Spillovers from R&D and other intangible investment: evidence from UK industries

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Spillovers from R&D and other intangible investment: evidence from UK industries *

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ABSTRACT
Many agree that evidence exists consistent with spillovers from R&D. But is there any evidence of spillovers from a broader range of knowledge (or intangible) investments, such as software, design or training? We build data on investment in this broader intangible range for 7 UK industries covering 1992 to 2007. Using the industry-level method in the R&D literature, Griliches (1973) for example, we regress industry TFP growth on external knowledge stock growth, where the latter is the outside industry knowledge stock growth weighted by matrices based on flows of intermediate consumption and workers. Consistent with spillovers from R&D, we estimate a positive statistically significant correlation between industry TFP growth and external R&D knowledge stock growth. Our main new result is that we find statistically significant correlations between TFP growth and external total intangible knowledge stock growth.

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1. Introduction

An important policy question for economics, and one of Mark Rogers’ central work themes, is what are the determinants of growth in income and living standards, and by what mechanism do they drive growth. One of the methods typically used to try and answer this question is the growth accounting framework, where growth is decomposed into contributions from capital deepening, labour services and total factor productivity (TFP). Conventional growth-accounting studies typically define capital as tangible assets with recent work adding software (for example Greenhalgh and Rogers, 2010, chapter 3 offer a survey; much recent work has used EU-KLEMS, O’Mahony, Timmer, van Ark, 2009).

However, it is now widely accepted that firms invest in assets other than the traditional tangible categories of buildings; plant & machinery and vehicles; for instance, to product and process innovations, and training of the workforce. The devotion of current resources to the pursuit of future returns would appear to meet the definition of investment. This view is slowly being incorporated into the official National Accounts, which, in the UK, includes investments in software, artistic originals and mineral exploration, and, in 2014, R&D.

The incorporation of R&D into official data links the measurement conventions to a wide literature on the impact of R&D on growth. Bearing in mind the potential public goods aspect of knowledge spending, that literature has looked for both private and spillover returns to R&D spend. The recent survey by for example, Hall, Mairesse, Mohnen (2009), and an earlier one by Griliches (1973), suggests that for R&D, social returns do indeed exceed private returns.

However it is well acknowledged that current official UK measures of private R&D only count a subset of the actual investments made in researching, designing, developing and commercialising innovations. A more complete framework for estimating a broader range of “intangible” investments is set out in Corrado, Hulten and Sichel (2005).¹

The incorporation of this broader range of knowledge acquisition raises the key question addressed in this paper: is there any evidence that other intangible investments, besides R&D, have social returns above private returns? It is, for example, perfectly possible that whilst a broader range of intangible
investments might accompany R&D, it is only R&D that has the spillover effects. Thus the intangible approach might offer a more complete measure of investment but the key policy insights from the spillover effects of R&D remain perfectly valid.

To the best of our knowledge, evidence for intangible spillovers is very thin on the ground. As Griliches pointed out many years ago, the lack of direct measures for knowledge flows makes gathering evidence very difficult. One important stream of the R&D literature has been to use patent citations, but this is unavailable in our case since non-R&D intangibles, such as software, design and training are not patentable (for example, UK software is not patentable, except under very special circumstances). Griliches’ survey therefore sets out the indirect methods used, going back to Schmookler (1966) and Scherer (1982), which are essentially to correlate TFP with some measure of external knowledge, with that external knowledge weighted in some way that might correspond to the possible transfer of knowledge to the firm or industry under analysis. A series of papers have used this approach for R&D using a variety of weights, see Hall et al (2011) for a survey.

What of non-R&D intangible assets? At the firm-level, Greenhalgh and Rogers (2007) find spillovers from firm-level productivity and industry-level trademark activity: since trademarks likely are generated by non-R&D intellectual property investment, this is suggestive of non-R&D spillovers. At a cross-country level, van Ark, Corrado, Hulten and Hao (2009) find a correlation between TFP growth and intangible investment for a sample of 8 countries. Similar evidence is presented for a wider sample of countries in very recent work by Corrado, Haskel, Iommi and Lasino (2011). Dearden, Reed and Van Reenen (2005) compare industry and individual level wage equations and find that the results suggest that the industry level analysis may capture externalities from training since industry wages, by aggregation, capture external influences on wages absent from individual data.

This paper attempts to complement this evidence base by studying the relation between TFP growth and intangible investment at the industry level. We use the data in Goodridge, Haskel and Wallis (2012)\(^2\), for 7 UK industries, 1992-2007.\(^3\) We adopt the industry-level method used in the R&D

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\(^1\) The broader set of knowledge investments are broadly (a) software and databases (b) innovative property (R&D, design, mineral exploration, financial product development and artistic originals) and (c) economic competencies (branding, training, organizational capital).

\(^2\) Goodridge, Haskel and Wallis (2012) is based on a dataset for 8 market sector industries, the eighth composed of personal, social and recreational services in SIC03 section O. That industry is excluded from this work due to issues in the measurement of output (inclusion of non-market services and seemingly implausible estimates of TFP).

\(^3\) In Haskel and Wallis (2010) we have used time series data for the UK market sector and find strong evidence for positive externalities from the conduct of publicly funded scientific research. That work relies on 18 time
literature by, for example, Griliches (1973) and Griliches and Lichtenberg (1984) which relies on weighting external measures of the knowledge stock: in their case, R&D, in our case, R&D, a range of other intangible asset categories, and total intangibles. We create two alternative sets of weights: the first based on flows of intermediate consumption built using the input-output (IO) supply use tables; and the second based on labour transition flows between industries, constructed from the Labour Force Survey (LFS).\footnote{We are extremely grateful to Richard Jones (ONS) for constructing these weights for us. It should be noted that they are built using data on labour flows in 2007, so we are implicitly assuming that the pattern of series observations, this work herein uses variation at the industry level. Economy-wide variables such as public R&D are subsumed into TFP.}

Such a method is of course subject to a number of criticisms. With our limited data available we shall try to meet some of them in the paper, but at the outset we emphasise we do not have a natural experiment and noise-free data. Of course, future work will improve methods and data. At this stage however, we believe there are four reasons for this work to be of interest. First, to the best of our knowledge, this approach has not been adopted for intangibles so as a first-pass at the data we believe it is worth exploring. Second, Hall et al (2009) in the conclusion to their recent survey, call for exploring the impact of wider innovation spending rather than just R&D, which is what we do. Third, and related, Hall et al (2009) also point out that much of the existing work has been done on manufacturing and suggest widening the focus to services and the non-R&D innovation spending therein: we do this as well. Fourth, many studies have been conducted using underlying data that has not been appropriately adjusted for the treatment of intangibles as capital, thus introducing potentially large additional bias into measured output, factor shares and TFP as pointed out for instance in Schankerman (1981). Our data correct for this.

Our findings are based on correlations between smoothed industry TFP growth and lagged “outside” knowledge stocks (lagged changes in other industry knowledge stocks weighted by the weighting matrices), controlling for industry and time effects. They are as follows. First, as a benchmark, we estimate a positive statistically significant correlation between industry TFP growth and outside R&D knowledge, when controlling for internal industry knowledge capital, using both outside weighting methods. This does not of course imply causation, but is consistent with spillovers of R&D, with the magnitudes in line with other studies. Second, we find a correlation between TFP growth and outside total intangible knowledge, again with controls, but only statistically significant using the intermediate-consumption weights. Multi-collinearity problems make exploring very detailed intangible categories very hard, but we find some correlation with outside firm competencies...
(branding, training and organisational capital) and outside software, although the latter correlations are less robust. Thus we conclude that, on the basis of these data and methods, our findings are consistent with (a) spillovers from R&D (b) potential spillovers from other intangible categories, but depending somewhat on method.

The rest of the paper is as follows. The next section sets out the conceptual framework and measurement, section 3 the data, section 4 the results and robustness checks and section 5 concludes.

2. Conceptual framework and measurement

2a. Model

Suppose an industry $i$ has a production function, which might be translog for example, of the form:

$$ Y_{it} = A_{it} F(L_{it}, K_{it}, N_{it}, N_{it-1}) $$ (1)

where $Y_{it}$, $L_{it}$ and $K_{it}$ are output, labour input and tangible capital input respectively. $N_{it}$ is intangible capital for the industry and $N_{it-1}$ is intangible capital outside the industry, some of which might be useful in production (or more precisely, yield a flow of productive services). It might include publically financed R&D; knowledge produced elsewhere in the world etc. $A_{it}$ is any increase in output not accounted for by the increase in the other inputs.

Denoting $\varepsilon$ as an output elasticity we can write, for, say a translog form of (1):

$$ \Delta \ln Y_{it} = \Delta \ln A_{it} + \varepsilon_{M,i} \Delta \ln M_{it} + \varepsilon_{K,i} \Delta \ln K_{it} + \varepsilon_{L,i} \Delta \ln L_{it} $$

$$ + \varepsilon_{N,i} \Delta \ln N_{it} + \varepsilon_{-N,i} \Delta \ln N_{it-1} $$ (2)

To convert this into something estimable we then make the following assumptions. First, $\Delta \ln A_{it}$ is industry-specific and includes an i.i.d. error term:

$$ \Delta \ln A_{it} = a_{i} + \nu_{it} $$ (3)

movements in 2007 is reflective of those in other years. In future work we hope to gain access to other cross-sections of LFS data.
where \( v \) is an i.i.d. error. Second, we assume the \( \varepsilon \) terms are industry-specific factor shares plus a term to account for either deviations from perfect competition, increasing returns or spillovers due to that factor:

\[
\varepsilon_{X,it} = s_{X,it} + d_{X,it}, X = M_{it}, K_{it}, L_{it}, N_{it}
\]

where \( s_{x,it} \) is the share in output, \( Y \), of spending on factor \( X \). Third, observed TFP growth is defined as:

\[
\Delta \ln TFP_{it} \equiv \Delta \ln Y_{it} - \sum_{X=L_{it}, K_{it}, N_{it}} \bar{s}_{X,it} \Delta \ln X_{it}
\]

Where the bar above \( s_{x,it} \) denotes a time average so that this expression holds if, for example, the underlying production function is translog, not just Cobb-Douglas.

Fourth, we turn to the \( \varepsilon_{N,it} \Delta \ln N_{it} \) term in (2). Consider \( \varepsilon_{N} \). If outside knowledge is freely available, \( \varepsilon_{N,it} > 0 \), but cannot be seen in the factor share. Thus we must determine it econometrically in this framework or by case studies. Second, consider \( \Delta \ln N_{it} \). Some proportion of this would be economy-wide information, such as publically subsidised R&D and/or knowledge in other countries. Some other proportion, our focus here, will be in other industries. With \( n-1 \) other industries, we have then potentially \( t(n-1) \) data points for \( \Delta \ln N_{it} \), which would provide insufficient degrees of freedom with \( t \) observations for industry \( n \). Thus as in other papers, we have to devise some sort of weighting matrix to combine these exterior sources of free knowledge. Hence our tests are joint tests of the hypotheses of (a) spillovers and (b) the correct form of the weighting matrix. Denoting this matrix by \( M \) we can write:

\[
\varepsilon_{N_{i,t}} \Delta \ln N_{i,t} = \alpha_i (M \Delta \ln N_{i,t}) + \lambda_i
\]

Where \( \lambda_i \) measures any common economy-wide knowledge e.g. on the internet, from universities, from abroad etc. All this gives us:

\[
\Delta \ln TFP_{it} = \alpha_i (M \Delta \ln N_{i,t}) + \lambda_i + \sum_{X=L_{it}, K_{it}, N^{new}} d_x \Delta \ln X + v_{it}
\]
which has the following intuition. Measured industry TFP growth will be driven by the following: (a) the first term on the right-hand side is freely available knowledge from external domestic industries (b) the second term is freely available knowledge originating from other sources, such as publicly funded research or foreign knowledge, (c) the third term, which is industry technical change (d) by the influence of spillovers or departures from perfect competition or increasing returns accruing to within-industry inputs, in the penultimate term, and (e) any residual mismeasurement captured here by \( \nu_t \), which may for instance incorporate unmeasured changes in capital utilisation. With a limited number of observations our central empirical exercise is to test for spillovers due to knowledge investment by other industries. Since we use UK market sector data, any other sources of knowledge e.g. public sector originating spillovers, such as public R&D, or foreign knowledge, should be captured by the time dummies.

It is worth noting the different interpretations of the right hand side depending on whether or not \( \Delta \ln \text{TFP} \) includes the contribution of industry-intangible capital. To interpret \( d_X \) as the excess return to industry-specific knowledge investment requires computing \( \Delta \ln \text{TFP} \) including the contribution of intangibles, that is to say, using (5), which is what we do here. If we do not, as is noted in the literature, e.g. Schankerman (1981), then \( d_{R&D} \) includes of course both the private and social returns to R&D, and the biases can be very large.

2b. Other studies and discussion of framework

As pointed out in Griliches (1973) and Hall, Mairesse and Mohnen (2009) many industry studies are based on something like (7), using as weights, for example, intermediate inputs (Terleckyj, 1980), flows of patents (Scherer, 1984) or survey-measures of innovations (Sterlacchini, 1989). As is usual in all indirect knowledge flow measures, such measures need to be interpreted carefully. If they track free use of knowledge, they might be knowledge spillovers. But, if they reflect mispricing, they might be rent spillovers. For example, using intermediates as weights, there might have been growth in intermediate quality, unaccounted for by measured intermediate prices. This shows up as higher measured TFP growth in the using industry, creating a direct link between innovation in one industry and measured TFP in another.

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5 Industries have different output elasticities due to the construction of TFP as in (5). (7) does impose the same elasticities with respect to weighted outside intangibles, \( \alpha_i \). However, the effect of a unit increase in outside knowledge varies by industry, since this effect is \( \alpha_i \) times the sum of outside weights, and this sum varies by industry: see section 4b.
One example of this mispricing effect may arise through branding. Suppose the manufacturing industry builds reputation by branding (cars for example). Thus demand rises for manufacturing and, downstream for retailing. Manufacturers, if they are doing the branding, would hope to appropriate returns from their investment in reputational capital by charging more to retailers. If we do not measure that, then the rise in retail car sales comes without any apparent increased payments for the better reputation goods retailers are selling on, which shows up as an increase in measured retailer TFP. So the spillover is a rent induced spillover, which might lead one to wrongly presume there ought to be a move to subsidise branding, if vertical relations between manufacturers and retailers internalise any externality present. Without detailed information for each industry this remains a caveat in our, and other, results.

Hall et al (2009) also points out that spillovers might be negative if they incorporate market-stealing effects from rival R&D (Bloom, Schankerman and Van Reenen, 2007) and that results tend to vary depending upon the weighting matrix used. Nonetheless, in their summary (Table 5) the elasticity with respect to external R&D is positive and between 0.68 (on firm data) and 0.006 (on country data).

3. Measurement

3a. Industries

We base this work on our industry-level dataset of UK market sector investment in intangible assets, for a full discussion of data derivation and detailed sources see Goodridge, Haskel and Wallis (2012). This work uses the seven broad industries as set out in Table 1. We use the seven broad industries due to limited industry detail in the intangible data. We have data from 1992 to 2007. We start in 1992 due to the IO tables not being available earlier. We end in 2007 since we rely on EUKLEMS data, and more up to date real industry intermediates are not available from the ONS. We exclude real estate from SIC K which therefore excludes imputed rents due to owner-occupied housing which is not counted as capital in our data.

<table>
<thead>
<tr>
<th>SIC(2003)</th>
<th>Industry Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABC</td>
<td>Agriculture, Forestry and Fishing</td>
</tr>
<tr>
<td>D</td>
<td>Manufacturing</td>
</tr>
<tr>
<td>E</td>
<td>Electricity, Gas &amp; Water Supply</td>
</tr>
<tr>
<td>F</td>
<td>Construction</td>
</tr>
<tr>
<td>GHI</td>
<td>Distribution; Hotels &amp; Restaurants; Transport, Storage &amp; Communications</td>
</tr>
<tr>
<td>J</td>
<td>Financial Services</td>
</tr>
<tr>
<td>K</td>
<td>Business Activities (excluding real estate)</td>
</tr>
</tbody>
</table>
Since our work is at the industry-level, some adjustments present measurement problems for certain industries. First, output in some industries is simply not well-measured, notably in financial services. This is clearly an area for more work, see e.g. Burgess (2010) for a discussion, but for the moment we note that the bulk of the measurement problems due to FISIM in the crisis are at the end of our data. In Agriculture and Construction land is a major factor of production, but is not treated as a capital asset in the National Accounts framework by (European) national accounting convention. This makes TFP difficult to interpret and in fact we find it to be measured as negative for agriculture over much of our data period. Industry TFP can also be hard to interpret in Electricity, Gas and Water due to the use of natural resources and likely increasing returns to scale. That said, Basu, Fernald and Kimball (2006) reports estimates of close to constant returns to scale for US industries (1.07 for durable manufacturing, 0.89 for nondurable manufacturing and 1.10 for non-manufacturing).

Second, the quality of most of our industry-level intangible investment data improves greatly from 1992, the first year of published IO analyses. Data are extended further back but there is inevitably some imputation for earlier years. Therefore we produce estimates of an initial capital stock in 1990 using a standard method as set out in Oulton and Srinivasan (2003)⁶, and using asset-specific data on the growth rate of investment and the rate of depreciation. In order for the estimates of the stock to settle down and not be too affected by initial values problems, we conduct our analysis over the period 1995 to 2007.

3b. Data on output and tangible investment

Our output and tangible data come from EUKLEMS which is based on UK National Accounts and uses a consistent set of real and nominal output variables which sum to the aggregate. In computing TFP we adjust both the input and also the output data. All the input shares sum to one and the rental prices are calculated consistently using the ex post method so that the sum of capital rental payments, including intangibles, equals total capital payments. Because we are working at the industry level, TFP is calculated on a gross output basis, which does not impose restrictions on the form of the production function that value added would.

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⁶ In the steady-state, investment (Iₜ) in period t can be represented as: Iₜ = (g + δ)Kₜ where g is the growth rate of real investment and the stock, δ is the depreciation rate and Kₜ is the capital stock in period t. Therefore the initial stock can be estimated as: Kᵦ = Iᵦ / (g + δ).
3c. Data on intangible investment, by asset

We now review the major categories of intangible investment. Table 2 provides an overview of the intangible assets included following the definitions developed by Corrado, Hulten and Sichel (2005) and first applied to the UK in Giorgio Marrano, Haskel and Wallis (2009). The sections below describe the data construction. For a fuller description of the data see Goodridge Haskel, and Wallis (2012).

The CHS framework for measuring intangible investment breaks spending down into three broad categories: i) software and computerised databases; ii) innovative property; and iii) economic competencies. Investment in Innovative property can be regarded as the spend on the development of the innovation, and so includes activities such as scientific or non-scientific R&D; design and the creation of blueprints, and the development of artistic originals and financial products. Economic competencies can be thought of as the co-investments that are essential to commercialising the innovation, and therefore includes activities such as: branding; improvement of organisational structures and business processes; and the training of the workforce in order to apply the newly acquired knowledge. It is therefore sensible to consider the data in these broader categories, as below.

Table 2: Intangible asset categories

<table>
<thead>
<tr>
<th>Broad category of intangible asset</th>
<th>Includes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Computerised information</td>
<td>Computer software, computer databases</td>
</tr>
<tr>
<td>Intellectual property</td>
<td>Artistic originals, Scientific R&amp;D, Non-scientific R&amp;D, Mineral exploration, Financial product innovation, and Architectural and engineering design</td>
</tr>
</tbody>
</table>

Notes to table: Source: Corrado, Hulten and Sichel (2005)

I. Computerised information

Computerised information comprises computer software, both purchased and own-account, and computerised databases. Software is already capitalised in the National Accounts, and our main
source for computer software investment is contained in the ONS work described by Chamberlin et al (2007).

II. Intellectual property

Artistic originals

Previous estimates for investment in Artistic Originals were based on official ONS estimates recorded in the National Accounts. We have since improved those estimates in terms of both data and methodology (Goodridge and Haskel, 2011 and Goodridge, Haskel and Mitra-Kahn, 2012). Using a variety of sources we construct new estimates of investment in the categories of Film, TV & Radio, Books, Music and Miscellaneous Artwork. Official estimates are soon to be improved based on that work.

Scientific R&D

For Scientific R&D performed by businesses in the UK, expenditure data are derived from the Business Enterprise R&D survey (BERD). To avoid double counting of R&D and software investment, R&D spending in “computer and related activities” (SIC 72) is subtracted from R&D spending, since this is already included in the software investment data. One component of BERD expenditure data is the spend on tangible assets used in R&D production. In estimating R&D investment we correctly convert estimates of the tangible stock used in R&D production into terms for the user cost of capital.

Another aspect of the BERD data is that one product category is R&D in R&D products, which is the R&D conducted by the R&D services industry (SIC 73) that is sold to outside industries. In accounting for this, we allocate own-account expenditure on production of R&D products to the industries that purchase R&D products from SIC73, using shares constructed from the IO tables.

Non-scientific R&D

R&D in social sciences and humanities is estimated as twice the turnover of R&D in the “Social sciences and humanities” industry (SIC 73.2), where the doubling is assumed to capture own-account spending. Turnover data are taken from Annual Business Inquiry (ABI) and are available from 1992. The estimates are small relative to other types of intangibles and we suspect the marginal benefit to improving the measurement is slight.

Mineral exploration
Like computerised information and artistic originals, *mineral exploration* is already capitalised in the National Accounts and the data here are simply data for Gross Fixed Capital Formation (GFCF) from Blue Book 2011. The data cover 1970 to 2010.

**Financial product innovation**

The measurement methodology for *new product development costs in the financial industry* follows that of own-account software, used by the ONS. In practice these numbers turn out to be rather small. Further details are in Haskel and Pesole (2011) but a brief outline is as follows. First, we interviewed a number of financial firms to try to identify the job titles of workers who were responsible for product development. Second, we compared these titles with the available occupational and wage data from the Annual Survey on Hours and Earnings (ASHE). The occupational classification most aligned with the job titles was ‘economists, statisticians and researchers’. Third, we asked our interviewees how much time was spent by these occupations on developing new products that would last more than a year. Some firms based their estimates on time sheets that staff filled out. Fourth, we asked firms about the associated overhead costs with such workers. Armed with these estimates, we went to the occupational data in the ASHE and derived a time series of earnings for those particular occupations in financial intermediation. Own-account investment in product development is therefore the wage bill, times a mark-up for other costs (capital, overheads etc.), times the fraction of time those occupations spend on building long-term projects. All this comes to around 0.52% of gross output in 2005 (note that reported R&D in BERD is 0.01% of gross output).

**Architectural and engineering design**

For new *architectural and engineering design* we use the software method for own-account, and purchased data are taken from the IO tables. Full details are set out in Galindo-Rueda et al (2010). To avoid over-estimating, based on industry discussions we assume that 50% of such expenditure represents long-lived investment, thereby excluding one-half of the expenditure figure. As described in Goodridge, Haskel and Wallis (2012), we also make a further adjustment to account for intra-industry outsourcing. That is, we subtract purchases of design made by and from the design industry itself, to avoid any possible double-counting.

**III. Economic competencies**

**Branding: advertising and market research**

*Advertising expenditure* is estimated from the IO Tables by summing intermediate consumption on advertising (product group 113) across all industries. Market research is estimated with data on market research from the IO tables. Of course not all expenditure on advertising and market research
constitutes investment. Therefore based on industry discussions we estimate investment in brands as 60% of expenditure. In doing so, we effectively remove all short-lived expenditure. Again, as with design, intra-industry purchases are removed to account for outsourcing and potential double-counting.

Firm-specific human capital (training)

Firm specific human capital, that is training provided by firms, was estimated using cross sections from the National Employer Skills Survey for 2004, 2007, 2009 and 2010. We also have data for 1988 from an unpublished paper by John Barber. The series is backcast using the EU KLEMS wage bill time series benchmarking the data to five cross sections.

Organisational structure

For purchased organisational capital we use data from the Management Consultancy Association (MCA). To measure own-account investment in organisational structure we use the now standard assumption in the intangibles literature that 20% of the wage bill of managers, where managers are defined using occupational definitions, is investment in organisational structure. Wage bill data are taken from the ASHE for all those classified as managers, excluding IT and R&D managers to avoid double counting.

3d. Industry weights: outside knowledge

We have constructed two alternative sets of weights. Each provides some measure of ‘industry closeness’ and the appropriateness of each depends on the asset type being considered. The first are based on data for intermediate consumption (IC), by product and industry, as recorded in the IO tables. The second are based on inter-industry labour force transitions (TR), estimated using Labour Force Survey micro data. Due to data availability, labour transition weights only apply to movements between 2006 and 2007 whilst the intermediate consumption weights are produced using a full set of published data from 1992.

Weights: inter-industry trade (Intermediate Consumption)

We use data from the official IO datasets, available for 1992-2007, which contain information on industry intermediate consumption by product, and we use that data to form a matrix of inter-industry flows, as in for example Griliches & Lichtenburg (1984). In doing so we assume that products purchased correspond to producing industries. IO data is aggregated to a broad seven-industry breakdown, and each cell is transformed into an industry share, where the shares sum vertically to 1 (i.e. across products or “selling industries”). In the case of Business Services, we appropriately
exclude data for dwellings (both actual and imputed rents) since dwellings are not part of the productive capital stock and were excluded from the calculation of TFP.

Weights: Labour force transition
Based on LFS micro data we have data on the flows of workers into each industry and which industry they have moved from, and again the data are constructed into industry shares.

Our final dataset consists of a series of vectors for both forms of industry-weight, where the weights in each sum to one. We then apply these weights to our industry estimates of knowledge stocks, by asset type. For each industry and asset we construct a term for growth in available outside knowledge as the industry weight multiplied by growth in the relevant capital stock from the other six industries. Therefore, say for example, 50% of IC in industry X comes from within the industry, the weights for other industries will sum to 0.5.

4. Results

4a. Graphs and raw correlations
We have potentially many assets and, it turns out, they are very collinear in the time series (although not in the cross section e.g. R&D is concentrated in manufacturing, software in financial services).

Thus we work with the following asset groups: just R&D since that is studied so much in the literature, all intangibles, all intangibles excluding R&D, computerised information, innovative property, innovative property excluding R&D and economic competencies. We also smooth TFP growth, as is done in many studies, since it is so noisy. We do so using forward weights of 0.25, 0.5 and 0.25 for t+2, t+1 and t respectively, to introduce an effective lag into our explanatory variables. The results for unsmoothed TFP growth are similar.

Figure 1 plots smoothed TFP growth and growth in the weighted (IC) outside stock, all in terms of deviation from time and industry means. Each point is an industry (1=agriculture and mining, 2 = manufacturing, 3=utilities, 4=construction, 5= distribution, 6 = finance and 7 = business services). Each panel corresponds to a different outside measure.
Consider then the upper left panel for R&D. The points labelled “3” show the 13 observations for utilities. Consider the points on the left-hand side of the graph. They generally lie below both the zero horizontal and vertical axes. This shows that for periods where utilities was relatively less exposed to outside R&D stock growth, subsequent TFP growth was low (these and later statements are, for exposure and dlnTFP, relative to the industry and time average). Now consider the points, again for utilities, on the right-hand side of the chart. These lie above both the zero horizontal and vertical axes, showing that following periods where utilities were relatively more exposed to outside R&D growth, subsequent TFP growth was higher.

The figures seem to suggest a positive relation with each category, although that for software appears weakest. The relation appears strongest for R&D and economic competencies. Note that manufacturing (2), consistently clustered around zero, is exposed to a relatively low amount of
outside capital growth relative to the average because a) much of its intermediate consumption comes
from within manufacturing and b) much of the growth in intangible capital takes place in
manufacturing itself. Therefore weighted growth of external knowledge is low for manufacturing.

Less of a correlation is found with the alternative (TR) weighting scheme, as shown in the Appendix
chart. Indeed for total innovative property and economic competencies the correlation appears
negative. It is worth noting however that the labour transition flows are only for 2006 to 2007.

4b. Regression results

To estimate (7) we proceed as follows. Even at these broader asset categorisations, the degree of
colinearity between our independent variables remains rather high. We therefore first run separate
regressions for different asset definitions and each alternative weighting scheme. Growth in internal
stocks is included to control for the effects of market power and/or increasing returns. The
interpretation follows equation (7), namely that the internal variable should appear in a regression
even with that effect accounted for in dlnTFP if there is some deviation of the output elasticity from
its factor share, which could be due to imperfect competition in the industry, non-constant returns to
scale etc. All regressions use data for 1995 to 2007, as data for the early 1990s are considered to be
of much lower quality and data post-2007 were not available, and estimation uses a fixed effects
model including year dummies (not reported) with robust standard errors. Finally note that
measurement error will bias our results downwards and therefore in this respect our estimates might
be a lower bound on the true effects.
Table 3: Regression estimates of equation (7) (dependent variable, smoothed ΔlnTFP (t+2, t+1, t))

<table>
<thead>
<tr>
<th>ASSET</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
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<td>IC TR</td>
<td>IC TR</td>
<td>IC TR</td>
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<td>IC TR</td>
<td>IC TR</td>
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</tr>
<tr>
<td>External R&amp;D</td>
<td>0.43***</td>
<td>2.31**</td>
<td>0.38***</td>
<td>1.57**</td>
<td>0.64***</td>
<td>2.08**</td>
<td>0.38**</td>
<td>1.96***</td>
<td>0.25*</td>
<td>1.71**</td>
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<tr>
<td>Internal R&amp;D</td>
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<td>0.074*</td>
<td>0.027</td>
<td>0.036</td>
<td>0.037</td>
<td>0.052</td>
<td>0.034</td>
<td>0.063</td>
<td>0.041</td>
<td>0.070</td>
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<td></td>
<td>(1.86)</td>
<td>(1.95)</td>
<td>(0.15)</td>
<td>(0.83)</td>
<td>(1.22)</td>
<td>(1.03)</td>
<td>(1.78)</td>
<td>(1.89)</td>
<td>(1.29)</td>
<td>(1.65)</td>
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<tr>
<td>Total External Intangibles</td>
<td>0.52**</td>
<td>0.58</td>
<td>(1.97)</td>
<td>(0.99)</td>
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<tr>
<td>Total Internal Intangibles</td>
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<td>-0.18***</td>
<td>(-5.06)</td>
<td>(-5.64)</td>
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<tr>
<td>Total External Intangibles excl. R&amp;D</td>
<td>0.39*</td>
<td>0.070</td>
<td>(2.22)</td>
<td>(0.074)</td>
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<tr>
<td>Total Internal Intangibles excl. R&amp;D</td>
<td>-0.17***</td>
<td>-0.16***</td>
<td>(-5.26)</td>
<td>(-5.14)</td>
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<td>External Software</td>
<td>0.031</td>
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<td>(1.01)</td>
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<tr>
<td>External Economic Competencies</td>
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<td>-0.63</td>
<td>(1.95)</td>
<td>(-0.84)</td>
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<tr>
<td>Internal Economic Competencies</td>
<td>-0.11**</td>
<td>-0.099*</td>
<td>(-2.66)</td>
<td>(-2.23)</td>
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<td>91</td>
<td>91</td>
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</tr>
<tr>
<td>R-squared</td>
<td>0.185</td>
<td>0.147</td>
<td>0.287</td>
<td>0.228</td>
<td>0.372</td>
<td>0.273</td>
<td>0.187</td>
<td>0.161</td>
<td>0.204</td>
<td>0.170</td>
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<td>7</td>
<td>7</td>
<td>7</td>
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<tr>
<td>Elasticity of external R&amp;D</td>
<td>0.25</td>
<td>0.21</td>
<td>0.30</td>
<td>0.054</td>
<td>0.22</td>
<td>0.15</td>
<td>0.26</td>
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<td>0.22</td>
<td>0.18</td>
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<td>Elasticity of other external variable</td>
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<td>-0.059</td>
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<td>-0.059</td>
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</table>

Notes to table: Dependent variable is dlnTFP smoothed, t+2, t+1, t. Independent variables are dated t, and are ΣwdlnK, that is weighted changes in outside intangible capital stocks, with the included intangible variables according to the row titles (see table 2 for details of what is included in each broad intangible class). Weighting schemes use intermediate consumption (IC) and labour transitions (TR). Estimation by fixed effects with time dummies. ***indicates significance at 1%, ** indicates significance at 5%, * at 10%. Final two rows show the estimated % change in TFP with respect to a 1% change in respectively, outside R&D, and all outside intangible capital. t-statistics reported in parentheses, using robust standard errors.

Column 1 and 2 of Table 3 set out the results using IC and TR weights to generate the external R&D variable. These regressions are similar to much of the previous in this area and like most of that literature external R&D is found to be statistically significant using either weighting scheme. The estimated elasticities with respect to a unit rise in all external capital growth rates, see penultimate row, are similar for each weighting scheme at 0.25 and 0.21: the survey paper by Hall et al (2009) reports elasticities with respect to external R&D using a production function method between 0.006 (on country data) and 0.68 (on firm data).

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7 This is derived as follows. Consider the coefficient in the body of the table using say the IC weights. As a matter of data in 2006, the manufacturing sector purchased 69% of its intermediate consumption from inside the sector, and 31% from outside. So for manufacturing dlnTFP, we weight outside DlnX with these 6 outside weights which add up to the total share of intermediate consumption from outside, in this case to 31%. Hence the coefficient that we then estimate is a coefficient on this “outside” DlnX variable, call it ΣwDlnX, as opposed to the DlnX variable itself. Thus the coefficient in the body of the table answers the question: what is the impact on DlnTFP of an increase in the outside variable, ΣwDlnX. This is not the same as the answer to the question: what is the impact on DlnTFP of an unit increase in all the outside DlnX’s. To answer this second question, one must multiply the body of table coefficient by the sum of the outside weights (in the case of
Columns 3 and 4 report results for all intangibles weighted together (including R&D). As these columns show, statistical significance depends on the weighting matrix used, with the IC matrix significant at the 5% level, although we do generate negative and statistically significant coefficients for the within-industry intangible stock. This negative dlnK is statistically insignificant when financial services is dropped, with all external measures remaining statistically significant. The estimated elasticity also varies greatly depending on which weighting scheme is used, with the IC matrix generating a much larger elasticity. In order to check that the result is not just due to the inclusion of R&D rather than other intangibles assets columns 5 and 6 show the results of using total intangibles excluding R&D. As before, intangibles are statistically significant using the IC weighting matrix but not the TR weighting matrix. Note to that external R&D remains statistically significant.

The final six columns attempt to determine which non-R&D intangible asset(s) are driving the result in column 5. Running regressions for each asset group alongside R&D, we only generate as statistically significant result for External economic competencies, which we found to be significant at the 10% level using the IC weighting matrix but not statistically significant using the TR matrix. The results therefore suggest that spillovers from intangibles other than R&D appear to derive from investments in training, organisational capital or reputational capital. In the case of the latter, one possibility is that the observation of rent spillovers as discussed above.

It is therefore difficult to identify which asset groups other than R&D are driving some of our results. There are two possible interpretations. First, statistical: elements of intangible investment are very collinear (e.g. due to complementarities), hence it is hard to statistically identify separate spillovers. Second, economic: spillovers come from rivals performing a bundle of non-R&D intangible investments.

Overall, our results are stronger using the intermediate consumption model rather than the labour transition model. It is of course perfectly possible that the appropriateness of the weighting scheme would differ by asset, with IC weights preferable for some, and TR weights for others. It may be that the estimation using the transition model could be improved with a more complete set of data.

**4c. Robustness**

How robust are these results? We tried a number of different variations, all of which for brevity are not reported here but available on request.

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manufacturing, 31%), for that year, then for each industry and then take a grand industry/year average. The elasticity in the bottom row is this.
First, although there is considerable collinearity between variables, Appendix Table A1 presents results for when we include all four asset groups together. The result is a weakly significant coefficient for External Economic Competencies at the 10% level when using the IC weights, and a strongly significant coefficient for R&D at the 1% level using the TR weights. We also run those same regressions but excluding the finance industry. In that case, we generate a statistically significant result for R&D at the 10% level using the IC weights, and a statistically significant result for both R&D and software, again at the 10% level, using the TR weights.

Second, to examine the absorptive capacity of firms and their ability to benefit from diffusion of outside knowledge, see for example Cohen and Levinthal (1989), we did try some specifications which included an additional interaction term between the outside stock and a measure of absorptive capacity based on industry investment intensity, with little success either in terms of statistical or economic (the coefficients for this term tended to be negative) significance.

Finally, we tried a number of more econometric robustness checks. Due to the presence of measurement error in our outside stocks we estimated the regressions above using instrumental variable methods (two stage least squares and two stage GMM). We used lagged values of outside stocks as instruments, which are valid instruments so long as the measurement error in the outside stocks is not serially correlated. The results were similar to the regressions above.

5. Conclusions

This paper asks if there is any evidence consistent with spillovers from R&D and other wider-knowledge (or intangible) investments. We use data on 7 UK industries, 1992-2007 and adopt the industry-level method used in the R&D literature by, for example, Griliches (1973) and Griliches and Lichtenberg (1984) which relies on weighting external measures of the knowledge stock: in their case, R&D, in our case, R&D and other intangibles. We create two weights: based on flows of intermediate consumption (IC) using the input-output (IO) supply use tables; and the second based on labour transition (TR) flows between industries, constructed from the Labour Force Survey (LFS). To the best of our knowledge, this approach has not been adopted for intangibles.

Our findings are based on correlations between industry TFP growth and lagged “outside” knowledge stocks (lagged changes in other industry knowledge stocks weighted by the weighting matrices), all in deviations from time and industry mean terms. Thus our results are not based on contemporaneous correlations between TFP growth and changes in capital stocks, which could be due to unmeasured utilization and imposes instant spillover transmission. Rather, we examine if more exposure to outside capital growth, over and above that industry’s average exposure and the
average exposure across all industries in that period, is associated with above industry/time average TFP growth in future periods. What do we find?

First, as a benchmark, controlling for industry and time effects, we estimate a positive statistically significant correlation between industry TFP growth and lagged external R&D knowledge stock growth. This does not of course imply causation, but is consistent with spillovers of R&D⁸.

Second, we also find a correlation between TFP growth and outside total intangible knowledge stock growth. Third, when we enter R&D and also other intangibles, we consistently find statistically significant correlations with R&D, regardless of choice of weighting method or other regressors. Multicollinearity problems make breaking out individual components of that stock hard however. We find some occasional statistically significant correlations with other components of intangibles, but they are few and depend on choice of weighting. Future work with longer data sets and improved measures is no doubt needed, but in sum, these data find consistent correlations with R&D and with total outside intangibles.

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⁸ Almost all international ratings of the UK science base rank it very highly (e.g. on citations of scientific papers, productivity of scientists, BIS, 2011). Thus one might expect that spillovers in the UK would be potentially high relative to other countries.
References


Galindo-Rueda, F., Haskel, J. and Pesole, A. (2010) How much does the UK employ, spend and invest in design?, Imperial College Discussion paper 2010/05


Appendix

Figure A1: Scatters with broad asset definitions (all in deviation from industry and time mean terms):
Labour Transition Weights

Notes to figure: rd = R&D; sof = software and computerised databases; IP = innovative property = scientific and non-scientific R&D; design, new products in finance, and artistic originals; EC = economic competencies = branding; improvement of organisational structures and business processes; and firm-provided training. TTIN is the total. Aggregation of growth rates of capital stocks is by rental share of each intangible. Outside capital weights are using the labour force transition based weighting matrix. Each point is an industry (1=agriculture and mining, 2 = manufacturing, 3=utilities, 4=construction, 5= distribution, 6 = finance and 7 = business services).
### Table A1: Regression estimates (dependent variable, smoothed $\Delta\ln TFP (t+2, t+1, t)$)

<table>
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<tr>
<th>ASSET</th>
<th>INCLUDING FINANCE (ind=6)</th>
<th>EXCLUDING FINANCE (ind=6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>IC</td>
<td>TR</td>
</tr>
<tr>
<td>External R&amp;D</td>
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<td>1.31***</td>
</tr>
<tr>
<td></td>
<td>(1.90)</td>
<td>(3.81)</td>
</tr>
<tr>
<td>Internal R&amp;D</td>
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<tr>
<td></td>
<td>(1.01)</td>
<td>(0.81)</td>
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<td>External Software</td>
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<td>(1.00)</td>
<td>(1.66)</td>
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<tr>
<td>Internal Software</td>
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<td>(1.57)</td>
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<td>External Intellectual Property excl. R&amp;D</td>
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<td>(0.94)</td>
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<td>External Economic Competencies</td>
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<td>(1.96)</td>
<td>(-1.36)</td>
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<tr>
<td>Internal Economic Competencies</td>
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<td>(-2.41)</td>
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<td>R-squared</td>
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<td>0.264</td>
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<td>Number of industries</td>
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<tr>
<td>Elasticity of external R&amp;D</td>
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<td>0.12</td>
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<td>Elasticity of external software</td>
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<td>-0.11</td>
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<td>Elasticity of external IP excl. R&amp;D</td>
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<tr>
<td>Elasticity of external economic competencies</td>
<td>0.056</td>
<td>0.0040</td>
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</table>

Notes to table: Dependent variable is $\Delta \ln TFP$, $t+2, t+1, t$. Independent variables are $\sum w \Delta \ln K$, that is weighted changes in outside intangible capital stocks, with the included intangible variables according to the row titles (see table 2 for details of what is included in each broad intangible class). Weighting schemes use intermediate consumption (IC) and labour transitions (TR). Estimation by fixed effects with time dummies. ***indicates significance at 1%, ** indicates significance at 5%, * at 10%. Final row shows the estimated % change in TFP with respect to a 1% change in all outside capital. t-statistics reported in parentheses, using robust standard errors.