addition to the significant spillover effect of local-level skills and qualification on firm-level productivity, the authors also undertake an assessment of the impact of local education levels on workers' remuneration. They find that for workers in single-plant manufacturing enterprises, an increase in the proportion of individuals resident in the local area in possession of Level 4 qualifications or above (undergraduate degree or equivalent) by 10% increases the average wage received by employees by approximately **9.9%**, implying that workers capture approximately three-quarters of the spillover effect (see also Rauch (1993) and Chevalier et al. (2004) for different analysis assessing the extent to which workers remuneration reflects increased productivity). However, when considering workers in multi-plant enterprises, the proportion of the aggregate spillover effect captured stands at approximately half of the spillover effect (6.3% out of a total of 12.4% assuming a 10% increase in the proportion of the resident adult population in possession of level 4 qualifications or above).

In another paper considering regional effects, Marrocu *et al*. (2009) evaluate the role of internal intangible capital on firms' productivity. They use data from Bureau van Dijk's Amadeus database for this purpose, and create an unbalanced panel dataset that contains information on a total of 107,000 firms in 116 regions of France, Italy, the Netherlands, Spain, Sweden, and the United Kingdom for the period 2002-2006. They estimate a production function for eight sectors, and include as regressors firm-level determinants such as tangible and intangible capital and employment. In addition, they generate *regional-level* determinants, such as human capital proxied by the share of the labour force with a degree ISCED 5 or 6 (undergraduate degrees and above); technological

[66] Local Authority.

[67] Note the results presented here relate to the model specification presented in Table 10 of the original Galindo-Rueda and Haskel (2005) report where both firm level and regional skills levels are incorporated in model specifications (column 3) and thus do not correspond directly with the results presented in Table 10 of this report

capital (represented by the number of patent applications made from the region in the last 10 years per 1,000 inhabitants); public capital; population density; and a variable to categorise the various regions. The results indicate that *intangible capital* is positively related to firm-level productivity in all the sectors with coefficients ranging from **0.020** to **0.099** (i.e. a 1% increase in intangible capital increases firm-level productivity by between 0.2% (personal services) to 0.099% (infrastructure services).

However, in terms of regional spillover effects, they find that for every sector, at least one of the regional determinants is significant in determining firm-level productivity. Specifically, the authors find that regional human capital affects firm-level productivity positively and significantly for all but one sector (science-based manufacturing). Table 17 presents some of the major findings across all countries (though the UK is excluded, as the model specification is not comparable with other countries, but we present some additional findings relating to the United Kingdom in Table 18). The analysis suggests that a 1% increase in the proportion of individuals in a region in possession of at least undergraduate degree level qualifications increases firm-level productivity by up to **0.363%** for firms who are advanced knowledge providers in the supply to manufacturers, and 0.331% in the network infrastructure industries. Interestingly, with the exception of science-based manufacturing, all sectors demonstrate a positive spillover from higher proportions of graduates (with the lowest statistically significant human capital spillover standing at 0.063% for those firms in the mass production sector involved in scale-intensive manufacturing).

Table 17: Estimates of impact of regional level qualifications on firm-level productivity by sector

	Advanced Knowledge Providers Knowledge Intensive	Advanced Knowledge Providers Specialised supplier manufact.	Mass Production Goods Science based manufact.	Mass Production Goods Scale based manufact.	Supporting infrastruct. Services Network infrastruct.	Supporting infrastruct. Services Physical Infrastruct.	Personal Goods and Services Supplier dominate goods	Personal Goods and Services Supplier dominate services
Human Capital	0.236***	0.363**	0.063	0.063*	0.331***	0.215***	0.273***	0.056*
Tech Capital	-0.001	-0.020	0.058***	0.050***	0.019	0.036***	0.016	0.035*
Public Capital	0.069***	0.054	-0.015	0.003	0.066***	0.029***	0.024*	0.016*

Source: Marrocu et al. (2009)

Period 2002-2006; HC: Regional Human Capital; TC: regional Technological Capital ; PC: Public Capital. UK firms are not included due to data unavailability on intermediate inputs. S1 Advanced knowledge providers—Knowledge-intensive business services: Computer and related activities; research and development; other business activities: S2 Advanced knowledge providers—Specialized suppliers manufacturing: Machinery and equipment; medical, precision and optical instruments; S3 Mass production goods—Science-based manufacturing: Chemicals; office machinery and computers; electrical machinery and apparatus; radio, TV and communication equipment; S4 Mass production goods—Scale-intensive manufacturing: Rubber and plastic products; other non-metallic mineral products; basic metals; fabricated metal products; motor vehicles; other transport equipment; S5 Supporting infrastructure services—Network infrastructure: Post and telecommunications; financial intermediation; insurance and pension funding; activities auxiliary to financial intermediation; S6 Supporting infrastructure services—Physical infrastructure: Wholesale trade and commission trade; land, water and air transport; supporting and auxiliary transport activities; S7 Personal goods and services—Supplier-dominated goods: Food and beverages; textiles; wearing; leather; wood and related; pulp and paper; printing and publishing; furniture; recycling

S8 Personal goods and services—Supplier-dominated services: Sales, maintenance and repair of motor vehicles; retail trade and repair of personal and household goods; hotels and restaurants. Controls included: firm's age and dummy variables for years, countries and firm's dimension. All variables are log-transformed and all regressions include a constant. Significance: * 10%; ** 5%; *** 1%

Again using information on UK firms' employees, their occupations, earnings and hours worked from the Annual Survey of Hours and Earnings (ASHE) and the Labour Force Survey and linked via the ONS Inter-Departmental Business Register (IDBR) to firms in the Annual Business Inquiry (ABI), Riley and Robinson (2011a) assess the extent to which regional city-region variables have an impact on labour productivity. Once again (as with the direct impact of intangible investment and its components on productivity), the dominant spillover component is organisational capital (economic competencies). ICT capital intensity in a city region also has a significantly positive association with labour productivity (**0.0226** implying that increasing the depth of city-regional organisational capital by 1% would increase firm-level productivity by 0.026%), which is about a third of the size of organisational capital intensity (**0.067**). R&D capital intensity is not significant in either specification (**-0.013**). The exact regression results are provided in Table 18.

Table 18: Productivity results, disaggregated intangible capital (random effects)

	Log GVA per hour	Log gross output per hour
Firm-level characteristics		
Log firm R&D capital intensity (per hour)	0.0589***	0.0310***
Log firm organisation capital intensity (per hour)	0.618***	0.364***
Log firm ICT capital intensity (per hour)	0.0215***	0.0137***
Log firm tangible capital intensity (per hour)	0.0182***	0.0103***
City-Region variables		
Log CR R&D capital intensity (per hour)	-0.0165	-0.0132
Log CR organisation capital intensity (per hour)	0.121***	0.0670***
Log CR ICT capital intensity (per hour)	0.0332**	0.0226***

Source: Riley and Robinson (2011a), Table 3

Building on the work undertaken by the same author (Moretti, 2004a) relating to the impact of the proportion of the population education to college degree at city level, Moretti (2004c) considers the impact of the proportion of college graduates on firm-level productivity outside the industry in which they are employed in and finds that a 1.0% increase in the proportion of college education graduates increases firm-level productivity by approximately **0.8%**. The analysis also considers whether the impact of average education level matters depending on whether the firm is a high-tech or low-tech firm. Interestingly, the analysis suggests that an increase in the proportion of college graduates in high-tech industries (other than the industry in question) increases productivity in that high tech industry by approximately **1.2%**, while there is also an impact on low-tech industries of **0.14%**. Similarly, if there is an increase in the proportion of college education graduates in low-tech industries (outside the industry in question), there is a productivity spillover effect of 0.26% in high-tech industries and 0.86% in low-tech industries. This supports the general conclusion that geographical, social and proximity may be important in exploiting spillovers where they may naturally occur.

In a recent paper considering human capital spillovers (region to firm), Bauer and Vorell (2010) estimate the extent of spillovers using data from a German matched employer-employee panel dataset, linking social security information with firm level data. The time period covered by the analysis is 1996-2001 and productivity is measured using wages (attention is restricted to full-time workers only). Given the poor quality of the variable identifying the highest qualification held by employees, they use the occupational structure to generate a proxy for the individual education level. The resulting classification divides the sample in three different types of workers, according to their skill level (low, medium and high-skilled workers). In their estimation strategy they employ both fixed effects (as well as pooled OLS), to control for time-invariant characteristics at individual and firm level, and an instrumental variable (IV) approach, using the (20 year) lagged regional share of workers with a university degree to instrument the share of high-skilled individuals in a region. They find that the regional shares of low-and-medium-skilled workers have no significant effect on wages, while the share of high-skilled workers in the region has a *positive but very small* impact on the wage of both high-skilled and low-skilled workers. Specifically, a one percentage point increase in the share of high-skilled workers at the regional level increase the wage of high skilled workers by **0.2%** and of low skilled workers by **0.6%**. However the latter effect may not be entirely attributable to spillovers, given that an increase in the share of high-skilled workers determines a reduction in the share of low-skilled workers and, potentially, a salary increase even in the absence of positive externalities. The authors also find evidence of intra-firm spillovers, but for high-skilled workers only, with an increase of one percentage point in the share of high-skilled worker in the firm resulting in a **3%** increase in the wage of high-skilled co-workers (see also Battu et al (2003) and Metcalfe and Sloane (2007)). In their conclusions they remark that their findings show that high-skilled workers benefit more from working alongside more educated co-workers and that spillovers effect beyond firm level and for low-skilled workers are very limited.

Bratti and Leombruni (2009) investigate the existence of local human capital spillovers in Italian manufacturing at the firm level. For their analysis, they merge 2001 Italian Population Census data on the regional stock of human capital with administrative information on earnings, as well as survey information on firm characteristics, focusing on the effect of local human capital externalities on the earnings of white and blue collar workers. In their methodology, the authors apply OLS wage regressions and, to overcome the potential endogeneity of local human capital levels, also IV regressions instrumenting the local level of human capital with the lagged change (between 1990-1995) in the university supply of manufacturing-related degree courses (i.e. degree courses whose graduates are more likely to find employment in manufacturing, and its interaction with 20-year lagged demographic structure). Their OLS regression results indicate that a one percentage point increase in the regional share of college-educated workers in manufacturing increases the wages of white-collar and blue-collar workers in the specified sector by **0.7-1.4%** and **0.4-1.0%**, respectively. The coefficients in the IV regressions are between **1.3-1.6%** and **0.7-0.8%**, respectively. Regarding the impact on blue-collar workers, however, the authors point out that the effect might not be entirely attributed to educational externalities, since an increase in the regional share of college-educated workers makes blue-collar workers relatively scarce, and, if blue and white-collar workers are not perfectly substitutable, could lead to an increase in wages for the former independent of human capital spillovers.

Local spillovers using individual data on wages[68]

In one of the earlier papers examining both the direct and indirect effects of education on wages, Rauch (1993) explores data from the 1980 Census of Population, and focuses on the impact of average human capital on individual earnings within Standard Metropolitan Statistical Areas (SMSAs) in the United States. Developing wage equations that include individual-level and SMSA characteristics, the proxies human capital by the level of individual and city formal education and work experience. Concerning direct effects, the author's findings imply that an increase in individual education and work experience by one year results in the individual wage rising by **4.8%** and 3.5 %, respectively. With respect to the spillover effects of human capital at the city level, the estimates exhibit a positive effect of an increase in average SMSA education (i.e. an increase in the latter will lead to a **2.8-5.1%** increase in individual wages in the respective cities). The resulting coefficients for the average work experience prove to be statistically insignificant, which the authors explain by the fact that spillovers of knowledge occur through the sharing of ideas for technological improvements, the communication skills for which are mainly taught through formal education, rather than work experience.

A common criticism which has been expressed concerning Rauch's (1993) work is that he does not take account of the potential endogeneity of location choices, so that the causality between the variables under investigation is difficult to establish, and his estimates should be considered as an upper bound. A study which attempts to overcome the endogeneity issues was conducted by Acemoglu and Angrist (2001), who employ US Census data on white males aged 40-49 born in the United States over the period 1960-1980, in order to estimate both the direct effect of a worker's education and the external effect of the human capital of others on individual wages. To achieve their estimates, the authors first implement ordinary least squares regressions, where education is considered an exogenous variable. However, due to the potential existence of reverse causation between the variables (i.e. higher earnings and income might induce higher levels of schooling), they also conduct a set of instrumental variable tests, exploiting differences in compulsory attendance and child labour laws.

While both tests suggest that an additional year of secondary schooling for a worker leads to a **7.3%** increase in individual earnings, they lead to significantly different results regarding the spillover effects of average education on individual wages in US states. In particular, results from the OLS test reveal significantly sizeable education spillovers of the same magnitude as the direct effects (i.e. a one year increase in state-level average education implies a **7.3%** increase in average individual wages). In contrast, employing the second set of tests, the authors find a statistically insignificant spillover effect of **1-2%**. While these external effects become larger and statistically significant when extending the period covered to 1950-1990, the authors assert that this effect stems from change in the education variable in the 1990s, and conclude that there *seems to exist little evidence of significantly sizeable effects* of the education of other workers on individual wages.

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[68] Smith (1999) investigates the nature of knowledge spillovers and their effect on output and growth in American states. She finds that knowledge spills over state borders at a rate that reverses comparative advantages (productivity convergence). Interstate knowledge spillovers are geographically limited, but are stronger than spillovers between technologically similar firms.

The most commonly cited paper considering human capital spillovers from the United States is that of Moretti (2004a). In this seminal work, he estimates how human capital generates productivity spillovers in American cities based on the Census of Manufacturing and the Census of Population. He uses two different instruments to address potential endogeneity affecting the wage equation: differences in the age structure of cities and an indicator to capture the presence of a land-grant college in the city[69]. He finds that a 1 percentage point increase in the share of college graduates in a city affects the wages of high-school drop-outs, high-school graduates and college graduates by **1.9%**, **1.6%** and **0.4%** respectively. Furthermore, Moretti finds that the increase in wages appears to be a consequence of increased productivity[70].

Muravyev (2008) uses the economic transition process of Russia, where education in cities was determined by the government (and therefore not by wages) before its transition. In order to overcome the problems concerning endogeneity, he establishes wage equations to investigate the impact of the individual stock of human capital as well as the effect of the average human capital in cities on the individual wages of the respective cities' residents. He uses the historical location of university establishments to instrument potential endogeneity affecting the wage equation. His analysis focuses on cross-sectional data from the 1994 Russian Longitudinal Monitoring Survey. His evidence regarding direct effects implies that an additional year of schooling for a single worker will increase individual earnings by **3.6-4.2%**, while an increase in a city's share of people with a college education by 1% will result in a **1-2%** increase in individual earnings in the respective city. Analysing 2002 data, he finds similarly-sized external effects.

Dissenting evidence

In a dissenting paper to the previous studies that have identified positive and significant human capital spillover effects, Ciccone and Perri (2006) criticise the assumptions of the individual wage regression approach (see, for example, Rauch (1993), Acemoglu and Angrist (2001) and Muravyev (2008)) for the estimation of human capital spillovers, and establish additional estimates for the latter at the state and city levels for the United States. Asserting that the use of individual wage equations leads to an upward bias in the estimates of local human capital externalities, they apply a decomposed approach to control for changes in the skill structure of the workforce, and instrument for average schooling levels. Their data is derived from aggregate data from the public-use microdata samples of the U.S. Census between 1970 and 1990. Based on this different approach, the authors find *no evidence of spillover effects from regional and state-level average schooling*.

Agglomeration effects

Artis et al. (2009) study agglomeration economies in Great Britain and their impact on productivity performance at a regional level. Agglomeration economies are generated from

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[69] As reported by the author, land-grant colleges were established more than 100 years before the period considered in the analysis.

[70] In addition, he estimates the impact of human capital on local crime rates and voting patterns, and finds that the social return to human capital in terms of lower crime rates is 14-26% of private return. He also finds that cities in the US which have a higher educated populace have greater voting rates

the concentration of economic activities (and employment), and are proxied in the study by total employment of a given area that is located within a series of driving-time bands around the centre of each area. As a measure of productivity, they use gross value added per job filled as a measure of outcome and productivity, and control for intangible assets (human capital, R&D activities. the number of employees working in high-technology industrial sectors, and patents application) at regional level, as well as physical capital and land. Their main findings suggest that agglomeration economies have a significant impact on regional economic performance, although their importance is reduced when the variables measuring intangible assets are introduced in the model. The variables measuring human capital, R&D and high-tech activities are all positive and highly significant (coefficients indicate that a one unit increase in each indicator has an effect of around 18%, 5% and 6% respectively). Conversely, they do not find any significant effect on productivity at regional level of occupational human capital and the number of patents applications. The authors also look for productivity spillovers arising from neighbouring regions, measured through a spatial lag of the dependent variable, and find that they are positive but very small (0.1% per unit increase in the indicator). They also suggest that several other factors (not identified in the study) may act as a source of cross-regional spillovers.

Rosenthal and Strange (2008) study the impact of agglomeration effects on human capital spillovers and labour productivity, using American census data. They build a series of concentric rings identifying varying distances from the place of work, and use wage as a measure of labour productivity. They proxy human capital quality using the number of highly educated (college degree or more) and less educated (less than a college degree) workers in employment, and then measure the value for these indicators at various distances from a worker's place of work. They use measures on geographical characteristics as instruments to control for possible measurement errors and endogeneity. They find that proximity with highly educated workers generates a positive spillover on labour productivity, while proximity to less educated workers generates a negative externality (possibly because higher geographical concentration increases congestion, travelling times and, as a result, negatively affects wages and productivity). Moreover, the effect attenuates with distance: adding 100,000 highly educated workers would increase wages by around **12%** in the 0 to 5 mile ring, around 5% in the 5 to 25 and 25 to 50 mile ring and has no effect on the 50 to 100 mile ring. Also, *transforming* 100,000 less educated workers into highly educated workers would increase wages by almost **20%** in the smaller ring, and around **7%** in the next two rings (up to the 50 mile ring). Both groups of workers significantly benefit from working with highly educated workers: adding 100,000 highly educated workers in the less than 5 mile ring increases wages by around **12%** for highly educated workers and around **9%** for less educated workers.

Cities as enhancers of productivity spillovers

Adopting a slightly different approach to assessing the impact of urban areas on individual-level productivity, Glaeser and Maré (2001) present the fact that workers in US urban areas earn an average wage premium of 33% compared to workers in non-urban areas. They impose the assumption that firms will only be willing to pay that extra wage if *firm productivity* is equally higher (the authors suggest that higher firm-level productivity resulting from locating in a large US city arises from lower transportation costs and a more productive workforce). Using individual-level data from the 1990 census, the Panel Study of Income Dynamics and the National Longitudinal Study of Youth, they try to establish whether workers in cities justify their higher wages because they are more productive, and why that might be.

Using this data, the authors are able to attribute 6.5% of the wage premium to observable properties such as education, experience, and race. Further, job tenure, occupation, and results of the Armed Forces Qualification Test explain 3% of the difference. The authors argue that unobserved ability could account for no more than one-third of the wage premium, unless it is distributed in a very different way to observable skills. They also argue that real wages (i.e. wages adjusted for local prices) do not appear to be higher in cities; that migrants to cities appear to experience real wage gains; and that the urban wage premium is largest among long- term urban dwellers. These results suggest that workers in urban areas are not particularly more able than workers in non-urban areas, and therefore the city must affect their productivity, which would explain why wages increase. Further analyses suggest that the wage premium earned by urban workers is a result of wage increases during the course of tenure, as opposed to a higher initial level. This in turn indicates that urban workers are more productive; indeed, workers that leave the urban areas do not experience a wage decline as a result, which is another indication that the wage premium earned in the city reflects higher productivity. *The evidence suggests that cities speed up the accumulation of human capital*[71].

Firm to region spillovers – reverse spillovers

In an analysis of the impact of local human capital on the propensity of firms to train their employees, Croce and Ghignoni (2009) undertake an assessment of the extent to which there are spillovers between firms and local areas. Using data on Italian local labour markets, the authors find that the average human capital level in the local labour market affects employers' propensity to invest in training. The analysis confirms some well-known outcomes in the economic literature. Specifically, employees working full time, having a permanent contract, with higher education degree and a longer specific experience face a higher probability of receiving employer-provided training, and that male workers are more likely to be trained than their female counterparts. The authors also demonstrate that higher-ability workers are more likely to receive firm-level training than less qualified counterparts (see Dearden et al. (1998) for an earlier analysis of the United Kingdom).

As for local factors, local human capital indicators in the model specification have a positive and significant impact on the likelihood of an individual receiving training within the firm (1.9% increase in probability of receiving training following 10% increase in local labour market skills at upper secondary level, and a **1.3%** increase in probability following 10% increase in local labour market skills at upper secondary and tertiary graduates). Moving from qualification levels to years of schooling, an increase in the average number of years of schooling in the local area by 1 year increases the probability of receiving firm training by **12%**. In other words, if there are two identical individuals living in two otherwise

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[71] Christoffersen and Sakissian (2009) explore the performance of fund managers to document differences in performance and productivity for funds in financial centres and for funds located outside major financial centres. They find that managers in funds in financial centres outperform their counterparts in smaller financial areas; that managers who have worked in the financial centre for a long time perform better, and that managers who have high tenure within the same fund perform well. The last two effects indicate that workers in financial centres benefit from more job-specific and sector-specific training than their counterparts, and that productivity spillovers may exist between individuals within larger financial centres.

identical areas, the individual who lives in the area with a higher share of educated population has a greater probability of receiving training from his/her employer; however, it is interesting that the proportion of university educated individuals in the local area does not appear to increase the probability of receiving employer provided training.

In a final paper in this section looking at spatial externalities, Ramos et al. (2009) use Spanish regional data covering the period between 1980 and 2007 to investigate the impact of human capital spillovers on productivity in Spanish regions. Furthermore, they test whether human capital spillovers work across regional borders. They find that physical capital positively affects productivity in a region, as well as neighbouring regions. The measure of human capital is broken down to account for different effects arising from primary, secondary and tertiary education. Secondary and tertiary studies affect own-region productivity positively and significantly. The test for inter-regional spillovers yields a negative result, which may be attributable to regional competition for individuals carrying high levels of human capital.

6.1.4 Sectoral level

Quella (2007) estimates knowledge spillovers within and between six macroeconomic sectors in the civilian economy in the United States over the period from 1948 to 1991 (updating Jorgenson et al. (1987) and Jorgenson (1991)), and explores the link between those knowledge spillovers and total factor productivity. Considerable knowledge spillovers within and between sectors are found.

The solid lines in Table 19 marshal sectors into three larger divisions of the economy: primary sector (agriculture), industrial or secondary sector (comprising manufacturing, mining, construction), and the tertiary sector (trade and transportation, services). The table shows that manufacturing and trade and transportation are the main sources of spillovers for the economy, whereas services and agriculture do not generate any knowledge outflows. Most flows occur between industrial and the tertiary sector, with industrial sectors being the most dynamic both internally and externally. In other words, industry as a whole generates and receives most flows in the matrix. All sectors receive spillovers from, at least, one other sector in the economy, but manufacturing and trade and transportation are the only sectors to learn from each other.

As for intra-sectoral flows, manufacturing is the only sector to learn from its own productive experience, above what it could learn from the rest of the economy as a whole. In contrast, mining, construction, and trade and transportation are completely dependent on one single sector for the totality of their spillovers. For both construction and trade and transportation, this unique source is manufacturing.

Table 19: Estimates of knowledge spillovers 1948-1991

	Sector of Origin						Spillover
	M	N	C	S	T	A	
Sector of destination							
Manufacturing	0.55				0.45		0.30
Mining					1.00		0.20
Construction	1.00						0.10
Services		0.30			0.70		0.25
Trade and transport	1.00						0.15
Agriculture			1.00				0.05

Source: Quella (2007)
Manufacturing (M), Mining (N), Construction (C), Services (S), Trade and Transportation (T), and Agriculture (A).

In addition to the assessment of knowledge spillovers, Quella (2007) also computes the gap between the market allocation, which ignores knowledge spillovers, the optimal allocation of labour across sectors, as well as the wedge between market and optimal wage rates by sector (given that spillovers create a wedge between the private and the social rates of return to the spillover-generating input). It is estimated that the optimal employment in the manufacturing industry should be 32% higher than the market allocation (i.e. a social planner aiming to internalise knowledge spillovers would employ 32% more workers in manufacturing (and pay 31% higher wages)). These estimates are not significantly different from those generated by Bernstein (1988) for Canada.

Thornton and Thompson (2001) explore the extent of spillovers in the specific case of shipbuilding in the United States during the Second World War. The institutional setting for the study was clearly very different to the current market climate in the sense that firms were not allowed to patent new innovations, the government arranged formal meetings between managers in the shipbuilding sector explicitly in order for them to learn from each other, and all ship yards received plentiful orders meaning that there was little chance of going bankrupt (and as a result there is no attrition from the dataset). In the analysis of the sector, productivity is measured using unit labour requirements for each type of ship and each shipyard. The authors find that internal productivity spillovers 'within shipyard and for the same ship design' amount to **6%** of the productivity improvement arising from an order for one more ship in the same design. Across shipyards, but within design, yields spillovers of 4%, while within shipyard, but for new design generates a spillover of 3% in terms of productivity. Across shipyards for new designs, the productivity spillovers amount to just over 1.5%. For an industry in which the government actively tried to promote spillovers in every way possible, the authors suggest that these results are modest; however, given the fact that shipbuilding is a labour-intensive industry, productivity increases may be harder to achieve in that industry in the first instance than in the economy as a whole.

In a piece of work from the mid 1990s relating to the pharmaceutical industry, Henderson and Cockburn (1996) assess that there are significant returns to size in pharmaceutical research, but that only a small portion of these returns are derived from economies of scale *per se*. The primary advantage of large firms appears to be their ability to realise returns to scope: to sustain an adequately diverse portfolio of research projects, and to capture and use internal and external knowledge spillovers. In particular, the estimate in the econometric analysis is that there is an elasticity of 0.2 (i.e. a 10% increase in external knowledge flow increases own firm productivity by approximately 2%). However, the authors caution that it may be costly to sustain the absorptive capacity (human capital) of the workforce to maximize the impact of these spillovers (see Mas and Moretti (2006) for a similar argument in relation workforce reallocation and re-organisation, and Crespi et al.(2007) for another analysis of the spillover effects associated with information flows)[72],[73],[74].

6.1.5 Intra-firm estimates – wage and productivity effects

Using the 1998 GB Workplace Employee Relations Survey, which is a unique matched employer-employee dataset, Battu *et al*. (2003) consider the spillover effect of co-worker education on a worker's own earnings. The WERS is a national sample of interviews with managers from 2,191 British establishments with at least ten workers (these establishments are workplaces that may be part of larger firms or enterprises). The establishment-level survey addresses the 'management of employees', with information on workforce composition and workplace performance. In addition, 25 employees at each workplace were randomly selected for individual survey. This survey asked questions about individuals' education, pay and job satisfaction, as well as a range of personal characteristics. The information set is therefore rich, with detailed information on multiple workers per workplaces (yielding information on 18,304 workers across 1,389 workplaces). Battu *et al*. (2003) make use of this data to estimate the impact of average years of education across the workplace on individual earnings (in addition to the 'own' earnings return, which stand at approximately 6% per year of additional schooling in line with many other estimates in the field and reviewed in section 5)). The modelling indicates that there is a substantive effect on individual earnings. An across-the-workplace increase in education of 1 year raises own worker earnings by 9.35% (though the premium to own education is reduced marginally) with a slightly stronger effect for men than women. The authors compute that a single co-worker's extra year of education is worth about 3.5% of a workers own schooling premium. Interestingly, this spillover effect is independent of own education level, which appears to be at odds with the idea of education aiding the capacity to absorb spillovers.

In related work, and again using the Workplace Employee Relations Survey, though with an updated financial performance questionnaire (not available in the 1988 WERS that the Battu *et al*.(2003) study was based on), Metcalfe and Sloane (2007) confirm the existence of human capital spillovers. As per the previous work, the analysis shows that there is an earnings premium for an individual year of education of **6.4%** (which is again consistent

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[72] Añon Higon and Vasilakos (2008) study the British retail industry in order to establish whether or not multinational enterprises induce productivity spillovers, and whether these spillovers are regional in nature. They find that multinational enterprises are more productive than strictly domestic firms, and that British-owned multinational enterprises perform better than foreign firms. Furthermore, they find that the presence of multinational enterprises increases productivity of the neighbouring domestic firms

[73] Blomström, M. and Sjöholm, F. (1998) use Indonesian micro level data to examine the effect of spillovers from foreign multinational affiliates. Foreign multinational affiliates are found to have a higher level of labour productivity, and domestic firms benefit from spillovers

[74] Branstetter (2000) investigates whether the Japanese "Vertical Keiretsu"[74] structure is conducive to knowledge spillovers. He finds that firms in Keiretsu enjoy knowledge spillovers three times greater than the counterfactual, and that the spillovers affect firm-level total factor productivity positively and significantly

with a wide array of existing literature). The analysis also suggests that the provision of training in the workplace significantly raises earnings: a worker who has been trained receives 10.4% more in earnings than a worker who has not been trained[75]. Once firm wide education is incorporated into the analysis, it is estimated that an *across-the-workplace* increase in education of one year raises earnings by 12%. A single co-worker's extra year of education is worth about **3.2%** *of a workers own schooling premium*. This is an important result in the sense that it illustrates some of the difficulties associated with estimating the size of spillovers (where they exist). The impact of an individual co-workers education may have a relatively small effect on own-earnings; however, the aggregate effect of all co-workers education may be particularly large.

The authors undertake some additional analysis to assess whether the impact of own training and the co-worker education levels on own earnings are linear. In some potentially important findings for policy makers, they find workplace education boosts *own earnings*, but at a diminishing rate, although co-worker education boosts own earnings for all meaningful levels of education (which implies that there is a diminishing return to own education but no diminishing return to wider increases in education levels (no saturation)). Another prominent result is that the greater dispersion of workplace training is associated with lower earnings (statistically significant), which implies that it is important for firm-level productivity to have a degree of common educational standards when employees are working closely with each other (the equivalent of technological proximity discussed in section 5.2).

In a more recent analysis of workplace productivity and worker organisation, Mas and Moretti (2006) use worker-level data from check-out workers in an American supermarket chain to estimate worker productivity and productivity spillovers between workers. They find that an increase in co-worker productivity by 10% leads to an increase in *own productivity* by **1.7%**, with a slightly greater spillover effect achieved by low productivity workers (they experience an increase of **2%** on own productivity). The analysis also suggests that workforce reorganisation may augment the extent of spillovers achievable (through pairing high-productivity workers with different groupings of less productive workers). Specifically, an optimal allocation of workers will increase store productivity by 0.04%, but as optimal assignment of shifts may induce higher wages and reorganisation efforts, it is not clear that the firm will maximise profit under this reallocation of work teams (see also Henderson and Cockburn (1996) in relation to workforce re-organisation).

In a final paper considering the role of different qualifications as the source of spillovers, Backes-Gellner *et al*. (2011) study the mechanics of workplace-level spillovers and particularly the educational background of those who benefit from spillovers (using the Swiss Earnings Structure Survey). They find that increasing the number of workers with apprenticeship qualifications improves the productivity (and wages) of university graduates. They argue that the theoretical approach of the graduate complements the practical approach of the apprentice[76]. In their recommendations for Swiss policy makers,

[75] The analysis also suggests that workplace training increases firm-level productivity though this is subjectively measured as part of the questionnaire.

[76] However, following the hypothesis of Aghion and Howitt (2006), the estimation results show, that an increase in the number of tertiary-educated workers results in a higher overall firm productivity, whereas an

the authors suggest that "*any stronger emphasis on tertiary education should not neglect the importance of investment in the training of workers with secondary education. Workers with an apprenticeship training are not only highly qualified workers with professional knowledge but also contribute to the wage of workers with a tertiary education. Moreover, the goal of increasing the number of workers with a tertiary education is reasonable only as long as the job requirements increase accordingly. Otherwise, these workers might be matched with jobs for which they are inaccurately qualified or even overqualified. A stronger emphasis on secondary vocational education could solve this problem*".

6.1.6 Knowledge absorption

To date, we have considered the evidence relating to human capital spillovers; however, the review of the literature has demonstrated that human capital has a direct spillover effect but also an indirect spillover effect (or double spillover effect). For instance, regional human capital appears to impact either the wages of workers or firm level productivity; however, it is also the case that human capital improves the ability of firms to absorb internal and externally sourced knowledge and exploit other sources of intangible capital (such as R&D). We discuss some of the evidence relating to knowledge absorption in this section.

National and regional level

In a paper considering the spillover effect of human capital in terms of the absorption effect, Frantzen (2000) analyses a cross-section of OECD countries between the early 1960s and the early 1990s. He finds that R&D efforts affect productivity across borders, and that countries that have a greater human capital stock are more likely to absorb those productivity spillovers. Unsurprisingly, larger countries are found to be more dependent on domestic R&D, whilst smaller countries benefit more from international spillovers. Engelbrecht (1997) also considers international productivity spillovers from R&D between OECD countries. The study includes a variable which accounts for human capital stock in the country. He uses OECD data to model total factor productivity as a function of key variables including domestic human capital, a weighted average of domestic R&D stocks of trade partners, and imports as a fraction of gross domestic product. The analysis demonstrates that human capital explains some of growth in total factor productivity in a country. He also finds that human capital and R&D capital is important for both domestic innovation and absorption of foreign knowledge spillovers.

Simões and Duarte (2007) analyse productivity spillovers in the Portuguese manufacturing sector focusing on the absorptive capacity of human capital. They find that the most important source for productivity spillovers is the technology within goods imported from another OECD country, and that in relation to absorption of any spillover effects, it is necessary to employ workers who have obtained at least secondary education for any productivity spillover to materialise (supporting the basic skills argument).

Regional level

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increase in the number of workers with apprenticeship degrees results in a lower overall firm productivity. Combining the results of both regressions, the authors note that while tertiary-educated workers have a positive impact on firm productivity, their wage depends strongly on the number of highly qualified apprenticeship graduates employed within a firm

Añon Higon and Sena (2006) analyse the impact of regional human capital on the productivity of British firms, using qualifications information from the Quarterly Labour Force Survey and measures of knowledge spillovers using information on R&D activities conducted in private firms recorded by the Business and Enterprise Research and Development (BERD) dataset. Firms located in regions with a more educated workforce (on average) tend to benefit more from inter-industry knowledge spillovers and to be more productive. This is true for knowledge spillovers generated at national, regional and county level. Across all specifications, however, the effect is not very large. Using a different dataset, they find that vocational qualifications help firms utilise the spillover knowledge, and thereby increase productivity. The authors indicate that "*geographic distribution of human capital matters and therefore policies that can address this geographical imbalance are welcome*".

Supporting this analysis, Geppert and Neumann (2011) also assess how investment in organisation, R&D and ICT affects economic performance in firms in German regions. They randomly select 30,000 firms from a firm-level dataset, which contains approximately 1.5 million enterprises and covers the years between 1999 and 2003. The performance measure employed in the analysis is average wage in the establishment, and the explanatory variables include regional indicators[77], number of employees, intangible capital intensity, tangible capital intensity[78], and a 3-digit NACE industry dummy. In addition, firm-specific regional information is added for robustness checks. The authors estimate that ignoring intangibles in national accounts implies an underestimation of labour productivity growth by 10 to 20%.

The analysis also suggests that doubling the intangible capital intensity of a regional economy (outside the own industry) increases the average wage of an establishment there by around **8.3%**. However, in this context, regional R&D and ICT capital appear to be more important, compared to organisational capital. Decomposing the results, the regressions reveal that regional R&D and ICT intangible capital intensity affects average wages in a firm with an estimated elasticity of **0.0183** and **0.016** respectively (i.e. a doubling in the level of R&D (ICT) intangible capital increases average wages by 1.8% and 1.6% respectively). Organisational capital affects own performance positively; competitors in the same industry's performance negatively; and does not impact the performance of firms in other industries. Interestingly, both R&D and ICT do not spill over to competitors in the same industry, but cross-industry spillovers are present, positive, and significant.

6.1.7 Firm-level estimates – knowledge absorption

A comparatively early study, conducted by Cohen and Levinthal (1989) suggests a unique relationship between a company's own investment in R&D and knowledge spillovers from its competitors. They assume that investing in R&D efforts does not only result in the creation of new information and innovation, but also increases a company's ability to identify, assimilate and exploit existing external knowledge, an ability which they refer to as 'absorptive capacity'. The firm's incentives to invest in research, in turn, depend on the

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[77] Large metropolitan areas with core cities with more than 500,000 inhabitants; small metropolitan areas with core cities with 200,000-500,000 inhabitants; intermediate regions with population density greater than 150 inhabitants per km^2; and rural regions with population density less than 150 inhabitants per km^2.

[78] Value of the capital type per employee hour.

quantity of external knowledge to be acquired and the ease with which learning occurs, among other factors. External knowledge in this case consists of extra-industry knowledge, such as university publications, and intra-industry knowledge spillovers between rival firms. Hence, the authors suggest that the occurrence of spillovers of external knowledge to a particular firm will not only depend on its competitors' investments in R&D, which creates the knowledge to be disseminated, but also crucially hinge on that company's own investment in innovative activities, since the latter ensures that the company is able to absorb the knowledge created by its rivals. Subsequent literature in the field has expanded Cohen and Levinthal's (1989) concept of absorptive capacity to include broader investments in intangibles, most prominently human capital, which is the relevant use for this section.

In a paper exploring the role of knowledge flows and total factor productivity growth, Crespi *et al*. (2007) use firm-level business surveys (the Annual Respondents Database (ARD) and Annual Business Inquiry (ABI), further augmented by responses from the Community Innovation Survey (CIS). The CIS includes information on the importance of different sources of knowledge[79] (from suppliers, purchasers, universities and competitors) for innovation effort, thereby allowing the authors to examine the effect of information spillovers in UK businesses. They find that total factor productivity growth is positively and significantly associated with above-average information flows from other firms in an enterprise group, competitors, and suppliers. They also find that the share of total factor productivity growth that arises from all three effects combined is 4.7%. The authors proceed to determine whether these effects on productivity growth can be thought of as spillovers. It is argued that information from other firms in the enterprise group should be internalised, and therefore it should be considered a spillover. Information from suppliers and especially competitors, however, can be considered spillovers. The estimated effects of these spillovers are 1.5% of total factor productivity growth for each.

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6.2 Scientific and creative property

In this section, we consider the extent of R&D productivity spillovers. Again, we consider papers addressing the issue at a national level (where the majority of the evidence exists), followed by an assessment of the information that exists at a more disaggregated level.

6.2.1 Summary of findings

The first strand of literature analyses the effect of knowledge spillovers at an international level. The classical approach employed inserts a measure of foreign R&D directly into a country's production function, while controlling for domestic R&D and other factors. The positive effects of R&D are thought to spill over beyond national borders mainly through international trade (with the exchange of knowledge embodied in intermediate goods) and foreign direct investments (through purchases from foreign-owned multinational subsidiaries). While the original approaches (Coe and Helpman, 1995) were criticised both for the weighting scheme used to account for the effect of foreign R&D and for the limitedness of the econometric techniques applied, recent literature, using a similar approach but correcting for potential biases, has found significant evidence of international R&D spillovers (Engelbrecht (1997), Coe *et al* (2009), Madsen (2008), Lumenga-Neso (2005)).

Several studies have identified the existence of productivity spillovers arising from R&D at the industry level. For example, Griffith *et al*. (2004) find that industries (and countries) further away from the technological frontier can potentially benefit the most from R&D spillovers. In addition, evidence of positive R&D spillovers has also been observed by Los and Verspagen (2000) for the US (using patents rather than R&D), and Scherngell *et al*. (2007) for the electronics and chemical industries in the EU (the analysis is performed using regional output disaggregated by industry). Bernstein (1988) also finds evidence for intra-industry spillovers, but emphasises that positive externalities from R&D between different industries are significantly larger.

At the regional level, the literature provides estimates for both spillovers across and within regions. Evidence of spillovers at the cross-regional level in the EU is found by Fischer et al. (2007) using the patent stock as a proxy for knowledge. Spillovers from regional R&D (and ICT) to firm-level productivity are identified by Geppert and Neumann (2011); however in contrast, both Piekkola (2011) and Riley and Robinson (2011a) estimate that there are no R&D spillovers. The latter two studies use the INNODRIVE methodology (see Section 4.2.1) and find no significant evidence of R&D spillovers on firm-level productivity, but observe positive spillovers associated with investment in IT. In general, at the firm level, there is robust evidence suggesting the importance of R&D spillovers on firm productivity, even if the effect can vary across R&D and non R&D firms or across technologically similar and dissimilar firms (see Ejermo, 2004 and Cincera, 2005).

These results are presented in summary form in Table 20.

Table 20: Estimates of spillover effects – Research and Development

Author	Year	Country	Level	Source of spillover (Channel)	Metric	Impact
Coe and Helpman	1995	OECD	National	(1% ↑ in) Foreign R&D expenditure	Total Factor Productivity	0.06-0.09% ↑ in TFP in aggregate 0.02-0.26% by country (UK 0.081%)
Frantzen	2000	OECD	National	(1% ↑ in) Foreign R&D expenditure	Total Factor Productivity	0.20% ↑ in TFP (larger than domestic R&D)
León-Ledesma	2000	OECD	National	(1% ↑ in) Foreign R&D expenditure	Exports	0.05-0.07% ↑ in exports (UK 0.0125-0.0188%)
Keller	1997	OECD	National	Foreign R&D expenditure	Total Factor Productivity	Trade channel not effective
Kao *et al.*	1999	OECD	National	Foreign R&D expenditure	Total Factor Productivity	No effect on TFP
Gumprecht *et al.*	2003	OECD	National	Foreign R&D expenditure	Total Factor Productivity	No effect on TFP
Lumenga-Neso *et al.*	2005	OECD	National	Foreign R&D expenditure	Total Factor Productivity	0.17-0.208% ↑ in TFP
Coe *et al.*	2009	OECD	National	Foreign R&D expenditure	Total Factor Productivity	Higher than original CH (1995)
Madsen	2008	OECD	National	Foreign R&D International patent stock	Total Factor Productivity	0.09-0.22% ↑ in TFP
Griffith *et al*	2004	International	Industry	R&D/Human Capital (HC)	TFP (UK)	R&D 14%-54% (36%); HC 15%-58% (39%)
Braconier and Sjöholm	1998	International	Industry	Domestic intra-industry expenditure on R&D Foreign intra-industry expenditure on R&D Domestic inter-industry expenditure on R&D Foreign inter-industry expenditure on R&D	Productivity growth	Zero Positive Zero Zero
Bernstein	1988	Canada	Industry	External R&D stock	Production costs	Both intra-industry and inter-industry spillovers reduce unit costs, but the effect for thelatter is substantially larger
Scherngell *et al*	2007	EU	Regional/Industry	Patent applications	Regional productivity at industry level	Positive in some industries (electronics and chemical industries)
Riley and Robinson	2011a	UK	Regional/Firm	10% ↑ regional R&D or ICT capital intensity	Labour productivity	R&D (-0.13%) not significant; ICT (0.23%) significant
Cincera	2005	International	Firm	10% ↑ external R&D spillover stock	Firm-level output	1.1-1.6% for technologically similar firms; 4.0%-6.2% for technologically dissimilar firms
Ejermo	2004	Sweden	Firm	R&D	Firm-level output	Small and not always significant among R&D firms; tiny but significant on non R&D firms
Blazsek and Escribano	2010	United States	Firm	Patent citations	Firm-level output	Positive
Piekkola	2011	Finland	Regional/Firm	10% ↑ regional R&D/ICT capital intensity	Firm-level output	R&D: no effect; ICT 0.12%
Geppert and Neumann	2011	Germany	Firm	10% ↑in regional R&D or ICT intensity	Firm-level productivity	Positive regional R&D and ICT spillovers (0.17 and 0.18%). No own-industry spillovers
Los and Verspagen	2000	United States	Industry	Patent count	Industry-level output	Positive
Aiello and Cardamone	2007	Italy	Firm	1%↑ External R&D stock	Firm-level output	0.14-0.35%
Fischer *et al.*	2009	EU	Cross-regional	↑ Patent Stock 1%	Regional TFP	Positive: 0.13% ↑ in TFP

Source: London Economics adaptation of different authors

Note: Estimates might not be directly comparable across studies

6.2.2 Cross-country and national level

Introduction

At the national and cross-country level, the majority of the work considering R&D spillovers follows the approach of Coe and Helpman (1995) on international R&D spillovers. According to their proposed theory and associated empirical findings, foreign R&D has a positive and significant effect on a country's productivity, and the channel of transmission of R&D spillovers is predominantly international trade. However, different features of their model were later questioned in the literature (e.g. the quality of the data available at that time, the measures of foreign R&D activity, the trade weighting scheme used in the analysis[80], and their econometric approach - although they could not make use of modern panel data techniques, which were quite limited at that time).

Subsequent literature failed to observe any significant effect of foreign R&D on a country's productivity, questioning the existence of international R&D spillovers and the effect of international trade as a relevant channel. Clearly, such findings would deny the presence of international spillovers and undermine their contribution to productivity growth. However, recent literature has re-examined the impact of international R&D spillovers (correcting for possible methodological biases and using advanced panel data econometric techniques) and found that international R&D spillovers do significantly contribute to economic growth. Below, we present in detail a series of articles focusing on international R&D spillovers and productivity growth, starting from the original work by Coe and Helpman (1995).

The Coe and Helpman approach

In the original work, Coe and Helpman (1995) estimate how a country's productivity levels are affected by domestic and foreign R&D stocks. The stock of domestic knowledge is proxied by domestic expenditure on R&D, while the foreign stock of knowledge is measured by R&D expenditure of a country's trading partners, weighted by the partner's share in imports. Foreign R&D expenditure can cause both *direct* and *indirect* benefits on the home country's internal productivity: direct benefits can be identified with the spread of knowledge associated with foreign R&D (the introduction of new technologies and materials, advances on production processes or organisational methods). In this sense, technology spillovers occur across countries through the channel of trade flows. The empirical model uses data from 21 OECD countries and Israel in the period 1971-1990. The authors find that, on aggregate, the estimated elasticities of total factor productivity with respect to the domestic R&D stock is around **0.08** for non-G7 countries and much higher (around **0.23**) for G7 countries (implying that a 1% increase in the stock of domestic R&D results in a 0.08% and 0.23% increase in productivity, respectively).

On the other hand, the effect of foreign R&D stock on domestic TFP (which is allowed to vary across countries and over time) has a larger impact on smaller countries, given the higher degree of openness of these economies. The analysis demonstrates that foreign R&D has the strongest impact on Belgium (0.26%), followed by Ireland (0.17%), the

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[80] The R&D measure was computed using a weighted sum of the R&D stocks of the country's trading partners where weights were determined according to the countries' bilateral import shares

Netherlands (0.16%) and Israel (0.15%)[81], with low spillovers achieved in countries such as the United States (0.033%), Japan (0.027%), France (0.067%), Germany (0.077%) and the United Kingdom (**0.081%**).

Related evidence

Other papers employed a methodological approach similar to Coe and Helpman (1995) and found comparable evidence. Using a similar framework to Coe and Helpman (1995), Evenson and Singh (1997) study the contribution of international R&D spillovers to productivity growth for eleven Asian countries over the period 1970-1993. They find strong evidence in favour of the existence of a positive effect of R&D investment made by a country's trading partners on domestic productivity, together with an effect of domestic R&D on productivity. In addition, they show the relevance of public policies on the creation and diffusion of spillovers: the block of South East Asian countries benefited more from technological spillovers than South Asian countries, thanks to higher degree of openness and a stronger focus on developing domestic technological capabilities.

Lichtenberg and van Pottelsberghe (1998) revisit the model developed by Coe and Helpman (1995), proposing an alternative weighting scheme to compute foreign R&D capital stocks (in the authors' view, the original was subject to an "aggregation bias"[82]) and also required a correction for an "indexation bias" occurring in the original model when foreign R&D capital stock was interacted with the import share. In their empirical approach, the authors focus on how the output elasticity of foreign R&D depends on a country's openness to trade. The empirical results confirm that the more open to trade a country is, the more likely it is to benefit from foreign R&D.

Frantzen (2000) expands on the Coe and Helpman model using a longer time series (1961-1991) and controlling for the level and growth of human capital. The findings of the analysis suggest that the effect of both domestic and foreign R&D on the long-run total factor productivity (TFP) growth is positive, with the elasticity of TFP to foreign R&D being larger than the effect of domestic R&D (effect around **0.2** and **0.1** respectively). Also, the effect of domestic R&D is bigger for G7 countries compared to smaller OECD countries.

León-Ledesma (2000) focuses on international trade as a driver for R&D spillover diffusion and productivity growth. However, rather than considering the extent of productivity spillovers per se, the author focuses explicitly on the impact of trade-related R&D spillovers on a country's own exports. Similarly to Coe and Helpman (1995), the estimation is performed on 21 OECD countries in the period 1971-1990. The elasticity of export performance to domestic R&D is around **0.25** on aggregate and significantly higher (around 0.50) for the G7 group. Basic results for foreign R&D do not show any significant

[81] Coe, Helpman, and Hoffmaister (1997) also extend the analysis to a sample of 77 developing countries and control for trade with industrial countries. Their findings highlight the existence of substantial spillovers of foreign R&D from industrial to developing countries, stressing the importance, for the latter group of countries, of openness to trade and trading with industrial countries. In particular, South East Asian countries seem to have benefited the most from foreign R&D.

[82] The aggregation bias implies that a country's foreign R&D stock increases following a (hypothetical) merger between two or more of its trading partners, even though their domestic R&D stocks and the trade flows between the countries remain unchanged.

impact on export performance. However, augmented specifications taking into account a country's degree of openness show a positive and significant effect of foreign R&D on export performance (around 0.05-0.07 (implying that a 1% increase in the stock of foreign R&D results in a **0.05-0.07%** increase in export performance)). Calculating export elasticities to foreign R&D growth by country show that, on average, the elasticity is higher for smaller, more open countries and that these estimated elasticities have increased over the period considered. Elasticity of exports to foreign R&D seems to be highest for Belgium and Ireland (around 0.049 and 0.038 respectively in 1990), while the UK elasticity was around **0.018** in 1990.

Criticism

Coe and Helpman's results and methodology were scrutinised and re-examined by various authors:

Keller (1997) conducted robustness tests on the model developed by Coe and Helpman, using the same OECD data with "randomly" generated trade shares and concluding that the role of international trade as a channel for propagation of R&D spillovers is not clearly supported from his findings. However, Coe and Hoffmaister (1999) revisit Keller's approach and dispute the methodological approach (and the "random" weights on trade shares) used in the paper, and confirm the validity of their original findings.

Kao *et al*. (1999) re-assess the (panel co-integration) approach applied by Coe and Helpman (1995) and find that domestic R&D has a strong effect on growth, which differs across G7 and non-G7 countries. However, they do not find any significant evidence supporting the hypothesis of the existence of international trade-related R&D spillovers (i.e. the impact of foreign R&D on domestic growth is not significant). Similarly, Gumprecht et al. (2003) review the original Coe and Helpman (1995) model and subsequent related empirical literature. Considering a variety of estimators used in the literature, the authors conclude that, while there is evidence of a positive impact of domestic R&D on total factor productivity, foreign R&D seems to have little or no effect on a country's total factor productivity.

Recent evidence

More recent evidence confirms the importance of international R&D spillovers on domestic productivity growth. For example, Lumenga-Neso *et al*. (2005) extend the original Coe and Helpman model (also incorporating and addressing the issues raised by Keller (1997)) and consider both the direct and indirect effects of foreign R&D. The authors argue that what matters for cross-country R&D spillovers is not the level of R&D internally produced by a foreign trading partner, but the level of R&D *available* in that foreign country[83]. Their findings show that indirect R&D spillovers account for over 91% of the total trade-related flow of R&D (and are therefore almost 14 times bigger than direct R&D spillovers). Moreover, the marginal effect of direct and indirect flows of R&D have a similar impact on

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[83] For example, if country A trades with country B (but not with country C) and country B trades also with country C, country A can still benefit from the R&D developed in country C through the R&D available in country B. In other words, international R&D spillovers can occur even if two countries are not trading with each other directly, and focusing on bilateral trade would not capture R&D spillovers occurring through international trade.

total factor productivity in the receiving country, implying that the overall effect on TFP of indirect foreign R&D flow is much larger than the direct effect of foreign R&D (given that the indirect stock is 14 times larger). The findings strengthen the evidence that international trade matters as a significant channel for the transmission of foreign knowledge.

Lee (2005) revisits the Coe and Helpman model using panel data econometric techniques for co-integration analysis and a more detailed dataset between 1971 and 2000 on a panel of OECD countries. Improved data availability implies that they can look at trade in intermediate goods (rather than overall goods trade) at a disaggregated industry level. The estimated results confirm that both domestic R&D and foreign R&D have a positive and significant effect on a country's productivity (with the magnitude of the second effect somewhat smaller). The paper restates the validity of the original Coe and Helpman results and underlines the importance of intermediate goods trade as a channel of international R&D spillovers. The same author (Lee, 2006) examines the importance of international knowledge flows transmitted through four different spillover channels: inflow and outflow FDI; flows of intermediate goods imports; and a 'disembodied' direct channel (knowledge spillovers that are not embodied in specific transactions of goods or investments). The empirical findings, on a sample of 13 OECD countries between 1981 and 1999, show that inflow and the disembodied direct channel have a positive and significant effect on international knowledge spillovers, while the outflow FDI and flows of imports did not act as an effective international transmission channel for knowledge.

Coe *et al*. (2009) expand and augment the original work of Coe and Helpman (1995) and confirm the original results after adding a measure of human capital to the analysis. The original sample is extended to 2004 and covers 24 countries. The main changes compared to the previous analysis following the introduction of the human capital variable are that the estimated coefficient on domestic R&D for G7 countries declines significantly; the elasticity with respect to domestic R&D capital tends to fall in the G7 countries but increase in the non-G7 countries; and the elasticities of total factor productivity with respect to foreign R&D capital increase. The measure of human capital introduced in the model has a large and significant effect on TFP. In addition, the authors explore the role of four institutional variables that could potentially affect the impact of R&D investment on productivity. They find that the 'ease of doing business' and the level of tertiary education are important determinants of total factor productivity growth arising from domestic and foreign R&D. In addition, strong patent protection and legal systems based on English or German law also help the absorption of spillovers[84].

International patents and economic growth

Madsen (2008) uses a long historical series to estimate the impact of international patents (patents applied for by non-residents) on TFP growth, controlling also for the domestic patent stock, imports of knowledge through the channel of trade, and the global stock of knowledge. Using data on 16 OECD countries between 1883 and 2004, the author shows that the average elasticity of TFP to the international patent stock is around **0.22** across

[84] The result on patent laws confirms the theoretical result on international property rights put forth by Barro and Sala-i-Martin (1997), see Section 2.1.2.

different specifications (reduced to 0.09 when time dummies are included)[85]. This implies that, as the volume of international patent stocks increases by 1%, there is, on average, a 0.22% spillover effect on total factor productivity domestically. The estimated elasticity associated with *knowledge spillover* through the channel of international trade is around **0.17**, while the impact of *domestic knowledge* stock on TFP is negligible (probably reflecting a better quality average of patents that are filed abroad). The world stock of knowledge significantly influences TFP across most specifications (between 0.25 and 0.40 when significant); however, the estimated coefficients of the propensity to import are not statistically significant, suggesting that the direct effect of openness on TFP is negligible[86]. Madsen (2008) finds evidence to support the hypothesis that skilled labour improves the absorptive capacity for spillovers (see also Cohen and Levinthal (1989), Henderson and Cockburn (1996) and Griffith et al (2003)).

6.2.3 Sectoral/ industry level

Turning to the analyses undertaken at a more disaggregated level, and still following the fundamental augmented approaches of the various authors since Coe and Helpman (1995), Griffith, Redding and Van Reenen (2004) use data on a panel of industries across twelve OECD countries (including the United Kingdom) between 1974 and 1990[87]. In addition to the conventional role of stimulating innovation, R&D enhances technology transfer by improving the ability of firms to learn about advances in the leading-edge countries ('absorptive capacity' – see section 6.1.6). As presented in Table 21, the analysis indicates that R&D technology transfer is responsible for between 14% and 54% of the total R&D effect on total factor productivity. The authors also indicate that the extent of technology transfers is less in those jurisdictions that might be closer to the technology frontier (i.e. US, Germany and France) compared to countries that are further away from the frontier (which will lead to convergence over time (see also Coe and Helpman (1995)).

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[85] The number of international patents per capita filed in 2004 was highest in Denmark, the Netherlands, Sweden and Switzerland (between 5 and 2.5) and lowest in Japan, the USA and Canada (0.3 to 0.45), while the value of international patents for the UK was around 0.69.

[86] The author also examines the bilateral flow of ideas between countries and the contribution of the growth in the international patent stocks to the average annual TFP growth by source and destination country over the period from 1890 to 2001. On aggregate, countries that have contributed most to world TFP growth through the channel of international patenting are Germany, the United States and the United Kingdom, while the highest contribution per capita have been provided by the Scandinavian countries, Switzerland and Luxembourg. The highest beneficiaries of international knowledge flows are Japan, the Netherlands and Portugal (with international patents contributing to more than a 0.4 pp increase in the TFP growth over the period considered), while Canada, Belgium and the United Kingdom are the countries whose TFP growth has least benefited from international patents (between 0.08 and 0.15 pp in TFP).

[87] The data used in the empirical application are derived from a number of sources. The main one is the OECD International Sectoral Data Base (ISDB), which provides information at the two-digit industry level on value added, labour, and capital stocks. This was combined this with data on R&D expenditure from the OECD ANBERD data set and information from several other sources. For information on occupational skills the authors use the UNIDO database; for education the authors use aggregate data from Barro and Lee (1994) and industry data from Machin and Van Reenen (1998). Trade data are derived from the OECD Bilateral Trade Database. The sample consists of twelve countries over the period 1974-1990. For some of the countries, information is available for nine two-digit industries (ISIC 31-39); for others, ISIC 38 is additionally broken down into five three-digit industries. Where the more disaggregated information is available for the three-digit industries, it is used.

Table 21:	Total R&D and human capital contributions to productivity growth			
	R&D Total effect	***of which* R&D Technology transfer**	**Human Capital Total effect**	***of which* Human Capital Technology transfer**
Canada	0.69	*0.18*	0.35	*0.10*
Denmark	0.81	*0.28*	0.42	*0.16*
Finland	1.05	*0.57*	0.56	*0.32*
France	0.67	*0.17*	0.34	*0.10*
Germany	0.64	*0.15*	0.33	*0.09*
Italy	0.88	*0.35*	0.46	*0.20*
Japan	0.83	*0.30*	0.43	*0.17*
Norway	0.98	*0.47*	0.52	*0.27*
Sweden	0.78	*0.27*	0.40	*0.15*
UK	0.77	*0.28*	0.40	*0.16*
United States	0.57	*0.08*	0.28	*0.04*

Source: Griffith, Redding and Van Reenen (2004).
Notes: Column (1) shows R&D's total contribution to productivity growth. Column (2) reports the percentage share of technology transfer in R&D's total contribution, based on a country's time-averaged TFGAP in total manufacturing. Column (3) shows human capital's total contribution to productivity growth, and column (4) reports the analogous contribution from technology transfer

In addition to the multiple effect of R&D, the authors also consider the impact of human capital (and trade flows) in the model, to assess the extent of human capital externalities. Using the proportion of the country's population in possession of tertiary level qualifications (following the Barro and Lee (1994) approach), the authors find that the estimated coefficient on human capital is positive and significant and is consistent with positive externalities from higher educational attainment in the firm (deriving from both a higher a higher rate of innovation and more rapid technology transfer). Again in Table 21, the analysis indicates that the contribution of human capital in the form of technology transfers to total factor productivity stands at between 15% and 58% (with the same distribution of countries depending on the closeness to the technology frontier). In the case of the United Kingdom, the analysis demonstrates that R&D and human capital technology transfer (i.e. externalities) account for **0.27%** and **0.15%** of total factor productivity growth (out of a total of 0.78% and 0.40% respectively). In contrast to the work undertaken by Coe and Helpman (1995), the authors do not find that international trade is one of the channels through which technology transfers are realised.

Citing the many studies assessing the extent of domestic and international R&D spillovers, Braconier and Sjöholm (1998) consider two models where productivity growth is caused by spillovers from R&D and analysed using a sample of nine manufacturing industries in six large OECD countries between 1979 and 1991 (France, Germany Italy, Japan, the United Kingdom and the United States). The first model is based on traditional productivity analysis, while the second model is built on endogenous growth theory. The empirical results indicate stronger support for the latter modelling approach (the endogenous growth theory approach)[88]. The results suggest that intra-industry spillovers from R&D exist but that these *intra-industry* spillovers are foreign in origin (**0.018** coefficient on 'foreign industry R&D expenditures' and statistically significant compared to a coefficient of 0.010 on 'domestic industry R&D expenditures' and statistically insignificant). There are no discernable inter-industry spillover effects.

[88] However, the results from the estimations do not provide any support for *intra-industry* spillovers from R&D. In addition, neither domestic R&D in other industries nor foreign R&D in other industries has a positive and significant effect. This suggests that there are no *inter-industry* spillovers from R&D in the traditional model.

The authors also undertake a disaggregated analysis and assess the extent to which the effect differs between R&D-intensive industries and others. In this analysis, industry-specific R&D has a positive and significant effect on productivity growth in R&D intensive industries. Counter-intuitively, there is a negative effect on productivity growth from own R&D in industries that are not R&D-intensive. Hence, the positive growth effect from industry-specific R&D is confined to the R&D intensive industries.

Bernstein (1988) studies productivity spillovers in Canadian industries[89], and finds substantial differences between industry level returns to R&D investment and investment in physical capital. Specifically, across the nine industries, the gross private rates of return on R&D capital were generally 2.5 to 4 times greater than the rates calculated for physical capital (see also Jaffe (1986) and Bernstein and Nadiri (1988)). Presented in Table 22, all nine industries had consistently high private returns (not just the R&D intensive).

Table 22: Private rates of return to R&D and physical capital (%)

	R&D Capital	Physical Capital
Primary Metals	0.26	0.09
Metal fabrication	0.29	0.10
Non-electrical machinery	0.24	0.10
Transportation equipment	0.28	0.09
Electrical products	0.38	0.11
Rubber and plastics	0.47	0.12
Petroleum products	0.40	0.11
Chemical products	0.25	0.10
Gas and oil wells	0.33	0.11

Source: Bernstein (1998)

In Table 23, the social rate for each industry is decomposed according to the spillovers that are generated by the industry, illustrating the spillover network linking the ‘origin’ and ‘destination’ industries. For example, R&D capital stock in the primary metals industry was estimated to only affect the production cost of metal fabricating industry with an associated 0.16 rate of return arising from this inter-industry spillover. Adding the private rate of return, which was 0.26 (see Table 22) to the spillover return, yielded a social rate of 0.42.

Table 23: Decomposition of social rates of return

	PM	MF	NEM	TE	EP	RP	PP	CP	GOW	SOC
Primary Metals		0.160								**0.42**
Metal fabrication										0.29
Non-electrical machinery	0.390			0.073	0.227			0.006		0.94
Transportation equipment						0.002			0.010	0.29
Electrical products										0.38
Rubber and plastics			0.422						0.002	0.89
Petroleum products	0.025		0.100		0.341					0.87
Chemical products	0.031						0.526			0.81
Gas and oil wells			0.040							0.37

Source: Bernstein (1998): SOC – Social rate of return

[89] Nine Canadian industries were considered: primary metals, metal fabricating, nonelectrical machinery, transportation equipment, electrical products, rubber and plastics, petroleum products, chemical products, gas and oil wells. The data for these industries were obtained from published sources of Statistics Canada for the period 1963 to 1983

However, the analysis is not all positive, and Bernstein finds that R&D obtained via spillovers is a substitute for R&D conducted by the firm itself in sectors with low propensity to invest in R&D. In other words, firms in low-propensity industries are deterred from investing in R&D if they can obtain the knowledge through spillovers. Conversely, firms in industries with high propensity to invest in R&D use the diffused knowledge as a complement to the knowledge acquired through own research, and thus increase spending on R&D (see also Quella (2007)).

Scherngell *et al* (2007) use a panel of 203 NUTS-2 regions covering the 15 pre-2004 EU-member-states to estimate the impact of knowledge spillovers over the period 1998-2003 (between five major industries[90]). They estimate these effects using patent applications as a measure of R&D output to capture the contribution of R&D to regional productivity at the industry level (directly and spillover effects). The study provides evidence that a region's total factor productivity depends not only on its own knowledge capital but also on inter-regional knowledge spillovers. There is also a substantial amount of heterogeneity across industries. The authors demonstrate that two of the industries considered (electronics and chemical industries) produce cross-regional knowledge spillovers that have positive and highly significant productivity effects. The coefficients on out-of-region stocks of knowledge from foods and beverages, textiles and clothing, and transport and equipment are not significant. The results also suggest that inter-regional knowledge spillovers and their productivity effects are, to a substantial degree, geographically localised (this finding is consistent with the geographic hypothesis of knowledge spillovers (see Aiello and Cardamone (2008) and the evidence presented in Section 7.3).

The same authors (Fischer et al (2009)) use patent stocks as a proxy for regional capital stock of knowledge in 203 European regions over the period 1997-2002. Their main results highlight the significance of cross-regional knowledge spillovers on TFP, suggesting that increasing the stock of out-of region knowledge capital by 1% raises the average TFP in the receiving region by around **0.13%**. Consequently, the findings support the hypothesis that regional TFP does not only depend on the internal stock of capital knowledge, but also on the stock of knowledge capital of neighbouring countries.

The final two papers in this section have similar aims as the previous work considered relating to R&D spillovers. Singh (2004) explores the relationship between productivity growth and both domestic and international knowledge spillovers in Korean manufacturing industries, using panel data for 28 industries over the period 1970-2000. To empirically verify the extent of domestic and international knowledge spillovers, the authors follow the endogenous growth approach. The analysis finds strong productivity effects from industry's own R&D (direct effect) as well as domestic and foreign knowledge spillovers. The authors find that international knowledge spillovers transmitted by trade played a dominant role in explaining productivity growth in the Korean manufacturing industries during the 1970s and 1980s, but the international knowledge spillovers did not play any significant role in the 1990s. In another paper focusing on Korean manufacturing industries, Kim, Maskus and Oh (2009) assess the contributions of patents to total factor productivity (TFP) performance during the period 1981–1999. The results show that both domestic and foreign-resident patent applications have significant positive effects on productivity and

[90] Food, beverages and tobacco (DA), textiles and clothing (DB, DC), fuels and chemicals (DF, DG, DH), electronics (DL), and transport and equipment (DM).

that foreign resident patent applications have a larger effect than domestic patents in improving TFP in Korean manufacturing. The authors also find evidence of knowledge spillovers among industries, in that the patent applications of other industries increase TFP in any single industry.

6.2.4 Firm level

In this section, we provide some additional information on the extent of R&D spillovers on firm-level outcomes. In general, the analyses broadly agree that spillovers do exist between firms, but the size of the spillovers depends entirely on the analysis adopted, the R&D channels considered and the level of aggregation. However, the analysis also presents some information on the nature of the barriers that may limit the extent to which spillover effects are exploited (such as the lack of human capital within firms and the extent of the interaction between firms in the R&D sector and those not actively engaged in R&D). In many respects, there is some degree of overlap between a number of the papers presented in this section and the equivalent section assessing the productivity spillover effect of human capital accumulation – especially in relation to the absorptive capacity of human capital.

In terms of the impact and extent of R&D spillovers at firm level, the work by Cincera (2005) is based on a representative sample of 625 worldwide R&D intensive firms, which are observed between 1987 and 1994. The estimation strategy used in the paper to measure R&D spillovers builds on the methodological approach developed by Griliches (1979) and first empirically implemented by Jaffe (1986). The author combines firms into clusters, based on their technological distance (i.e. facing similar technological opportunities). Division by clusters allows splitting the total stock of spillovers into a local (firms in the same cluster) and external stock (firms facing different technological opportunities). The empirical findings suggest that both local and external R&D stocks have a significant effect on firms' productivity growth, with external R&D stocks having the larger effect. In fact, output elasticity to local R&D spillover stock ranges across different specifications between **0.11** and **0.16** (implying that a 1% increase in the volume of local R&D results in a 0.11%-0.16% increase in firm-level output), while the elasticity of output with respect to external R&D spillover stock is estimated to be between **0.40** and **0.62**. Interestingly, the analysis also considers the impact of R&D undertaken within the firm itself on output and finds that the estimated elasticities are around **0.24**. The results seem to suggest that inter-industry spillover effects are relatively more important than the intra-industry ones.

In a second piece of analysis considering the same issue, Ejermo (2004) uses cross-sectional data on Swedish firms to examine both the direct impact on firm's own productivity and productivity spillovers across firms and industries. The starting point for the analysis is the apparent paradox of "over-investment" in R&D and patented technological development occurring in Sweden, possibly associated with a relatively limited spillovers effect. The author uses data on 264 R&D-performing firms and 160,000 non-R&D-performing firms, to examine the extent to which R&D spillovers extend beyond the R&D sector itself. The results show that R&D expenditure has a large and positive impact on own TFP growth in Sweden, with the rate of return around 23%. There is also some evidence of R&D spillovers among the R&D performers, around 0.2%, although these estimates are not entirely robust. On the other hand, there is evidence of a very small but significant effect of R&D spillovers of non R&D firms. While this effect is small at firm level (around **0.0005-0.001%**), it is likely to have a substantial effect on TFP at aggregate level (see also Battu *et al* (2003)). The author also suggests that the low level of R&D spillovers to Swedish firms may be explained by a high degree of interaction between R&D performers and foreign firms, and a lack of absorptive capacity by Swedish non-R&D firms resulting from low education levels in parts of the industry.

Blazsek and Escribano (2009) investigate US patent data to account for observed and unobserved spillovers between American firms from 1979 to 2000. They find that both observable and unobservable knowledge spillovers exist, and are significantly positive. Following the approach of Fung (2005)[91], they argue that patents have two economic functions: (1) legal protection of knowledge capital and (2) disclosure of the specifications of innovations. The second function facilitates information-sharing agreements among firms (such as licensing and patent-sharing agreements) and imitation of past innovations. The authors suggest that patents and patent citations may be good measures of R&D spillovers. The authors describe patent citations as observable knowledge spillovers and, using some highly complex econometric modelling, demonstrate significant inter-industry observable R&D spillovers (see also Mason et al. (2007)).

Recent literature making use of the INNODRIVE methodology

We have already introduced in section 2.1 the recently developed INNODRIVE methodology, which constructs values for intangible capital stocks, disaggregated by IT, R&D and organisational capital. Evidence on the direct impact of organisational capital on productivity was presented in section 5.1. Below, we present the findings of the effect of R&D and IT spillovers on productivity.

Linking the assessment of the extent of intangible investment and the effect of intangibles on productivity, Piekkola (2011) uses linked employer-employee data[92] to assess the importance of intangible capital across the three main categories - organisational, R&D and ICT capital – for the economic performance of firms and regions in Finland. From a previous paper (Ilmakunnas and Piekkola (2010)), it was assessed that Finland is one of the most R&D-intensive economies in Europe (intangible capital investment accounts for 6.7% of value added and intangible capital stock is 42% of the fixed non-residential capital stock of firms and is evenly spread between small and large firms). In firm-level panel regressions for the years from 1998 to 2008, unsurprisingly, the authors find robust evidence of intangible capital increasing both productivity and profitability. Doubling the intangible capital intensity of firms increases average productivity by approximately 7% (ranging from 5-9% depending on the model specification). The estimate of the impact of intangible assets is approximately 7/12ths that of tangible capital and 1/7th the impact of human capital. In comparing the impact of the various intangible asset components, the analysis indicates that the elasticity of output with respect to organisational capital stands

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[91] Fung, M. K., 2005, Are Knowledge Spillovers Driving the Convergence of Productivity among Firms? *Economica*, 72, 287-305

[92] This analysis is based on a combination of LEED data from the Confederation of Finnish Employers, Statistics Finland Regional Accounts and balance sheet data collected by private company (Suomen Asiakastieto). The dataset offers information on, e.g., employment, wages, tangible and intangible capital, output, value added, covers the period from 1995 to 2008, comprises around 1850 firms per year with turnover more than 1.5 million€ with around 390 000 employees, allocates establishment employment to two-digit manufacturing and three-digit service industries (NACE rev.1) and to 65 economic regions based on 74 NUTS4 regions in 2008

at 3.5% (i.e. a 100% increase in organisational capital increases productivity by 3.5%), while the elasticity with respect to R&D stands at 8% and the elasticity with respect to IT stands at -10%.

However, of more interest and relevance to this section of the report, the authors also demonstrate that the effect of regional spillovers on productivity is positive, while the effect on profitability is zero. Specifically, the effect of regional intangible capital intensity on productivity is around 1.6%. However, disaggregating by specific intangible component shows that the positive spillovers are completely driven by the ICT intensity (elasticity stands at 1.7%), while both R&D and organisational capital do not seem to have any significant spillover effect on productivity. However, of particular interest is the fact the regional level R&D is estimated to have a negative impact on firm-level productivity (see also Riley and Robinson (2011a) for a similar result in relation to R&D which was presented in section 6.1). Overall, the analysis illustrates that the elasticities are of the same magnitude as found in Germany (Geppert and Neumann (2010)), but less than in the UK (Riley and Robinson (2011b))[93]. Regional spillovers were evident for all intangibles irrespective of their type in Germany, while in the UK only organisational spillovers mattered (similar to Finland).

In terms of other spillover effects addressed in the paper, the authors also consider the impact of firms clustering and the impact of regional population density on firm performance. The authors find that firms in large metropolitan areas are 10% more productive, for unexplained reasons, than those located in rural regions, and about 5% more productive than establishments in small metropolitan areas. It should be noted that the metropolitan effect is over 6 percentage points higher if human capital is not controlled for, and the authors suggest that a significant part of all urbanisation effects relate to agglomeration of skilled workers (see also Henderson and Cockburn (1996) and Glaeser and Maré (2001)).

6.2.5 Other international papers

Los and Verspagen (2000) use American manufacturing data at the micro level to investigate the theoretical results from the basic endogenous growth model. In particular, they assess the impact of technology spillovers on productivity at the firm level (using patent information to proxy technology spillovers). Panel data for American manufacturing firms on sales, physical capital inputs, employment, and R&D investments are linked to R&D data by industry. The authors construct four different sets of 'indirect' R&D stocks, representing technology obtained through spillovers. Spillovers are found to have significant positive effects on productivity, although their magnitudes differ between high-tech, medium-tech and low-tech firms.

Aiello and Cardamone (2008) use panel data for the Italian manufacturing sector to investigate the effect of R&D spillovers on firms' productivity, using panel data between

[93] Note also that Riley and Robinson (2011) also consider the impact of location in an urban area on firm-level productivity and labour productivity. They find that location in a heavily populated area (more than 5000 individuals per square kilometre) increases firm-level productivity by approximately 7%, while labour productivity is increased by approximately 5%.

1998 and 2003[94]. They find that spillovers from R&D affect Italian manufacturing firms' productivity positively. Specifically, the authors demonstrate that all output elasticities are positive and highly significant. For conventional inputs (i.e. capital and labour), output elasticities range from 0.37 to 0.49 in the case of labour (implying that doubling the stock of labour would increase output by between 37% and 49%), while the maximum and the minimum elasticities associated with physical capital are 0.23 and 0.17. The authors also demonstrate a relatively consistent contribution of the internal stock of R&D capital to output (output elasticity is about 11%). However, the authors find that the magnitude of the impact of R&D spillovers on the level of firm production is high (0.35) when considering geographical R&D spillovers, but lower (0.14) when the geographical aspect of the models is ignored. This result provides indirect evidence of the importance of geographical proximity capturing R&D spillovers in Italy.

6.3 Summary of direct to indirect effects

In an attempt to draw conclusions regarding the relative importance of the direct and indirect effect of investment in intangible assets, Figure 6 summarises the findings from studies that provide estimates of both the direct and spillover effects for any of the three main types of intangible assets (individually or combined) on the outcome measure of interest. This is also presented in Table 24.

The shaded areas in Figure 6 represent the level at which spillovers might occur according to the analyses undertaken by the various authors, with the individual (worker) in the upper left corner, moving outward through firms, regions (and intersected with industry), the national level and international level. The arrows indicate the exact direction of the separate effects arising from investments in economic competencies, ICT capital, and R&D, and their thickness illustrates the size of the external impact relative to the direct effect of increasing each type of intangible. Several conclusions can be drawn from this cross-study analysis.

The evidence seems to indicate that externalities from increases in regional **ICT capital** on firm-level productivity seem to be larger than the direct effects of raising that firm's own investment in computerised information (see Riley and Robinson (2011a) and Geppert and Neumann (2011)).

Considering spillovers from investment in **R&D**, the evidence suggests that these are strongest at an international level, where the spillover effects are larger than the direct effects, with some additional evidence indicating relatively strong R&D externalities within regions. In particular, as emphasised by the results of Engelbrecht (1997), Coe and Helpman (1995), Coe et al. (2009), Madsen (2008) and Lumenga-Neso (2005), a country benefits at least as much from an increase in international R&D investment in terms of increased domestic total factor productivity, than from an increase in its own national R&D expenditures. In addition to this international perspective, Geppert and Neumann (2011) show that the externality effect of raising a region's investment in R&D on the labour

[94] 4,500 observations per year are composed for the universe of manufacturing firms with more than 500 employees and a stratified sample of firms with more than 10 employees)

productivity of firms in that region is larger than the direct effect on productivity of a firm's own R&D activities. The work of Aiello and Cardamone (2008) reaches the same conclusions for intra-regional spillovers within industries.

While the evidence regarding the relative size of spillovers from **economic competencies**, i.e. education and training, varies across studies, some main points can be established.

There is some evidence that there is a high ratio of indirect to direct effects from regional human capital to firm-level productivity (see Riley and Robinson (2011a)). Focusing on the manufacturing sector, Galindo-Rueda and Haskel (2005) confirm that a firm benefits more from an increase in aggregate education in the region it operates in than from raising the share of highly educated workers in its own workforce.

The spillover effects of increasing *regional education* levels on the wages of individuals may be substantial (see Moretti (2004a), Muravyev (2008) and Rauch (1993).

Some of the evidence indicates that a worker gains larger individual wage increases from an increase in industry-level human capital than if their own level of training were increased by an additional year (see Dearden et al., 2005).

Within-firm human capital externalities also appear to be relatively large when compared to the direct effects. Battu *et al*. (2003) and Metcalfe and Sloane (2007), who analyse both the spillovers stemming from increasing an individual co-worker's education and of raising a firm's entire workforce education on individual wages in that firm, find that increasing the education of all co-workers by approximately one year results in larger wage increases for a worker than if the latter raised his own education by one year. In contrast, a one-year increase in a single co-workers education leads to wage increases for an individual worker that are much weaker than the direct effect of raising his own education (approximately 3.5% of the effect of raising own-worker training).

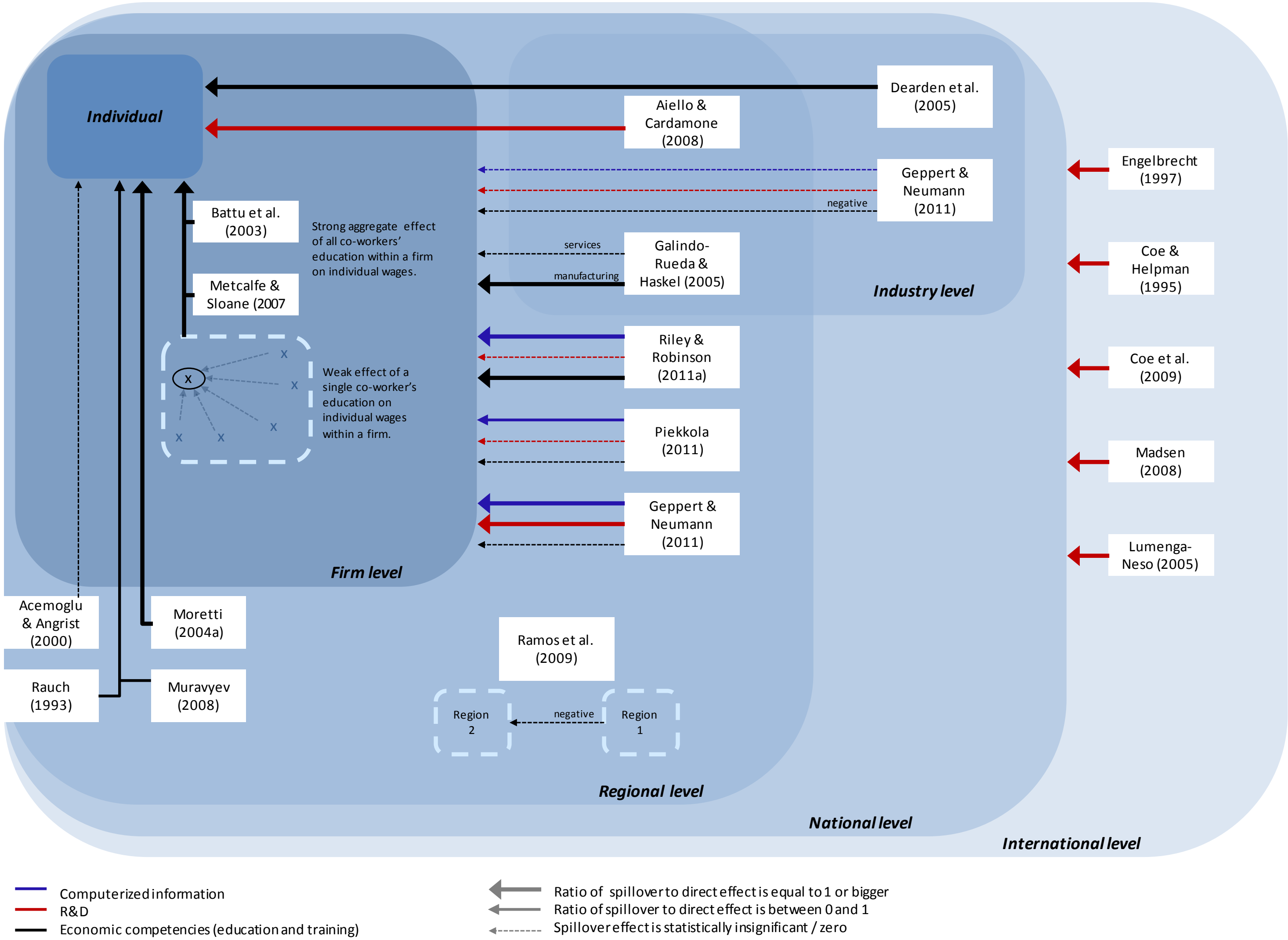
In summary, a significant amount of evidence points to productivity spillover effects arising from the three types of intangible assets that are at least as large as the direct productive effects of the latter, highlighting their impact at different levels of the economy.

Table 24: Direct effect and spillovers of intangible capital investment (by category) on productivity

Source	Country	Metric	Direct impact of 1% ↑ in:				Spillover	Spillover impact of 1% ↑ in:				
			Computerised Info	R&D	Economic Competencies	Total IIA		Computerised Info	R&D	Economic Competencies	Total IIA	Ratio I:D
Riley & Robinson (2011a)	UK	Firm-level labour productivity	0.014% ↑	0.031% ↑	0.036% ↑	n.a.	Regional	0.023% ↑	0.013 % ↓[1]	0.067% ↑		1.5-2.0:1
Piekkola (2011)	FIN	Firm-level labour productivity	0.105%↓	0.082%↑	0.035%↑	0.073%↑	Regional	0.012%↑	0.001%↑[1]	0.002%↑[1]	0.016%↑	1:5
Geppert & Neumann (2011)	GER	Firm-level labour productivity	0.005%↑	0.006%↑	0.005%↑	0.01%↑	Regional, Own-industry	0.018%↑, No effect	0.017%↑, No effect	No effect, 0.001%↓	0.083%↑ 0.001%↑	8:1 1:10
Coe & Helpman (1995)	OECD	National TFP	n.a.	0.078-0.097%↑	n.a.	n.a.	International	n.a.	0.06-0.092%↑, 0.081%↑ (UK)	n.a.		c. 1:1
Coe et al.(2009)	OECD	National TFP	n.a.	0.072-0.134%↑	n.a.	n.a.	International	n.a.	0.165-0.213%↑			1.5-2.0:1
Engelbrecht (1997)	OECD	National TFP	n.a.	0.057-0.08%↑	n.a.	n.a.	International	n.a.	0.061-0.087%↑	n.a.	n.a.	1:1
Madsen (2008)	OECD	National TFP	n.a.	No effect	n.a.	n.a.	International	n.a.	0.09-0.22%↑	n.a.		
Lumenga-Neso (2005)	OECD	National TFP	n.a.	0.019-0.023%↑	n.a.	n.a.	International	n.a.	0.17-0.208%↑	n.a.		14:1
Aiello & Cardamone (2007)	ITA	Firm-level output	n.a.	0.105-0.144% ↑	n.a.	n.a.	Intra-industry/Regional	n.a.	0.14-0.35% ↑	n.a.		1.5-2.0:1
Battu et al. (2003)	UK	Individual wages	n.a.	n.a.	1 year ↑ in own education → 5.88% ↑ wages	n.a.	Intra-firm	n.a.	n.a.	1 year ↑ in 1 co-workers education is worth 3.5% of a 1 year ↑ in own education		1:28 (1.5:1)*
Metcalfe and Sloane (2007)	UK	Individual wages	n.a.	n.a.	1 year ↑ in own education → 6.4% ↑ wages	n.a.	Intra-firm	n.a.	n.a.	1 year ↑ in 1 co-workers education is worth 3.2% of a 1 year ↑ in own education		1:31 (1.5:1)*
Ramos et al. (2009)	ESP	Regional labour productivity	n.a.	n.a.	0.017% ↑[2]	n.a.	Inter-regional	n.a.	n.a.	Negative		
Moretti (2004a)	US	Wages of workers with certain level of educ	n.a.	n.a.	0.4% ↑in graduate wages[3]	n.a.	City-individual	n.a.	n.a.	1.6% (1.9%) ↑ in wages for high school completers (non)[3]		4:1
Dearden et al. (2005)	UK	Individual wages	n.a.	n.a.	0.30% ↑[4]	n.a.	Intra-industry	n.a.	n.a.	Approx half (0.15%) attributable to spillovers		1:1
Galindo-Rueda & Haskel (2005)	UK	Firm-level productivity	n.a.	n.a.	0.218% ↑ in services 0.303% ↑ manufacturing	n.a.	Regional-firm	n.a.	n.a.	↑0.32% (services)[1] ↑1.36% (manufacturing)		0 4.5:1
Acemoglu & Angrist (2000)	US	Individual wages	n.a.	n.a.	7.3% ↑[6]	n.a.	State-individual	n.a.	n.a.	1-2% ↑[1]		0
Rauch (1993)	US	Individual wages	n.a.	n.a.	4.8% ↑[7]	n.a.	City-individual	n.a.	n.a.	2.8-5.1% ↑		0.5-1:1
Muravyev (2008)	RUS	Individual wages	n.a.	n.a.	3.6-4.2% ↑[8]	n.a.	City-individual	n.a.	n.a.	1-2% ↑[3]		0.33:1

Note:
IIA = investment in intangible assets
Ratio I:D represents the ratio of the indirect effect to direct effect (where both effects are estimated)
1 statistically insignificant
2 corresponding to a 1% increase in the regional average years of tertiary studies
3 corresponds to a 1% increase in the city share of college graduates
4 corresponding to a 1 percentage point increase in the proportion of employees trained
6 corresponds to a 1 year increase of individual schooling (and a 1 year increase of average schooling for the external effects reported)
7 corresponds to a 1 year increase in individual formal education (and a 1 year increase in average city-level education for the external effects reported)
8 corresponds to a 1 year increase in individual schooling
*Note that the upper ration refers to the ratio of the indirect to direct effect if 1 co-worker receives additional education, while the lower ratio represents the ration if all co-workers receive additional education
Source: London Economics (2011)

Figure 6: Direct effect and spillovers of intangible capital investment (by category) on productivity



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7 Knowledge spillovers

The literature on knowledge spillovers mainly focuses on R&D, although there is a link between these R&D spillovers and human capital in terms of absorptive capacity. Three main strands of research have emerged: papers focusing on patent issuance or applications and citations; papers focusing on innovative or imitative R&D; and finally, papers that focus on the absorptive capacity of the spillover recipient. We discuss these interchangeably at the different levels at which the knowledge spillovers may exist, along the lines of previous sections.

7.1 Summary

This section presents the empirical evidence on knowledge spillovers. Knowledge spillovers can be thought of as an outside influence of a firm's knowledge base, without that influence being identified to carry through to firm productivity. On the whole, the literature shows that knowledge spillovers exist and account for an important share of knowledge production of innovation.

One stream of literature suggests that knowledge externalities from other firms at the international level appear to affect domestic firms' knowledge production. These studies differentiate between technological leaders and followers, and show that leaders' knowledge spills over to followers, and that knowledge in follower countries grows more quickly than would otherwise be the case. The estimates frequently provide values between 20% and 50%. University research affects firms' knowledge accumulation positively and significantly, and although the studies apply different estimation approaches, employ different data, and achieve different results, there seems to be a general agreement in the literature that a 10% increase in spending on university research leads to an increase in patents for firms around 1%. There are some issues in relation to the nature of the firms that might benefit from university research (i.e. only the technologically advanced), as well as the fact that the knowledge spillovers identified operate only from universities to businesses, and not in the opposite direction.

Using patent data, there is a wealth of literature studying the spatial or geographic elements of knowledge spillovers. The general consensus is that knowledge can only spill across a certain distance. Different studies identify different distances, often between 50 miles and 200 miles. Another approach to the study of the geographical dimension of spillovers is to observe where firms locate. These studies show that technologically advanced firms locate close to universities and less advanced firms locate closer to other firms.

7.2 Cross-country and national level

One way for knowledge to diffuse from one firm to another is via *co-operative* R&D activities. Cassiman and Veugelers (2002) study the extent of co-operation among Belgian firms using the responses given to the Community Innovation Survey (CIS). The dependent variable in the estimation is a dummy variable (taking value 1 if the firm engaged in R&D with another firm and 0 otherwise). To understand the determinants of co-operation, the authors collapse measures of the 'perceived' importance of knowledge spillovers to firms in order to generate a one-dimensional measure of incoming spillovers between 0 and 1.[95] They also construct measures of firms' appropriability of incoming spillovers on the basis of their valuation of the effectiveness of legal and strategic protection of innovations.[96] Legal protection is included as an industry-wide background variable, whereas appropriability (based on strategic protection) enters at the firm level. The variable is designed to assess the extent to which effectiveness of protecting innovative advances influences firms' propensity to co-operate. Firms with high values of appropriability (i.e. firms that protect innovations effectively) may have a different view on investing in co-operative R&D than firms that are less effective due to the lower risk of disclosing advances to competitors. The authors include permanent R&D in the estimated equation, to account for firms' own R&D activity. The variable is constructed as a dummy taking the value 1 if the firm's R&D activities have a "permanent character".[97] Reflecting the empirical evidence on absorptive capacity (see section 5), firms' ability to absorb knowledge spillovers is a function of the number of highly skilled workers employed, or their own knowledge production (and as such permanent R&D activity provides a proxy for the ability of firms to absorb knowledge spillovers).

Abramovsky *et al*. (2009) build on Cassiman and Veugelers (2002) study of the Belgian manufacturing sector, and also study the determinants of co-operative research using data on innovative firms in manufacturing and services in the United Kingdom, France, Germany, and Spain from the same data source. The marginal effects of incoming spillover and appropriability from both papers are presented in Table 25, along with the coefficients to the industry level of legal protection, the absorptive capacity of the firm measured by permanent R&D expenses, and the industry-level of co-operation.

Table 25: Determinants of firms undertaking co-operative R&D activities

	United Kingdom	France	Germany	Spain	Belgium[a]
Incoming spillovers	0.174**	0.242***	0.009	0.031	0.472***
Appropriability	0.078**	0.195***	0.242***	0.079***	0.195*
Industry-level legal protection	-0.133	0.101	-0.195	-0.040	-0.297
Permanent R&D	0.371	0.186**	0.638*	0.180*	0.288***
Industry-level of co-operation	0.943***	0.733***	0.744***	0.699***	0.930***
N:	1,145	3,590	1,183	2,747	411

Source: Cassiman and Veugelers (2002) and Abramowsky et al. (2005)
***: significant 1% level, **: significant 5% level, *: significant 10% a: Belgian results specific to manufacturing sector.

[95] The original parameters were patent information; specialist conferences; meetings and publications; trade shows and seminars.

[96] The original parameters for this measure were secrecy for protecting new products; complexity of products or process design for protecting new products; lead time on competitors for protecting new products, as well as secrecy for protecting processes; complexity of product or process design for protecting processes; and lead time on competitors for protecting processes.

[97] Cassiman and Veugelers (2002) Table A1, p. 1180.

The table shows that firms emphasising *incoming spillovers* in their R&D procedures (i.e. perceiving knowledge spillovers to be more important) generally engage in co-operative R&D. The positive coefficient relating to appropriability (i.e. the result that improved ability of protecting innovation is conducive to R&D co-operation) is not surprising, as the risk of losing an edge gained from R&D is less than for other firms. The coefficient on permanent R&D (the measure of firms' absorptive capacity) should be interpreted differently to the other variables. The variable is a dummy variable, and as the presented estimates are marginal effects from a probit model, the coefficient is interpreted as the change in the probability of engaging in co-operative R&D if permanent R&D changes its value from 0 to 1. The positive estimate means that better absorptive capacity makes it more likely that a firm would undertake co-operative R&D, which makes sense, as better absorptive capacity indicates that the firm is able to reap the spillovers from its partner.

Houser (1996) estimates international knowledge spillovers from R&D between France, Germany, Japan and the United States. The author distinguishes between innovative and imitative R&D on the basis of patent data and Basic Science and Technology Statistics from the OECD, and estimates spillovers from innovators to imitators. Innovators are defined as the firms that take out a patent, and imitators are the firms who win the right to imitate the innovator's product. The author finds that imitators absorbing spillovers from innovators may be 36% more effective in adding to their own stock of knowledge (i.e. the knowledge they succeed in extracting from the innovator). In addition, it is found that imitative R&D costs 73% of the R&D cost for innovators, meaning that the firms that undertake imitative R&D efforts gain access to the same levels of knowledge and information as innovators at a significantly lower price. Using a different specification, however, it is found that imitators would be approximately two-thirds as effective as they would have been in the absence of knowledge spillovers. Both results, she argues, are plausible, because the positive effect arising from an increased knowledge base may be counteracted by the subcontracting expenses.

Mancusi (2008) analyses knowledge spillovers for selected OECD countries on the basis of patent citations. The findings indicate that knowledge transfers from technology leaders (Germany, Japan and the US) impact domestic knowledge production more than spillovers from the other countries. International spillovers from leaders affect the probability of taking out an extra patent with an elasticity of 0.07, meaning that following a 10% increase in the number of patents applied for by technology leaders, the number of patents applied for by domestic firms increases by 0.7%. This estimate corresponds to approximately half the estimate of the elasticity of patent applications with respect to own R&D. In addition, the author shows that the greater a country's absorptive capacity, as measured by the share of patents that cite previous work by the applicant, the larger the impact of spillovers on knowledge production, and that the effect of absorptive capacity is increasing in the technological distance to the technological frontier. The technological distance to the frontier is measured by foreign citations to domestic patents. The combined results indicate that countries that are far from the technological frontier are able to catch up at a lower cost than countries on the frontier, because the knowledge they can source from leaders is cheaper than generating new knowledge. The analysis also implies that the acquisition of knowledge is less expensive than for those countries that are closer to the technological frontier. This finding also reinforces the findings of those studies that suggest productivity convergence between countries over time (see also Coe and Helpman (2005) and Griffith, Redding and Van Reenen (2003)).

7.3 Regional and local level

University Research

The impact of university research on private firms' R&D production has been studied intensely. Jaffe (1989) uses US state-level time-series data to study the existence of geographically mediated spillovers from university research. Firms' R&D production is represented by the number of patents issued to corporations at the state and industry levels. The data allow Jaffe to include private expenditures on R&D, but only at the aggregate state level and not in individual industries. University research is represented by expenditures, which is available at the academic departmental level. The industries specified in patent issuances are based on more than 300 patent classes; however, in order to assign university research and patents to the same categories, the author settles on five groups. In order to estimate the geographic dimension of spillovers, the author includes geographic coincidence, which is the (un-centered) correlation between university expenditure and the total number of professionals employed in R&D laboratories in the same region (to understand the extent of available university research on potential beneficiaries). The correlation is calculated at the state level using a formula that aggregates the information from all standard metropolitan statistical areas in each state. The estimated equation is logarithmic in all variables[98], which means that the coefficients can be interpreted as elasticities[99]. Jaffe (1989) finds that the elasticity of patent issuance with respect to industry R&D is 0.940, with the individual industries ranging from 0.844 to 0.989. This implies that following a 10% increase in R&D expenditure, the model predicts a 9.4% increase in the number of patent applications. The elasticity with respect to university research is 0.103. This suggests that following a 10% increase in university expenditure, a 1.0% increase in the number of patent applications from industry would be expected.

Acs *et al*. (1994) build on Jaffe's model and reuse some of his data. They are interested in shedding light on the paradox that some small firms innovate despite spending negligible sums on R&D. They find that total industry R&D in a state impacts large firms with an elasticity of 0.950 and small firms by 0.550, meaning that large firms are better at appropriating the industry-wide knowledge base than small firms. A large firm in a given state and industry increases its innovation output by 0.95% if the industry-wide R&D stock increases by 1%, while the corresponding figure for small firms is just 0.55% or 40% less. However, as data are at the state level and large firms are likely to spend more on R&D in absolute terms than small firms, it is not entirely clear that the large firms benefit through spillovers rather than the direct effects arising from the firms' own R&D activity.

The analysis also demonstrates that university research affects large firms with an elasticity of 0.446 and small firms by 0.661. Interacted with the measure of geographic coincidence, large firms benefit with an elasticity of 0.033 and small firms by 0.111. The last result shows that small firms benefit from university research occurring in the same locality to a significantly greater extent than large firms (i.e. a small firm will increase its innovation output by approximately 1.1% following a 10% increase in university research

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[98] Originally, the dependent variable was an integer, and some state-industry combinations did not take out any patents in some years. In those cases, the values of the logarithmic representation of the variable were set to -1.

[99] The elasticity of X with respect to Y is the answer to the question: How many percent does X change if Y increases by 1%.

expenditure compared to a 0.33% impact on large firms). As discussed in section 3, academic research is more basic and broad than corporate research, so knowledge of academic findings equips employees to utilise more specific and complex industrial R&D obtained through spillovers[100]. Another suggested reason for the greater effect on small firms is that they are more dependent on hiring graduates from the local area, as the geographical reach of small firms may be limited.

Faggian and McCann (2006) establish an indirect channel between research conducted by universities and the innovation output of firms in the same region. They investigate the effect of British university graduates on regional R&D performance, using data from the Higher Education Statistics Agency questionnaire on 190,000 UK students for the year 2000. R&D performance is measured by the number of patent applications, provided by Eurostat data. They find little or no evidence of a positive significant effect of university research on regional innovation, implying that research conducted by universities does not constitute a source of significant knowledge spillovers for the productivity of firms located in the same region. However, they suggest an indirect link between universities and regional innovation performance. In particular, they find that universities attract potential high-quality human capital in the form of students to their regions, and that many of these students tend to stay in these regions to enter employment after graduation and subsequently contribute to regional productivity. Hence, the authors' evidence emphasise that spillovers from universities are embedded in students who, after graduation, stay in the same region and improve its productivity as highly skilled human capital, rather than arising from the direct co-operation between firms and universities.

The geographic limit of knowledge spillovers – US evidence

The importance of geographic proximity as a facilitator of knowledge spillovers, which was a parameter in Jaffe's (1989) paper, has been studied further by a number of authors. Audretsch and Feldman (1996) use a database of 8,074 commercial innovations introduced in the US in 1982. They perform their analysis at the US state level, and group innovations according to four-digit SIC codes. They include the *Gini coefficient* of industry-specific state output[101] and find that the propensity for innovative activity by firms in industries where R&D intensity is large (i.e. high ratio of R&D expenditure to turnover) exceeds that which might be predicted by the Gini coefficient. This implies that the innovation over and above the volume predicted may be a result of knowledge spillovers. Using survey data, Adams (2001) studies localisation of academic and industrial knowledge spillovers in the United States. He finds that spillovers from university research are concentrated within 200 miles of the university, whereas spillovers from industrial research flow beyond 200 miles from the firm[102].

Anselin *et al*. (1997) study knowledge spillovers from universities to private firms at the US state and metropolitan statistical area (MSA) level. Their dataset is an expanded and

[100] This result is in line with the Guellec and Van Pottelsberghe (2004) who found that academic research has more general applications. See Section 5.2.

[101] Defined as the share of national value added in an industry that is created in the state, normalised by total value added from the manufacturing industry.

[102] The geographic boundary of 200 miles is included in the survey questions that have been tested amongst R&D practitioners.

improved version of the information used in the Jaffe (1989) analysis, which now holds more US states and at finer levels of disaggregation. The improved data allow the authors to use spatial lags in concentric circles rather than Jaffe's 'coincidence index' for determining the extent of localisation[103]. The authors find that knowledge accumulated at universities spills over to private firms over a range of 50 miles from the MSA in which the university is located. Perhaps an under-stated finding is that private R&D does not spill over in the opposite direction (from private firms to universities).

Belenzon and Schankermann (2010) utilise patent citations to study the geographical aspects of knowledge spillovers from university research. They find that the extent of spillovers from universities is highly dependent on proximity for the first 150 miles, and stable beyond. Controlling for distance, they also find that US state borders are highly significant for the likelihood of citing a patent held by a university, but insignificant when considering citations from academic publications[104],[105].

The geographic limit of knowledge spillovers – European evidence

Giuri and Mariani (2008) investigate the geographical extent of knowledge spillovers using the personal networks of holders of 6,750 European patents. They find that the educational background of the inventor is very important in determining knowledge spillovers. In particular, the analysis finds that inventors who hold a Ph.D. are especially likely to absorb knowledge from greater distances, but benefit comparatively less from local innovation. This result is robust to controls for moving patterns and sector. The analysis also finds that although knowledge spillovers are enhanced through geographic proximity, in localities where there is intensive R&D and associated knowledge spillovers, there may be some reluctance to engage with R&D activity taking place further afield. In particular, the analysis demonstrates that inventors in the top 1% of European regions, where the bulk of research in a specific technology are located, have a greater probability of benefiting from local spillovers, and a lower probability of seeking more distant inputs than other inventors.

If knowledge spills over between firms in a region or a locality, it is likely that entrants to the marketplace factor these effects into their localisation decision. Harhoff (1999) studies the effect of regional spillovers on firm formation in the electrical engineering and mechanical engineering, automotive and computer equipment sectors in the pre-1990 West German counties (i.e. the equivalent of a Local Authority in the United Kingdom (rather than a Government Office Region or Länder in Germany)). The author finds a high correlation between the regional knowledge base and firm formation, but stresses that the correlation could be caused by unobservable factors correlated with both variables. Alcácer and Chung (2007) use a similar approach, and hypothesise that firms choose their

[103] An archery target is an example of concentric circles. Assuming that the MSA is the centre of the target (yellow area), spatial lags is a way of including values of R&D from different distances to the centre. This means that all firms in the red, blue, black areas of the target enter the regression with their values aggregated with other firms of the same "colour".

[104] Based on Spanish regional data, Cabrer-Borrás and Serrano-Domingo (2007) find that local R&D carried out by public institutions affects firms' propensity to innovate positively. The same holds for innovation activity and public R&D available to trade partners.

[105] Artis *et al.* (2009) and Rosenthal and Strange (2008) study productivity spillovers from a geographic perspective. See Section 6.1.

location so as to maximise net inward spillovers. They test the hypothesis by investigating a dataset of firms or subsidiaries of foreign firms entering the United States between 1985 and 1994. They argue that there are three potential sources of spillovers: namely universities, federal research laboratories, and industrial research, and explore entrants' preferences across the three. By dividing the entrants into groups according to technological capability, they show that less advanced firms locate geographically close to industrial research centres and more advanced firms locate close to academic research centres. They argue that industrial research is more easily accessible than academic research, which implies that the effort and skill level needed to appropriate industrial research is less costly than academic research. The authors suggest that highly technologically skilled firms maximise net inward spillovers by minimising outward spillovers, whilst less technological firms have fewer outward spillovers to worry about, and therefore seek to maximise inward spillovers.

The above evidence implicitly assumes that knowledge spillovers are a positive activity. A firm, region, sector or country sharing knowledge with another leaves none of them worse off but at least one of them better off. That assumption is only valid if the region that generated the knowledge in the first place is able to reap some of the benefits from the innovation.

Caragliu and Nijkamp (2008) reverse this line of thought, and study the reasons why knowledge spills out of a region. They estimate the effect of *absorptive capacity*[106] on the retention of knowledge in a region (i.e. the ability to limit spillovers from a European area). They find that areas with low absorptive capacity tend to spill more knowledge to areas with higher levels of absorptive capacity than vice versa. Caragliu and Del Bo (2011) extend the idea and estimate outward spillovers from Italian regions. They base their analysis on social capital, R&D expenditure, and innovation in 'main' as well as 'neighbouring' regions. They find that innovation in neighbouring regions affects outward knowledge spillovers positively, which is expected, as the neighbouring regions improve their absorptive capacity through innovation. Social capital in the producing region is estimated to limit outward spillovers, which means that it helps to contain knowledge. The social capital is constructed on the basis of measures of the social infrastructure, trust and volunteering in the region.

7.4 Sectoral level

Griliches (1992) provides a review of the literature on the returns to own R&D and R&D performed by other firms. The review is segmented into two industry sectors: agriculture and manufacturing. For agriculture, the evidence suggests that the estimated returns to public R&D range from 11% to 83%, although most results lie between 30% and 50%. Within manufacturing, the range of estimates is wider, but the magnitude of the estimated returns is consistently large. In particular, the rate of return to outside R&D exceeds the rate of return to within-firm R&D in four of the studies, and in a fifth, the range of results extends beyond the return to R&D within the firm. Table 26 shows the main results from Griliches (1992). The conclusion drawn by the author on the basis of his work is that

[106] See Section 6.1 for an introduction to Cohen and Levinthal's (1989) concept of absorptive capacity.

"*taken individually, many of the studies are flawed and subject to a variety of reservations, but the overall impression remains that R&D spillovers are both prevalent and important*"

Table 26: Selected estimates of return to R&D and R&D spillovers		
	Rates of return to R&D	
	Within firm	From outside
I-O weighted approach		
Terleckyj (1974) (Total)	28	48
Terleckyj (1974) (Private)	29	78
Sveikauskas (1981)	10-23	50
Goto-Suzuki (1989)	26	80
R&D weighted (Patent flow) approach		
Griliches-Lichtenberg (1984)	46-69	11-62
Mohnen-Lepine (1988)	56	28
Proximity (technological distance) approach		
Jaffe (1986)		30% of within returns
Cost functions approach		
Bernstein-Nadiri (1988, 1989)		20% of within returns
Varies by industry	9-27	10-160
Bernstein-Nadiri (1991)	14-28	evaluated at the median: 56% of within returns

Source: Griliches (1992) p. 38

Supporting the idea that knowledge spillovers flow from high-innovation industries to low-innovation industries, Schettino (2007) uses US patents and patent citations data at the sectoral level to analyse knowledge spillovers within and between sectors. He finds that firms in low-tech sectors are more dependent on patents taken out by firms in high-tech sectors, than patents taken out by other firms in the low-tech sector. Similarly, firms in high-tech sectors depend more on patents taken out by other firms in high-tech sectors. However, it is also the case that the pace of innovation is important in determining the realisation of knowledge spillovers. Levin (1988) finds results that support the idea that investment in R&D is conducive to rapid technological progress. He argues that industries in which technological progress happens continuously should benefit more from spillovers than industries that innovate in jumps.

In a final paper considering the impact of knowledge spillovers at the sectoral level, Yao (2006) distinguishes between two types of knowledge externalities; one competitive and the other diffusive. The competitive externality relates to the effect whereby more knowledge accumulated at rival companies squeezes or forces firms out of the market, and can be thought of as rivals beating firms to innovative improvements, which in turn means that competitor's products are more attractive for the end-user. The *diffusive* externality represents the event that knowledge spills over from one innovator to another.

Yao uses NBER patent and patent citation data for the US to estimate the respective effects of both externalities on firm's patent grants. The estimation of the competitive externality requires a measure of rival firms' competitive position. The value of competitors' R&D stock is used to account for this. The magnitude of the diffusive externality is estimated using rival firms' patent grants, where the actual measure is the quality of competitors' patents represented by a quality-weighted average of number of patents. The quality of a patent is quantified using total number of citations to and by the patent. As patents are publicly available, he argues, they are good candidates for diffusive externalities, and taking that into account leaves R&D a good candidate for the competitive externality. Using different GMM approaches, he finds that competitive externalities do indeed work against firms' probability of having a patent granted, and that diffusive externalities work positively. The estimated coefficients are presented in Table 27 overleaf, which also summarises a number of other results.

Gallié and Legros (2007) show a competition effect from locating too close to rivals within French cities, which implies less patenting activity and can be interpreted as a negative spillover; however, the authors argue that the reason could be that firms resort to secrecy in order to protect their innovations, rather than intellectual property rights. In addition, they show that positive externalities can be transmitted geographically to the next neighbourhood. Both results together suggest that there is an optimal location that maximises the extent of positive spillovers. They further show very strong spillovers between sectors, but not to firms that are geographically distant.

Table 27:	**Comparison of different studies on patent-R&D relationship.**					
	Data sources	**Number of firms**	**Methods**	**R&D***	**R&D spillovers**	**Patent spillovers**
Hausmann, J., Hall, B. H., Griliches, Z. (1984)	Matched data	128 US firms	OLS or MLE	0.21-0.75		
Mairesse and Sassenou (1991)	Survey of nine studies on research elasticity	17-491 (US, France, Japan)	OLS or MLE	Elasticity of productivity with respect to R&D capital 0.07-0.26		
Crepon and Duguet (1997a)	Matched data	698 French firms	GMM	Elasticity of patent with respect to R&D capital 0.26-0.75		
Crepon and Duguet (1997b)	Matched data	451 French firms	MLE	Elasticity of patent with respect to R&D capital 0.95-1.05	-0.22 to -0.27	
Cincera (1997)	Matched data	181 international firms	MLE or GMM	0.29-0.44 for current R&D; 0.35-0.89	0.7-2.5†	
Blundell *et al.* (2000)	Matched data	407 US firms	GMM	0.033-0.898		
Adams (2000)	Survey of Industrial, laboratory, technologies 1996	116 US firms	OLS	0.6-1.0	Direct learning experience from industrial R&D (0.16); that from academic R&D (0.11)	
Mairesse and Mohnen (2004)	CIS 3 survey	5,500 French manufacturing firms in high-tech sectors	OLS	Elasticity of probability to innovate with respect to R&D/employee (0.20)		
Yao (2006)	NBER	1365 US firms	GMM	1.087-1.534	-1.495 to -1.806	1.138-2.119

Note: OLS, ordinary least square; MLE, maximum likelihood estimator; GMM, generalized method of moments.
* Elasticity of patent with respect to R&D expenditure unless otherwise explained.
† Cincera (1997) explains the negative R&D spillovers as that diffusion spillovers are more important than competitive ones.
Source: Yao (2006) p. 130

7.5 Firm level

Finally, in this section, we consider the evidence relating to knowledge spillovers at the firm level. Jaffe (1986) introduces the concept of technological distance in the measurement of knowledge spillovers and uses US patent data to compute a measure of technological proximity on the basis of the 328 technology categories into which patents are segmented. He aggregates the categories into 49 groups, and computes the correlation between firms' patenting activity in each group. Two firms that have patents in the exact same groups are assigned the value 1, whereas firms that have no overlapping patents are assigned a 0. Jaffe estimates the effect of knowledge spillovers on stock market value and includes firm-specific information in the equation (such as market power).

Evaluated at the mean, he finds that an extra US$1m spent on own R&D yields two more patents and that other firms spending US$1m extra on 'technologically close' R&D yields 0.6 own-firm patents. In addition, he finds that the R&D stock of firms affect absorption of spillovers. Specifically, he finds that firms whose R&D stock is about 0.6 standard deviations below the mean do not benefit from spillovers. For firms with less R&D stock, spillover effects are negative.

Building on the work by Jaffe (1986), Jaffe et al. (1993) test for the existence of a localisation effect of knowledge spillovers by constructing a matching group for citation. That is, they observe the technological and temporal properties of patents and use patents that did not get cited as a control group. The parameters of interest are the geographical properties of the control patents, and whether they differ from those of the treated group (i.e. the cited patents). The authors present two sets of results, namely including and excluding self-citing patents. Unsurprisingly, the likelihood of a patent citing within geographical area is greater including self-citations. Excluding self-citing patents, they find that patents are up to 1.2 times more likely to cite a domestic patent; 2-6 times as likely to cite patents originating in the standard metropolitan statistics area (MSA); and roughly twice as likely to cite a patent from the same state as the control patents.

However, Thompson and Fox-Kean (2004) argue that the control group constructed by Jaffe et al. (1993) is inadequate for the purpose and causes biased results, because the control group is matched at the three-digit classification level, which is too broad. In addition, since each claim in a patent is assigned to a technological class, there is a risk that the claim in the control patent and the claim in the citing patent are very different from each other. Thompson and Fox-Kean (2004) create a new dataset of control patents, such that it fulfils technological criteria at the technology subclass level rather than the three-digit level, as well as requiring that all three patents (originating, citing and control) share at least one subclass. They then apply the same methodology to the data as Jaffe et al. (1993) and the results indicate that patents are 1.2 times more likely to cite domestic patents, 1.6 times more likely to cite a patent within the same state, and 1.5 times more likely to cite a patent originating from the same SMSA. Thompson and Fox-Kean's results suggest that the localisation effects in patent citation are linked to technological specificities, as the effects are reduced when the technological sub-categorisation is more precise.[107]

Belenzon (2006) uses NBER patent citations to distinguish between internalised and externalised knowledge spillovers. The idea is that a spillover is internalised if a patent application by a firm cites its own patent or a patent that cites one of its own patents. External spillovers are identified as patents whose contribution to overall innovation does not find its way back to the inventor. The return to spillovers is measured on the basis of firms' stock market value. The effects are evaluated at the mean values and show that a one standard deviation increase in the value of spillovers that can be internalised increases the effect on stock market value of R&D expenditure by 30%. A one standard deviation increase in externalised spillovers lowers the market value of R&D expenditure by 10%. As expected, the type of spillovers generated by a firm matters for the firms' decision to invest in R&D. Evaluated at the mean, the author finds that a one standard deviation increase in internalised spillovers causes a 33% increase in R&D spending.

Yang et al. (2010) expand on this idea by studying 87 telecommunications equipment manufacturers over ten years. They find that firm innovation is improved by a larger spillover pool, (i.e. more knowledge available), and by the spillover pool's technological proximity to the firm's own R&D efforts. If the firm is responsible for the invention that spawned the expansion of a share of the spillover pool, then naturally the technological distance is limited.

Jirjahn and Kraft (2006) use German establishment data and find that knowledge spillovers from rivals have a positive impact on what they call incremental innovation (i.e. improvements of existing products or processes). R&D from cooperative efforts with other firms assists in the absorption of spillovers, and makes it more likely that spillovers cause radical innovation, (i.e. new products or new processes). Finally, they find that firms' own R&D efforts and knowledge spillovers are substitutes. The substitutability between own and outside R&D efforts indicates that at least some firms expect that the benefits from spillovers will exceed the returns generated through own R&D activity. The result implies that knowledge spillovers have the potential to crowd out own R&D expenditure and therefore that aggregate R&D investments are lower than they would have been in the case of no substitutability. The effect, the authors argue, is confined to firms far from the technological frontier, whereas firms on the frontier necessarily have to research new ideas themselves if they wish to remain competitive.

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[107] Responding to Thompson and Fox-Kean (2004), Henderson *et al.* (2005) argue that classifying patents by subclass is too restrictive. They back that point through the size of Thompson and Fox-Kean's control sample. Out of an initial 18,551 patents, the final control group holds only 2,122 patents, which they argue exposes the result to sample selection bias. Thompson and Fox-Kean (2005) reply to the points brought out by Henderson *et al.* (2005) by stating the basic principles of estimating average treatment effects using matching methods, and argue that the matching parameters in Jaffe *et al.*'s (1993) approach leads to inconsistent estimates of the treatment effect. The classical trade-off between sample size, econometric specification, and precision seems very much a part of measuring knowledge spillovers using patents.

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8 Next Steps – strengthening the current evidence base

Any analysis on the sources, magnitude and direction of productivity spillovers resulting from an investment in intangible assets is a challenging exercise for a number of reasons:

- Traditionally, it has proven to be difficult to identify and measure the different types of intangible assets, and it is only relatively recently that methodological advances have been achieved to improve their classification and estimation; and

- The evidence on productivity spillovers is by definition indirect. The majority of studies in the economics literature have focused on the direct effect associated with the role of intangible assets; while the estimation of spillovers has relied on a 'residual' approach (i.e. what is not explained by other factors implies the remaining contribution is as a result of spillovers).

8.1.1 Possibilities for future research in the shorter term

Developing consistent definitions and measurement of externalities

There are a large number of studies dealing with direct and indirect effects associated with the investment intangible assets; however given the range of objectives, methodological approaches and data, there is a degree of (understandable) inconsistency between the analyses. We believe that there may be an opportunity to undertake some research work to establish a coherent and consistent definition of the various sources of spillovers, as well as developing a consistent approach to the measurement of spillovers. Although this is inherently difficult, and depends significantly on the level at which spillovers occur, it might provide a basis for further analyses to estimate the various spillover components and allow for ongoing comparison.

Allocation of benefits and estimating optimal levels of investment

A key use for generating spillover estimates is to improve the figures on the overall economic value from skills. There are very good measures of the wage gain and employment effect, broken down by various characteristics including type and level of learning, type of person, age at acquisition, and route of attainment (i.e. college or workplace)[108]. However, there is relatively little information on the benefit to the firm or to other parties. Currently, the approach adopted within the Department is to sum the earnings and employment appropriately, and then use a series of multipliers to arrive at total value. These factors take into account all the remaining components – the value to the employer and other employees separate from wage of the person trained; the value to future firms that employ the trained person; the value to firms and people who benefit through geographical or sector networks; and the additional value to the economy through threshold effects. Having estimated the total value, the allocation of which elements accrue to (a) the firm, (b) the trained individual and (c) other parties (externalities) is undertaken.

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[108] See London Economics (2011a) and London Economics (2011b)

Given the evidence collected and reviewed as part of this research work, it might be desirable to improve this approach through the use of better estimates of the multipliers, potentially also providing a breakdown of the distribution of the benefits realised at a more disaggregated level (for example, by the characteristics of the worker in receipt of training or the nature of the training).

Furthermore, having identified the total value including the external elements, it would be highly beneficial to derive an estimate of the optimal level of investment in skills, and to compare this to current levels, and hence assess the likely impact of the incentives and externalities, which will then inform possible policy interventions.

Understanding the investment incentives facing firms

Linked to the previous potential option for further analysis, it is clear that the incentives facing firms to invest in education and training for their workers will be crucially dependent on the extent to which the benefits associated with the potential productivity gains might be accrued by the firm. We think that it would make sense to further develop some of the existing analyses that have been undertaken assessing the returns to employers from investment in education and training (e.g. see the Institute for Employment Research (2008) research for an assessment of the costs, benefits and breakeven point associated with the provision of apprenticeship training). However, of particular interest would be to extend this type of modelling to incorporate different allocations of the direct benefit associated with education and training between workers and firms (depending on labour market mobility), as well as the potential size and nature of the externalities associated with firm level training.

8.1.2 Possibilities for future research in the longer term

Analytical extensions of INNODRIVE dataset

In addition to these more general issues, the type of approach undertaken varies substantially depending on whether the analysis focuses on a specific type of investment in intangible assets (e.g. skills or R&D) or tries to capture the impact of all investment in intangible assets. The recently developed **INNODRIVE** dataset provides estimates of investment in the different types of intangible assets for UK firms (as well as other EU countries) and has already been used for analysis on productivity spillovers. However, further refinements and extensions to the analysis are possible and desirable, especially as a longer time series becomes available. In fact, as acknowledged by existing studies, the availability of a short time series limits the ability to control for local unobserved characteristics and endogeneity. In the absence of suitable external instruments (based on historical characteristics), lagged values are normally used. However due the high persistence in the regional share of intangibles over time, only a long panel may provide suitable instruments. Future analysis may also explore in more detail whether spillovers are likely to arise from own-industry or rest-of-the-economy investments in intangible assets and disaggregate the analysis by sector of industrial activity.

In particular, the fact that recent papers have failed to observe any significant spillover effects from R&D investments suggest exploring further whether R&D spillovers vary across sectors and whether the effect varies for R&D intensive and non-R&D intensive firms and industries.

Exploring the complementarities between existing firm-level human capital and investment in intangible assets is another potential area of analysis although current data availability restricts the scope for this type of analysis in the UK. However, the presence of a standardised approach to measuring intangibles in the EU may also lead to more robust cross-country analyses and to revisit the effect of foreign knowledge stock and activities on productivity.

Analysis of matched employer-employee data

The component of intangible assets that can be most accurately measured arguably relates to the investment in human capital, with the level and type of human capital identifiable using a rigorous qualification framework alongside the nature (i.e. academic or professional/vocational) of the investment being undertaken. As shown by the weight of the previous literature, analyses of the impact of human capital can be undertaken by considering the stock of human capital at different levels (firm-level, city or regional level, industry level). Future analyses should attempt to shed more light on the sources and recipients of human capital spillovers in the UK. For instance, do spillovers only stem from university-educated workers, as suggested by much of the previous literature, or can they also arise from other levels or types of education (apprenticeships or other forms of vocational qualification)? Moreover, who most benefits from the external effects derived from investment in human capital - similarly skilled workers or workers with a different type or level of ability? Are the effects stronger at firm-level than regional level? Are they still significant at regional level after controlling for firm and industry-level spillovers? Do they differ across industries?

Clearly all these questions do not have a straightforward answer and the scope for further analysis and the validity of the analysis will depend on data quality; the presence of a long time series; and on the availability of suitable instruments[109] to tackle possible endogeneity.

However, no firm-level panel dataset is currently available containing information on firm-level productivity and wages and data on skills level and training. Ideally, one approach would be to exploit the richness and comprehensiveness of a matched employer-employee dataset containing detailed data on firm and individual characteristics, including productivity, average firm wage, individual wages and information on education and training for the individual and the co-workers. Currently, the Workplace Employee Relations Survey (WERS[110]) provides some detail based on a random sample of employees within the firm that could be exploited in the future (and it might be possible to link such a database with existing administrative sources).

[109] Using either geographical or demographical characteristics or features of the education system in the UK

[110] The WERS is a national sample of interviews with managers in approximately 2,200 firms with more than 10 employees, alongside a survey of up to 25 (randomly selected) employees in those firms incorporating the collection of personal and socioeconomic information (and training). Clearly, given the sample structure, there may be some issues about the representativeness of the findings (especially the selection of employees within firms); however, this source of information is likely to offer significant opportunities for assessing a number of issues including intra-firm spillovers, deadweight loss and additionality.

Analysis of specific spillover effects

Although significant volumes of research have been undertaken to assess the extent of spillover effects, further analysis could be undertaken to assess the extent of particular components of spillover effects that have been hypothesised. In particular, it is clear that labour mobility plays a role in generating and facilitating spillovers; however, there is relatively limited evidence given its importance. In addition, there is some research into the area of threshold effects, whereby the extent to which spillovers are realised reflect the distribution of skills in the economy. More research could be undertaken to determine the extent to which spillovers result from different types of qualification (i.e. apprenticeships rather than just higher education qualifications); occur within different sectors within the economy; different types of learner (e.g. by prior qualification or learner age); and by size of firm. The disaggregated analysis should result in a quantification of the spillover effects (that would also feed into the short term analysis relating to the aggregate valuation of spillover effects and their distribution with the economy).

Analysis of agglomeration effects

In his 2004 paper, Moretti investigated the social returns to investment in education and whether these differ from private returns to education. In order to do that, he looked at the effect of the share of college educated workers in cities on wages of otherwise similarly individuals. If social returns to investment in education exist, we would expect to see higher wages in cities with a higher proportion of college educated workers after controlling for own education, while if private returns equal social returns we expect to see a negligible impact of the share of college educated workers on wages in cities. However, estimates by OLS may be biased for two orders of reasons: firstly, there may be **unobservable individual characteristics**, such as ability, that are correlated with both the graduate share in a city and individual wages. If a larger share of college educated workers in a city is associated with a higher return to unobserved ability, individuals with high levels of unobservable ability will sort into cities with a high share of college educated workers. The second potential source of bias is related to city specific characteristics correlated with the graduate share in the city, such as geographical location, industrial structure, weather, amenities. Cities where the productivity of skilled workers is particularly high due to city-specific unobserved characteristics may pay higher wages and therefore attract high skilled workers.

The author used a **fixed-effects** model to control for time invariant effects at individual and city level and an **instrumental variable** (IV) approach to isolate the effect of the graduate share on wages from city level unobserved characteristics. In other words the IV estimation strategy relies on finding a variable explaining the graduate share in the city, but uncorrelated with unobserved characteristics at city level affecting wages. The author uses two different IV approaches: the first uses the lagged age structure to predict changes over time in the graduate share at city level (using the fact that younger cohorts are on average more educated than older ones). The second instrument used reflects the presence of colleges and universities at city level. However using the contemporaneous presence of college and university is not likely to be a suitable instrument, given that their location might be positively correlated with local wealth and therefore non-random. To tackle this problem, Moretti uses the presence of a land-grant college in a city. US land-grant colleges were awarded (independently from natural resources or other local level characteristics) following a federal programme at the end of the 19th century and remain a significant determinant of higher education in city, but should not be correlated with unobservable characteristics affecting wages a century later. However, this instrument is only available in the cross section, given that would be absorbed by a city fixed effect in a fixed effect model.

The author also investigated whether externalities only arise from the share of the population with a college degree or above or whether the proportion of high-school graduates has a significant effect and finds that this latter impact is negligible. Moreover spillovers can benefit individuals with different skills to a varying extent. In particular, an increase in the share of highly-educated workers should have a non-negative effect on the wages of low-skilled individuals if there is imperfect substitution between low and high skilled workers and an increase in the labour supply of high skilled workers tend to increase wages for the group of (relatively) scarce workers. An increase in wages for the low-skilled group could therefore reflect both shift in labour supply and the presence of spillovers. For the group of high-skilled workers the two effects move in opposite directions and finding a positive effect of the proportion of high-skilled workers on wages would indicate that spillovers are positive and offset potential negative effects due to shifts in labour supply.

The findings indicate that a one percent increase in the share of college educated workers raises the wage of college graduates by 0.4%, workers with some college by 1.2%, high school graduates by 1.2% and high school dropouts by 1.9%. The effect is larger for less-educated individuals as predicted by the economic theory, but still positive for highly educated individuals.

This paper and similar papers that have investigated the same topic in different countries have demonstrated the source and recipients of human capital spillovers. We are not aware of similar analyses undertaken for the United Kingdom. Clearly the possibility of using a similar approach may be hindered by the absence of suitable instruments and/or the availability of a large longitudinal dataset with data on individual characteristics and wages. Moreover, controlling for spillovers potentially arising from different levels and types of education requires the presence of different instruments: a variable suitable to instrument the local share of graduate may not be a valid instrument for the local share of A-level achievers. For the UK it would be particularly interesting to study the social effect of vocational/applied education such as apprenticeships.

We would recommend further exploring the possibility to undertake similar analyses investigating the social effect of education, and the extent to which data quality may limit the possibility to draw strong conclusions from the analysis.

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Annex 1 Cross-country growth regressions

Table 28: Cross-country growth regressions

Study	Dependent Var.	Human Capital Proxy	Flow/Stock	Estimated Coefficient	Interpretation
Barro (1991)	Growth rate of real per capita GDP annually between 1960-85	School enrolment rate: number of students enrolled in the designated grade levels (primary and secondary respectively) relative to the total population of the corresponding age group in 1960	Initial flow Mean: Prim60=0.78 Sec60=0.23	prim=0.025 sec=0.030	A 1 percentage point increase in primary (secondary) school enrolment rates is associated with a 2.5 (3.0) percentage points increase in per capita GDP growth rate
Levine and Renelt (1992)	Growth rate of real per capita GDP annually between 1960-89	Secondary school enrolment rate in 1960	Initial flow	high=3.71 base=3.17 low=2.5	A 1 percentage point increase in secondary school enrolment rate is associated with a between 2.5 and 3.7 percentage points increase in per capita GDP growth rate
Murphy, Schleifer and Vishny (1992)	Growth rate of real per capita GDP between 1970-85	Primary school enrolment rate in 1960	initial flow	full sample: 0.022 (OECD: not significant)	A 1 percentage point increase in primary school enrolment rate is associated with a 2.2 percent age points increase in per capita GDP growth rate
Barro (1997)	Growth rate of real per capita GDP over period 1965-75, 1975-85, 1985-90	Average years of attainment for males aged 25 and over in secondary and higher schools at the start of each period	Initial stocks in 1965, 1975 and 1985 Mean in 1990 = 1.9 years	0.012	An extra year of male upper-level schooling is associated with a 1.2 percentage point increase in per capita GDP growth rate
Hanushek and Kim (1995)	Growth rate of real per capita GDP (´100) between 1960-1990	Average years of secondary schooling of adult male population at beginning of period	Initial stock	0.036	An extra year of male secondary schooling is associated with a 0.36 percentage point increase in per capita GDP growth rate

Gemmel (1996)	Growth rate of real per capita GDP annually between 1960-1985	Constructed human capital stock in 1960 and human capital annual average growth rates at primary, secondary and tertiary levels. These measures are both entered in the equation simultaneously.	Initial stock
			
			Mean: Prim=72.8
			Sec=19.5; Tert.=4.0)
			
			Annual flows
			Mean: Prim=2.5;
			Sec=3.7
			Tert =2.7
				full sample:
				prim stock =0.81; prim flow =2.68;
				
				poorest LDCs:
				prim stock =0.91; prim flow =4.19;
				
				intermediate LDCs: sec stock =1.09
				
				OECD:
					A 1 percent increase in tertiary human capital stock is associated with a 1.1 percentage point increase in per capita GDP growth rate. A 1 percentage point increase in tertiary human capital growth is associated with a 5.9 percentage point increase in per capita GDP growth rate.

Table 28: Cross-country growth regressions

Study	Dependent Var.	Human Capital Proxy	Flow/Stock	Estimated Coefficient	Interpretation
				Tert stock =1.10; Tert flow =5.89	
Judson (1998)	growth rate of real GDP: 5-years averages, between 1960-1990	Growth of her constructed measure of human capital stock	Period Flows	10.8 low-efficiency countries =3.0 high-efficiency =12.9	A 1 percentage point increase in human capital growth is associated with an 11 percentage points increase in GDP growth rate.
Englander and Gurney (1994)	Growth of labour productivity (and total factor productivity) over four time periods	School enrolment rates: number of students enrolled in secondary school relative to the total population of the corresponding age group in beginning of period	Initial flow	1.45-1.78	A 1 percentage point increase in secondary school enrolment rate is associated with around 1.5 percent age point increase productivity growth.
Barro and Lee (1994)	Δ ln GDP per worker	Average years of secondary schooling of adult male population at beginning of period	Initial Stock	0.014	An extra year of male secondary schooling is associated with a 1.4 percent increase in per worker GDP growth.
Benhabib and Spiegel (1994)	Δ ln GDP per worker	Human capital stock estimates from Kyriacou: average level of log human capital over the period (log of average level of human capital; log of average levels)	Average Stock	0.12-0.17	A 1 percent increase in the stock of human capital is associated with a 12 to 17 percent increase in per capita GDP growth.
Mankiw, Romer and Weil (1992)	ln GDP per working-age person	Average percentage of working-age population in secondary school, 1960-85	Period Flow	0.66 implied output elasticity with respect to human capital stock = 0.3	A 1 percent increase in the average percentage of working-age population in secondary school is associated with a 0.7 percent increase in GDP per working-age person. A 1 percent increase in human capital stock is associated with a 0.3 percent increase in GDP

Source: Van Reenen and Sianesi (2000), Barro, R. (1991), Levine, R. and Renelt, D. (1992), Barro, R. and Lee, J. W. (1994), Murphy, K, Shleifer, A, and Vishny, R (1991), Hanushek, E. A. and Kim, D. (1995), Mankiw, N. G., Romer, D. and Weil, D. N. (1992), Gemmell, N. (1996), Judson, R (1998), Englander, A. S. and Gurney, A. (1994), Barro, R. (1997), Benhabib, J. and Spiegel, M. (1994)

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