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SPILLOVERS FROM R&D AND OTHER INTANGIBLE INVESTMENT: EVIDENCE FROM UK INDUSTRIES

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Many agree that evidence exists consistent with spillovers from R&D. But is there any evidence of spillovers from a broader range of intangibles, such as software, design or training? We collect investment data for these wider intangibles for a panel of seven UK industries 1992–2007. Using the industry-level method in the R&D literature, e.g. Griliches (1973), we regress industry TFP growth on lagged external knowledge stock growth, where the latter are outside industry measures weighted by matrices based on (a) flows of intermediate consumption or (b) workers. Our main new result is that we find (controlling for time and industry effects) statistically significant correlations between TFP growth and knowledge stock growth in (a) external R&D and (b) total intangibles (excluding R&D). We show our results are robust to controls for imperfect competition and non-constant returns; likewise they are robust to including foreign R&D, and other controls, and various lags.

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1. INTRODUCTION

An extensive literature studies private and spillover returns to R&D. The recent survey by for example, Hall *et al*. (2009), and an earlier one by Griliches (1973), suggests that for R&D, social returns likely exceed private returns.

However it is well acknowledged that R&D is only a subset of the actual investments made in researching, designing, developing and commercializing

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innovations. A framework for estimating a broader range of "intangible" investments is set out in Corrado *et al*. (2005).[1]

This paper therefore asks: *is there any evidence that other intangible investments, besides R&D, have social returns above private returns*? It is, for example, perfectly possible that a broader range of intangible investments might accompany R&D, but *only* R&D has 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 (over and above R&D) is very thin on the ground. As Griliches (1992) 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 (see e.g. Jaffe and Trajtenberg, 2002, for a survey and citations), but this is unavailable in our case since non-R&D intangibles, such as software, design and training are not patentable (for example, U.K. software is not patentable, except under very special circumstances). Griliches' (1992) 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*. (2009) and Eberhardt *et al*. (2013) 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, Corrado *et al*. (2009) and Corrado *et al*. (2012) find a correlation between TFP growth and intangible investment for a sample of countries.[2] Dearden *et al*. (2006) 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 *et al*. (2012),[3] for seven U.K. industries and covering the period

[1]The broader set of knowledge investments are (a) software and databases (b) innovative property (scientific and non-scientific R&D, design, mineral exploration, financial product development and artistic originals) and (c) economic competencies (branding, training, organizational capital). If this spending devotes current resources to the pursuit of future returns, it would meet the official definition of investment and hence such spending is being incorporated into National Accounts as investment: the UK National Accounts currently count as investments software, artistic originals and mineral exploration, and, in 2014, will count R&D.

[2]These are raw correlations implied by scatter plots between measures of intangible capital and TFP at the aggregate level. In this paper we look for correlations based on regressions of measures of intangible capital on industry TFP.

[3]Goodridge *et al*. (2012) is based on eight market sector industries, the eighth composed of personal, social and recreational services (SIC03 sector O). That industry is excluded from this work due to issues in measurement of output (and inclusion of non-market services and seemingly implausible estimates of TFP).

1992–2007.[4] We 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, a range of other intangible asset categories, and total intangibles. We create two alternative sets of weights based on (1) flows of intermediate consumption built using the input-output (IO) supply use tables; and (2) labor transition flows between industries, constructed from the Labour Force Survey (LFS)[5] (in robustness checks we also examine foreign R&D weighted by import purchases).

Such a method is of course subject to a number of criticisms. In particular, we have only industry data. It would of course be of great interest to have firm-level data with a long run of intangible spending on software, marketing, R&D etc. To the best of our knowledge such data are not available: for example, O'Mahony and Vecchi (2009) are forced to merge firm data on R&D with industry data on advertising, skills and the like, due to lack of data. In addition, firm-level data raises its own problems e.g. lack of firm-specific deflators (Hall *et al.*, 2009). We comment below on the possible biases due to lack of firm-level data. In addition, like other studies, we have noisy data and lack a natural experiment (Greenstone *et al.*, 2010 and Kantor and Whalley, 2014 for example, use (quasi-)experiments). Of course, future work will improve methods and data, but here we describe how we try to control for these issues as best we can.

At this stage we believe there are four main reasons for this work to be of interest. First, to the best of our knowledge, looking for non-R&D spillovers using the R&D spillovers approach has not been adopted for intangibles so as a first-pass at the data we believe it is worth exploring. Indeed, Hall *et al.* (2009) in the conclusion to their recent survey, call for exploring possible spillovers from wider innovation spending rather than just R&D, which is what we do.

Second, 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 (Higon, 2007, uses eight two-digit U.K. manufacturing industries 1970–97 for example: her Table 1 lists the preceding most recent U.K. industry panel study as ending in 1992).

Third, many TFP-based 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.

Fourth, we examine our results for robustness to imperfect competition and non-constant returns. Our key results turn out to be robust and we think the proposed robustness method is new.

We look at the relation between industry TFP growth and lagged "outside" knowledge stocks (lagged changes in other industry knowledge stocks weighted by

[4]In Haskel and Wallis (2013) we have used time series data for the U.K. market sector and find strong evidence for positive externalities from the conduct of publicly funded scientific research. That work relies on 18 time series observations, this work herein uses variation at the industry level. Economy-wide variables such as public R&D are subsumed into time dummies.

[5]We are extremely grateful to Richard Jones (ONS) for constructing these weights for us. They use labor flows in 2007, so we are implicitly assuming that the pattern of 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.

the weighting matrices). All findings are controlling for industry and time effects. Thus our results are *not* based on contemporaneous correlations between TFP growth and changes in outside 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, 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. Multicollinearity problems make exploring very detailed intangible categories very hard, but we find some correlation with outside firm competencies (branding, training and organizational 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 and (b) potential spillovers from other intangible categories, but depending somewhat on method. These findings are robust to non-constant returns and imperfect competition, and foreign R&D.

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

2.1. *Model*

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

$$Y_{it} = A_{it} F(L_{it}, K_{it}, M_{it}, N_{it}, N_{\_it}) \tag{1}$$

where Y_t, L_t, K_t,M_t are output, labor, tangible capital and intermediate inputs respectively. N_{it} is intangible capital for the industry and $N_{\_it}$ 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_t is any increase in output not accounted for by the increase in the other inputs.

Denoting ε as an output elasticity we can write, for any form of (1):

$$\begin{aligned} \Delta\ln Y_{it} = {} & \Delta\ln A_{it} + \varepsilon_{M,it}\Delta\ln M_{it} + \varepsilon_{K,i}t\Delta\ln K_{it} + \varepsilon_{L,it}\Delta\ln L_{it} \\ & + \varepsilon_{N,it}\Delta\ln N_{it} + \varepsilon_{\_N,it}\Delta\ln N_{\_it} \end{aligned} \tag{2}$$

In this section we assume perfect competition and constant returns to focus on spillovers. In the robustness section we extend the framework to allow for non-constant returns and imperfect competition and show our results are robust. Proceeding, to convert (2) into something estimable we make the following assumptions. First, $\Delta \ln A$ is industry-specific and includes an i.i.d. error term:

$$\Delta \ln A_{it} = a_i + v_{it} \tag{3}$$

where v is an i.i.d. error. Second, under perfect competition and no spillovers, the ε terms equal factor shares, since this is simply what cost-minimizing firms will choose. With spillovers, industries get extra output than that due to their own choice of capital and so the output elasticity differs from the factor share. Following Stiroh (2002) we therefore write

$$\varepsilon_X = s_X + d_X,\ X = M_{it}, K_{it}, L_{it}, N_{it} \tag{4}$$

where s_x is the share in output, Y, of spending on factor X and d a term to account for either deviations from perfect competition, increasing returns or spillovers due to that factor (a formal demonstration of this is set out in the robustness section). Third, observed TFP growth is defined as:

$$\Delta \ln TFP_{it} \equiv \Delta \ln Y_{it} - \sum_{X = L_{it}, K_{it}, M_{it}, N_{it}} \bar{s}_X \Delta \ln X \tag{5}$$

Where the bar above s_x denotes a two year time average (t and t-1) so that this expression holds if, for example, the underlying production function is translog, not just Cobb-Douglas.

Fourth, we turn to the "outside knowledge term," $\varepsilon_{\_N,it} \Delta \ln N_{\_it}$ in (2). Consider $\varepsilon_{\_N,it}$. If outside knowledge that affects ΔlnY is free, $\varepsilon_{\_N,it} > 0$, but cannot be measured in a 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 subsidized R&D and/or knowledge in other countries. Some other proportion, our focus here, will be in other industries. With *i-1* other industries, we have then potentially *t*(*i-1*) data points for $\Delta \ln N_{\_it}$ for each industry i, which would provide insufficient degrees of freedom with *t* observations. 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:

$$\varepsilon_{N_{\_i,t}} \Delta \ln N_{\_i,t} = \alpha_1 (M \Delta \ln N_{\_i,t}) + \lambda_t \tag{6}$$

Where λ_t measures any common economy-wide knowledge e.g. on the internet, from universities, from abroad etc. (we experiment below with more measures of this). All this gives us:

$$\Delta \ln TFP_{it} = \alpha_1 (M \Delta \ln N_{\_i,t}) + \lambda_t + a_i + \sum_{X=L,K,M,N^{PRIV}} d_X \Delta \ln X_{it} + v_{it} \tag{7}$$

which has the following intuition. Measured industry TFP growth[6] 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 v_{it}, which may for instance incorporate unmeasured changes in capital utilization. With a limited number of observations, our central empirical exercise is to test for evidence consistent with spillovers due to knowledge investment by other industries. Since we use U.K. 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 $\Delta \ln TFP$ includes the contribution of industry-intangible capital. To interpret d_X as the excess return to industry-specific knowledge investment requires computing $\Delta \ln TFP$ *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.

What biases might be induced by our use of industry data in the presence of firm heterogeneity? In the appendix, available on request, we model a firm-level production function where *firm* $\ln Y_j$ depends upon within and outside firm inputs ($\ln X_j$ and $\ln X_{\_j}$). Heterogeneity raises at least two issues. First, available industry data is ΣY_j. However, the log of industry data, $\ln(\Sigma Y_j)$ is not the same as $\Sigma(\ln Y_j)$. The appendix describes a closed form solution for this problem, using the property that for log normally distributed variables $\log(\Sigma_j X_j) = \Sigma_j (\log X_j) + (1/2)\sigma^2_{\log X}$. Hence log industry TFP data (derived from $\ln(\Sigma Y)$ less terms in $\ln(\Sigma X)$) introduces a "mix" term being the standard deviation of inputs less outputs in the industry. We have no information on this and so our outside spillover results are biased to the extent that changes in such terms are not controlled for by industry/time and are correlated with the outside spillover measures. Second, when we use industry data we implicitly sum over the firm-specific "outside" terms. If we suppose the outside terms are those outside the firm (a) but within the industry and (b) outside the industry, industry data gives two outside firm terms: (a) an outside term but within the industry (b) an outside term summing across firms outside the industry. The first of these is measured in the dx_{it} and the second is the outside term that we measure. If the coefficient on these outside spillovers depends upon

[6]We allow for industries to have different output elasticities via the construction of TFP as in (5), since they differ in terms of factor shares. But (7) does impose the same elasticities with respect to weighted outside intangibles, α_1. That is, the coefficient, α_1, is the same across all industries. However, the effect of a unit increase in outside knowledge still varies by industry, since this effect is α_1 times the sum of outside weights, and this sum varies by industry: see section 4.2.

firm characteristics, we will again omit a "mix" term. Thus we should be cautious in the interpretation of our outside industry terms as spillovers.

2.2. Other Studies and Discussion of Framework

As pointed out in Griliches (1973) and Hall *et al*. (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.

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 subsidize branding, if vertical relations between manufacturers and retailers internalize any externality present. Without detailed information for each industry this remains a caveat in our, and other, results. However, this effect might be less when we use labor transition weights than with intermediate consumption weights.

Hall *et al*. (2009) also points out that spillovers might be negative if they incorporate market-stealing effects from rival R&D (Bloom et al., 2013), in that case the gain in market share from new R&D has a negative effect on the productivity of outside firms (although likely in the same industry). The same authors also note 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) (and Bloom *et al*., 2013, find positive spillover effects when controlling for firm prices, see their Table 5).

3. Measurement

3.1. Industries

We base this work on our industry-level dataset of U.K. market sector investment in intangible assets, for a full discussion of data derivation and detailed sources see Goodridge *et al*. (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

TABLE 1
Industry Breakdown

SIC(2003)	Industry Description
ABC	Agriculture, Forestry & Fishing; Mining & Quarrying
D	Manufacturing
E	Electricity, Gas & Water Supply
F	Construction
GHI	Distribution; Hotels & Restaurants; Transport, Storage & Communications
J	Financial Services
K	Business Activities (excluding real estate)

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.

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 "Financial Intermediation Services Indirectly Measured" (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.[7] That said, Basu *et al*. (2006) estimate close to constant returns to scale for U.S. 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. We estimate initial capital stock in 1990 using the standard method (e.g. as in Oulton and Srinivasan (2003)). So that estimates are not too affected by initial values problems, we conduct our analysis over the period 1995 to 2007.

3.2. 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

[7]Better data is clearly desirable, but we note that we use industry and time dummies. So if for example, true agricultural $\Delta\ln TFP$ is positive but we incorrectly measure it by a constant industry or time factor, we are controlling for this. That is, for measurement error to be driving all our results, it would have to be measurement error that is causing deviations of $\Delta\ln TFP$ from its industry and time means.

TABLE 2

Intangible Asset Categories

Broad category of intangible asset	Includes
Computerized information	Computer software; computer databases
Innovative property	Artistic originals; Scientific R&D; Non-scientific R&D; Mineral exploration; Financial product innovation; and Architectural and engineering design
Economic competencies	Branding (Advertising and market research); Firm-specific human capital; and Organisational Structure.

Source: Corrado *et al*. (2005).

consistently using the ex post method so that the sum of capital rental payments, including intangibles, equals total capital payments. As 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.

3.3. 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 *et al*. (2005) (hereafter, CHS) and first applied to the U.K. in Giorgio Marrano *et al*. (2009). The sections below describe the data construction. For a fuller description of the data and robustness checks see Goodridge *et al*. (2012): (e.g. ΔlnTFP is quite robust to changes in depreciation rates).

The CHS framework for measuring intangible investment breaks spending down into three broad categories: i) software and computerized 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; mineral exploration; 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 commercializing the innovation, and therefore includes activities such as: branding; improvement of organizational 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.

Computerized Information

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

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, 2014). Using a variety of sources we construct new estimates of investment in the categories of Film, TV and Radio, Books, Music and Miscellaneous Artwork. Official estimates have since been revised based on that work.

Scientific R&D: For *Scientific R&D* performed by businesses in the U.K., 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 convert estimates of the tangible stock used in R&D production into terms for the user cost of capital. Note too that in the BERD data 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. Thus our spillovers, if any, from the business services industry, do not reflect these measured purchases.

Non-scientific R&D: This 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 (this number is very small).

Mineral exploration: Data on *mineral exploration* are already capitalized in the National Accounts and the data here are simply data for Gross Fixed Capital Formation (GFCF) from Blue Book 2011.

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, and is based therefore on financial service occupations; further details are in Haskel and Pesole (2011). In practice these numbers turn out to be rather small: spending is about 0.52 percent of industry gross output in 2005 (note that reported R&D in BERD is 0.01 percent of gross output in this industry).[8]

[8]In brief, we interviewed a number of financial firms to try to identify the job titles of workers responsible for product development and mapped these titles to available occupational/wage data from the Annual Survey on Hours and Earnings (the occupational classification most aligned with the job titles was "economists, statisticians and researchers"). We asked our interviewees for the time spent by these workers on developing new products that would last more than a year, noting that some firms based their estimates on time sheets that staff filled out, and on overhead costs. Own-account investment in financial product development is therefore that occupation wage bill, times a mark-up for capital, overheads etc., times the time fraction spent on long-term projects.

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 percent of such expenditure represents long-lived investment, thereby excluding one-half of the expenditure figure. As described in Goodridge *et al*. (2012), we also subtract purchases of design made by and from the design industry itself, to avoid any possible double-counting due to intra-industry outsourcing.

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. Following CHS we subtract off 40 percent of 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 organizational capital we use data from the Management Consultancy Association (MCA) on industry sales. To measure own-account investment in organizational structure we use the now standard assumption in the intangibles literature that 20 percent of the wage bill of managers, where managers are defined using occupational definitions, is investment in organizational structure. Wage bill data for each industry are taken from the Annual Survey of Hours and Earnings (ASHE) for all those classified as managers, excluding IT and R&D managers to avoid double counting.

3.4. Industry Weights: Outside Knowledge

We have constructed two alternative sets of weights. Each provides some measure of "industry closeness" and the appropriateness of each may depend 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 labor force transitions (TR), estimated using Labour Force Survey (LFS) micro data. Due to data availability, labor transition weights only apply to movements between 2006 and 2007 whilst the intermediate consumption weights are produced on an annual basis 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 and 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 horizontally to unity (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 percent of IC in industry X comes from within the industry, the weights for other industries will sum to 0.5.

3.5. *Descriptive Statistics*

Before proceeding to our results, we first present some descriptive statistics from our dataset. Since estimation is conducted over the period 1995 to 2007, we present mean industry values for those years.

Table 3 reads as follows. Column 1 is nominal gross output in £bns, with the largest industries in terms of gross output being manufacturing (D) and the distributive trades (GHI). Column 2 is nominal investment in scientific R&D in £bns, with most R&D spend occurring in the manufacturing industry. Column 3 is intermediate consumption from outside industries as a proportion of all intermediate consumption e.g. Industry ABC consumes 24 percent of intermediate consumption from itself and 76 percent from outside. Note that the sum of weights is low for both manufacturing (0.28) and business services (0.32) since the majority of their intermediate consumption is sourced from inside the industry. Column 4 is the percentage of labor transitions from outside industries. Note that the sum of weights for labor transitions is much lower than that for intermediate consumption, with most labor transitions occurring within industries. Column 5 is growth in R&D capital services internal to the industry. Column 6 is growth in total intangible capital services (excluding R&D) internal to the industry. Column 7 is weighted growth in R&D capital services external to the industry, weighted using intermediate consumption weights. Column 8 is weighted growth in total intangible capital services (excluding R&D) external to the industry, weighted

TABLE 3

Descriptive Statistics, Mean Values (1995 to 2007)

	Mean values: 1995–2007	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Nominal Gross Output	Nominal R&D investment	Sum of IC weights (outside)	Sum of TR weights (outside)	Gowth in inside R&D capital services	Gowth in inside total intangible capital services (excl. R&D)	Weighted (IC) growth in outside R&D capital services	Weighted (IC) growth in total outside intangible capital services (excl. R&D)	TFP
SIC 2003	Industry Description	$P^{Y}Y_{i}$	$P^{N}N_{i}$	$\sum m_i^{IC}$	$\sum m_i^{TR}$	$\Delta \ln N_i^{R\&D}$	$\Delta \ln N_i^{TTINxR\&D}$	$\sum m^{IC}{}_i \Delta \ln N_{\_i}{}^{R\&D}$	$\sum m^{IC}{}_i \Delta \ln N_{\_}^{TTINx}{}_i{}^{R\&D}$	$\Delta \ln TFP_i$
ABC	Agriculture, Forestry and Fishing; Mining	55.0	0.1	0.76	0.09	−1.79%	−5.08%	3.69%	3.31%	−0.85%
D	Manufacturing	412.1	9.4	0.28	0.05	4.40%	2.59%	0.90%	0.77%	0.55%
E	Electricity, Gas & Water Supply	51.4	0.1	0.74	0.20	−3.19%	3.54%	0.93%	−0.72%	0.46%
F	Construction	140.4	0.0	0.50	0.10	0.11%	3.32%	2.48%	1.87%	0.07%
GHI	Distribution; Hotels & Restaurants; Trans port, Storage & Communications	411.6	0.8	0.65	0.04	6.87%	6.22%	3.42%	2.84%	0.72%
J	Financial Services	134.5	0.1	0.78	0.06	7.81%	5.70%	4.86%	5.02%	0.91%
K	Business Activities (excluding real estate)	202.5	0.2	0.32	0.09	7.13%	7.82%	1.81%	1.56%	0.76%

Notes: Data are mean values over the period 1995 to 2007, for each industry labeled on the left-hand side. Column 1 is nominal gross output in £bns. Column 2 is nominal investment in scientific R&D in £bns. Column 3 is intermediate consumption from outside industries as a proportion of all intermediate consumption e.g. Industry ABC consumes 24% of intermediate consumption from itself and 76% from outside. Column 4 is the percentage of labor transitions from outside industries. Column 5 is growth in R&D capital services internal to the industry. Column 6 is growth in total intangible capital services (excluding R&D) internal to the industry. Column 7 is weighted growth in R&D capital services external to the industry, weighted using intermediate consumption weights. Column 8 is weighted growth in total intangible capital services (excluding R&D) external to the industry, weighted using intermediate consumption weights. Column 9 is unsmoothed industry TFP, estimated from an industry gross output production function.

using intermediate consumption weights. Note these are low in manufacturing, since growth in R&D and other intangible capital is strong in manufacturing and it purchases much of its intermediates from itself. Column 9 is unsmoothed industry TFP, estimated from an industry gross output production function.

4. Results

4.1. *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, computerized 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. Our explanatory variables are dated *t*, implying a lagged relation between outside knowledge and $\Delta \ln TFP$, which seems reasonable. The results for unsmoothed TFP growth, with explanatory variables dated *t, t-1* or *t-2*, 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 labeled "3" show the 13 observations for the utilities industry, 1995–2007. Consider the points on the left-hand side of the graph. They 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 ΔlnTFP (recall outside variables are dated t, ΔlnTFP smoothed t+2, t+1, t) was low (these and later statements are 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 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 (labeled 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 labor transitions weighting scheme, as shown in the Appendix chart. Indeed for total innovative property and economic competencies the correlation appears negative.

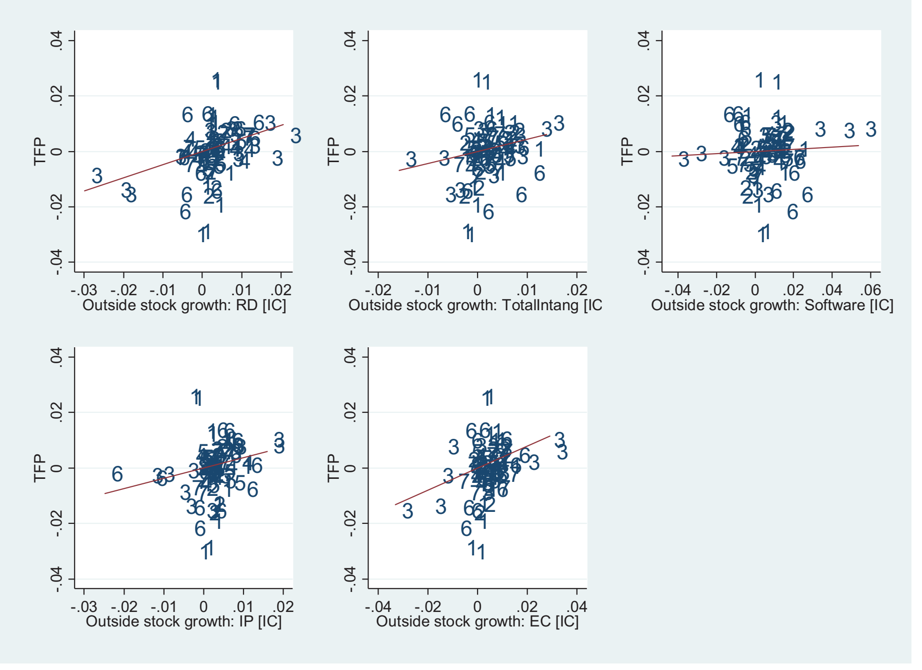

Figure 1. $\Delta \ln TFP_i$ against $M\Delta \ln N_{\_i}$ (outside industry $\Delta \ln N$, weighted by intermediate consumption of industry $\_i_{\ i}$ by the industry i), all in deviation from industry and time mean terms, $\Delta \ln TFP$ smoothed (t+2, t+1, t).

Notes: All estimates for TFP and outside stock growth are in deviations from the time and industry mean. Outside $\Delta \ln N$ are, clockwise from top left, RD = R&D; TotalIntang = total intangibles, Software = software and computerized databases; IP = innovative property (scientific and non-scientific R&D; mineral exploration, design, new products in finance, and artistic originals); EC = economic competencies (branding; improvement of organizational structures and business processes; and firm-provided training). Aggregation of $\Delta \ln N$ is by rental share of each intangible. Outside industry $\Delta \ln N$ weighted using the intermediate consumption-based weighting matrix, see text. Each point in graph is an industry (1=agriculture and mining, 2 = manufacturing, 3=utilities, 4=construction, 5 = distribution, 6 = finance and 7 = business services).

4.2. Regression Results

To estimate (7) we proceed as follows. Even at these broader asset categorizations, the degree of collinearity between our independent variables remains rather high. We therefore first run separate regressions for different asset definitions using the intermediate consumption weighting scheme (we test robustness to using our labor transition weights in a following section). 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 $\Delta \ln TFP$ if there is some deviation of the output elasticity from its factor share, which could be due to within-industry spillovers, industry imperfect competition, 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 all estimation includes industry fixed effects and aggregate 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 4 sets out the results using IC weights to generate the external intangible variable. Column 1 considers R&D. 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. The estimated elasticity with respect to a unit rise in external R&D capital growth rates,[9] see penultimate row, is 0.25 (note in a later section we show that the estimated elasticity using labor transition weights is similar, at 0.21): the survey paper by Hall *et al*. (2009) reports elasticities with respect to external R&D using a production function method of between 0.006 (on country data) and 0.68 (on firm data).

Column 2 reports results for all intangibles weighted together (including R&D). External intangibles are significant at the 5 percent level, although we do generate negative and statistically significant coefficients for the within-industry intangible stock. This negative internal term is statistically insignificant when financial services is dropped, with the external measure remaining statistically significant. The estimated elasticity is 0.30. In order to check that the result is not just due to the inclusion of R&D rather than other intangibles assets, column 3 shows the results of using total intangibles excluding R&D. As before, intangibles are statistically significant. Note too that external R&D remains statistically significant.

The final three columns attempt to determine which non-R&D intangible asset(s) are driving the result in column 3. 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 percent level using the IC weighting matrix. The results therefore are consistent with spillovers from intangibles other than R&D, that appear to derive from investments in training, organizational capital or reputational capital. In the case of the latter, one possibility is the observation of rent spillovers as discussed above.

To explore further these variables, we entered an inside and outside term for each asset individually, in separate regressions without the R&D term but using industry fixed effects and aggregate year dummies, and found statistically significant effects for outside training and management, (coefficient 0.39 (t=4.91), 0.28 (t=2.05) and 0.33(t=4.66)) but insignificant effects for branding (0.013 (t=0.14)). However, including the R&D term renders them all insignificant (0.16, (t=1.71),

[9]This is derived as follows. Consider the coefficient in the body of the table. As a matter of data in 2006, the manufacturing sector purchased 69 percent of its intermediate consumption from inside the sector, and 31 percent from outside. So for manufacturing DlnTFP, we weight outside DlnX with these six outside weights which add up to the total share of intermediate consumption from outside: here 31 percent. Hence the coefficient that we then estimate is a coefficient on this "outside" DlnX variable, call it $\sum$mDlnX, 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, $\sum$mDlnX. This is not the same as the answer to the question: what is the impact on DlnTFP of a 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 manufacturing, 31 percent), for that year, then for each industry and then take a grand industry/year average. The elasticity in the bottom row is this. This then is an average effect on industry gross output TFP growth: the effect on aggregated value added requires Domar-Hulten weighting, see section 4.4.

TABLE 4

Regression Estimates of Equation (7) using Intermediate Consumption Weights, with Industry Fixed Effects and Aggregate Year Dummies (Dependent Variable, Smoothed ΔLNTFP (T+2, T+1, T))

Using intermediate consumption weights:						
ASSET	(1)	(2)	(3)	(4)	(5)	(6)
External R&D	0.43***		0.38***	0.44***	0.38**	0.25*
	(4.61)		(7.42)	(5.91)	(2.76)	(2.14)
Internal R&D	0.043		0.0027	0.037	0.034	0.041
	(1.86)		(0.15)	(1.22)	(1.78)	(1.29)
Total External Intangibles		0.52**				
Total Internal Intangibles		(2.97)				
		−0.20***				
		(−5.06)				
Total External Intangibles			0.39*			
excl. R&D			(2.22)			
Total Internal Intangibles			−0.17***			
excl. R&D			(−5.26)			
External Software				0.031		
				(0.18)		
Internal Software				−0.0030		
				(−0.054)		
External Intellectual					0.17	
Property excl. R&D					(1.78)	
Internal Intellectual					−0.024	
Property excl. R&D					(−0.28)	
External Economic						0.24*
Competencies						(1.95)
Internal Economic						−0.11**
Competencies						(−2.66)
Observations	91	91	91	91	91	91
R-squared	0.185	0.287	0.372	0.187	0.204	0.304
Number of industries	7	7	7	7	7	7
Elasticity of external R&D	0.25	0.30	0.22	0.26	0.22	0.14
Elasticity of other external variable			0.22	0.018	0.10	0.14

Notes: Dependent variable is dlnTFP smoothed, t+2, t+1, t. Independent variables are dated t, and are $\sum$mdlnN, that is weighted changes in outside intangible capital stocks, and internal dlnN, 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 scheme uses inter-industry intermediate consumption (IC). Estimation using industry fixed effects with time dummies (not reported). ***indicates significance at 1 percent, ** indicates significance at 5 percent, * at 10 percent. Final two rows show the estimated % change in TFP with respect to a 1 percent change in respectively, outside R&D, and other outside intangible capital. t-statistics reported in parentheses, using robust standard errors. IP = innovative property (scientific and non-scientific R&D, mineral exploration, design, new products in finance, and artistic originals); EC = economic competencies (market research branding; improvement of organizational structures and business processes; and firm-provided training).

0.074(t=0.47), 0.16(t=1.29)), with the R&D term significant in all cases. It is therefore difficult to identify which asset groups other than R&D are driving some of our results. There are two possible interpretations. The first is statistical: elements of intangible investment are very collinear (as might be expected e.g. due to complementarities), hence it is hard to statistically identify separate spillovers (the correlation between demeaned ΔlnN R&D and training is 0.63; management 0.69, branding −0.21). The second is economic: spillovers arise from the bundle of non-R&D intangible investments not just each element.

4.3. Initial Robustness Checks

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.

First, as discussed above, we have an alternative weighting scheme based on labor transitions between industries. Those transitions apply to movements of workers between 2006 and 2007, and we apply the same weights to all years in our dataset. We therefore test robustness to using this alternative weighting scheme by re-running all of the regressions in Table 4 using these weights. Results are presented below in Table 5.

Using the alternative labor transition weights, we again find external R&D to be statistically significant, with an estimated elasticity with respect to a unit rise in external R&D capital growth rates of 0.21. Here we also find internal R&D to be statistically significant at the 10 percent level, consistent with within-industry spillovers from R&D.

Column 2 reports results for all intangibles weighted together (including R&D). Using these weights, external intangibles are no longer significant and we again generate negative and statistically significant coefficients for the within-industry intangible stock. Similarly, in columns 3 to 6, we find no statistically significant effects for any of our other measures of external intangible capital growth, although in each case the coefficient for external R&D remains statistically significant with implied elasticities of 0.15 to 0.19.

Overall, our results are statistically better determined (for non-R&D assets) using the intermediate consumption model rather than the labor transition weights, with the implied elasticities to the outside variable slightly lower with labor transitions. Kantor and Whalley (2013) find that spillovers from U.S. universities seem to be mediated via labor market transitions and Greenstone *et al.* (2010) find stronger effects of U.S. plant-opening spillovers via labor market transitions than intermediate consumption. 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, or that the U.K. might be different.

Second, 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 percent level when using the IC weights, and a strongly significant coefficient for R&D at the 1 percent 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 percent level using the IC weights, and a statistically significant result for both R&D and software, again at the 10 percent level, using the TR weights.

Third, 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 $\sum \frac{P^N N_{it}}{P^Y Y_{it}} * M\Delta \ln N_{\_it}$, with little success either in

TABLE 5

Regression Estimates of Equation (7) using Labor Transition Weights, with Industry Fixed Effects and Aggregate Year Dummies (Dependent Variable, Smoothed ΔLNTFP (T+2, T+1, T))

ASSET	(1)	(2)	(3)	(4)	(5)	(6)
External R&D	2.31**		1.57**	2.08**	1.96***	1.71**
	(3.05)		(2.52)	(3.05)	(3.85)	(2.52)
Internal R&D	0.074*		0.036	0.052	0.063	0.070
	(1.95)		(0.83)	(1.03)	(1.89)	(1.65)
Total External Intangibles		0.58				
		(0.59)				
Total Internal Intangibles		−0.18***				
		(−5.64)				
Total External Intangibles excl. R&D			0.070 (0.074)			
Total Internal Intangibles excl. R&D			−0.16*** (−5.14)			
External Software				0.52		
				(1.01)		
Internal Software				0.012		
				(0.29)		
External Intellectual Property excl. R&D					−1.06 (−1.24)	
Internal Intellectual Property excl. R&D					−0.054 (−0.73)	
External Economic Competencies						−0.63 (−0.84)
Internal Economic Competencies						−0.099* (−2.23)
Observations	91	91	91	91	91	91
R-squared	0.147	0.228	0.273	0.161	0.170	0.226
Number of industries	7	7	7	7	7	7
Elasticity of external R&D	0.21	0.054	0.15	0.19	0.18	0.16
Elasticity of other external variable			0.0065	0.049	−0.098	−0.059

Notes: Dependent variable is dlnTFP smoothed, t+2, t+1, t. Independent variables are dated t, and are $\sum$mdlnN, that is weighted changes in outside intangible capital stocks, and internal industry dlnN, 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 scheme uses inter-industry labor transitions (TR). Estimation using industry fixed effects with time dummies (not reported). ***indicates significance at 1 percent, ** indicates significance at 5 percent, * at 10 percent. Final two rows show the estimated percentage change in TFP with respect to a 1 percent change in respectively, outside R&D, and other outside intangible capital. t-statistics reported in parentheses, using robust standard errors. IP = innovative property (scientific and non-scientific R&D, mineral exploration, design, new products in finance, and artistic originals); EC = economic competencies (market research branding; improvement of organizational structures and business processes; and firm-provided training).

terms of statistical or economic (the coefficients for this term tended to be negative) significance. We may have insufficient cross-section variation to identify these effects.

Fourth, 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. 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: see Appendix A2, although we note that, when using IV, total external intangibles (excluding R&D) is no longer statistically significant.

Fifth, we added controls for utilization, following Basu *et al.* (2006), Δln(H/N), where H/N is hours per worker at the industry-level, into the industry spillover regressions. H and N are taken from KLEMS. Note that we control for utilization somewhat by smoothing ΔlnTFP, using ex post factor shares (Berndt and Fuss, 1986; Hulten, 1986), and including time dummies. So we tried this utilization term with unsmoothed ΔlnTFP and dropping time dummies: the utilization term was generally insignificant and the other effects unchanged.

Sixth, any other outside effects are relegated here to time dummies. To examine this further, we entered U.K. public R&D spending on the science budget, interacted with $\frac{P^N N^{R\&D}{}_{it}}{P^Y Y_{it}}$, so year dummies could still be included. We found that this was statistically significant and the coefficient on outside R&D remains statistically significant and fell somewhat. We also entered ΔlnN of foreign industry R&D, using country/industry R&D capital stocks from Helmers *et al.* (2009), interacted with industry intermediate imports computed from WIOD (Timmer, 2012). Without time dummies this was positive and bordering on statistical significance, with time dummies, it was statistically insignificant.

Finally, we noted above that there are measurement issues associated with ΔlnTFP in various industries, in particular agriculture, fishing and mining (ABC). Therefore we re-ran all of the regressions in Table 4 excluding this industry, and found that none of our findings were adversely affected by the omission of this industry. In fact, excluding the industry greatly improves the precision of our results and often increases the magnitude of the coefficients.[10]

4.4. *Robustness to Imperfect Competition and Non-Constant Returns*

In the above, we suppressed imperfect competition and non-constant returns into *d*. We now set out a more formal model, based on a stream of work by Basu *et al.* (2006) and summarized in, for example, Basu and Fernald (2001). In a series of papers (see e.g. Basu *et al.* (2006)), those authors show results for the U.S. economy that approximate perfect competition and constant returns to scale. Consider (2). As they point out, profit maximizing implies that

$$\varepsilon_X \equiv \frac{\partial F}{\partial X}\frac{X}{F} = \mu s_X, X = M_{it}, K_{it}, L_{it}, N_{it} \tag{8}$$

Where μ = a mark-up of output prices over marginal costs, if any and s_x as the share in output, Y, of spending on factor X. Note that μ is common to all inputs, since it refers to a product market mark-up (the firm is assumed to have no monopsony power in the input market).

[10]For instance, comparing to Table 4, in column 1, the t-statistic for external R&D is increased to greater than 9. In column 3, the t-statistic for external R&D increased to 11.4 and that on external intangibles (excluding R&D) to 3.62. In column 4, the t-statistic for external R&D is increased to 8. In column 5, the t-statistic for external R&D is increased to 7.4. In column 6, the t-statistic for external R&D is increased to 3.85 and that for external economic competencies to 2.64. Similarly, using the TR weights as in Table 5, in column 1 the t-statistic is increased to 4.8. In column 2, the coefficient on external total intangibles is more than doubled and the t-statistic increased to 1.79. In column 3, the coefficient on external R&D is increased to 2.14 and the t-statistic to 8.26. In column 4, the coefficient on external R&D is increased to 2.45 and the t-statistic to 5.17. In column 6, the coefficient on external R&D is increased to 2.32 and the t-statistic to 8.31.

As they point out, imperfect competition and returns to scale are linked. We can show this by noting first the definition of returns to scale, γ, is

$$\gamma = \sum_{X=M_{it},K_{it},L_{it},N_{it}} \varepsilon_X \tag{9}$$

Combining (8) and (9) implies that

$$\gamma = \sum_{X=M_{it},K_{it},L_{it},N_{it}} \mu s_X \tag{10}$$

As they point out, mark-ups over marginal costs ($\mu>1$) require increasing returns ($\gamma>1$) as e.g. in Chamberlinian/Robinson monopolistic competition. As it turns out we find, econometrically, that $\mu=\gamma=1$ (statistically speaking). We comment how perfect competition can co-exist with knowledge production below.

Given the issues with measuring *ex ante* returns to capital, especially intangible capital, we adopt a residual or *ex post* approach here. As Hulten (2001) points out, constant returns to scale is required if capital returns are calculated residually. We have two capital terms, K and N. We have independent measures of the shares of labor and materials. Denoting our measured shares with the superscript MEAS the residual approach assumes that

$$1-\bar{s}_{L,it}-\bar{s}_{M,it}=\bar{s}_{K,it}^{MEAS}+\bar{s}_{N,it}^{MEAS} \tag{11}$$

Where the bars denote Tornqvist averages and s_L and s_M are their "true" values (if we could observe them). ΔlnTFP is then defined in terms of these measured shares and is:

$$\Delta\ln TFP_{it} \equiv \Delta\ln Y_{it} - \sum_{X=M_{it},L_{it},} \bar{s}_X \Delta\ln X - \sum_{X=K_{it},N_{it}} \bar{s}_X^{MEAS} \Delta\ln X \tag{12}$$

Adding these new terms to the substitutions in section 2, we may generalize (7) to read

$$\begin{aligned} \Delta\ln TFP^{MEAS}{}_{it} = {} & \alpha_1\left(M\Delta\ln N_{\_it}\right)+\lambda_t+a_i+\left(\sum_{X=M,L,K,N} d_X \Delta\ln X_{it}\right) \\ & +(\mu-1)\left(\sum_{X=M_{it},L_{it},K_{it},N_{it}} \bar{s}_X \Delta\ln X\right) \\ & +(\gamma-\mu)\left(\bar{\theta}_{K,it}^{MEAS}\Delta\ln K+\bar{\theta}_{N,it}^{MEAS}\Delta\ln N\right) \end{aligned} \tag{13}$$

$$\text{where}\ \bar{\theta}_{K,it}=\frac{\bar{s}_{K,it}^{MEAS}}{\bar{s}_{K,it}^{MEAS}+\bar{s}_{N,it}^{MEAS}},\ \bar{\theta}_{N,it}=\frac{\bar{s}_{N,it}^{MEAS}}{\bar{s}_{K,it}^{MEAS}+\bar{s}_{N,it}^{MEAS}}$$

So the first line is exactly the same as before, but there are two new terms on the next lines. Note that these new terms all involve ΔlnX, X = inputs, so can be written in terms of the *d* above, but here we use theory to place more structure on the expressions.

In (13), the second line is 0 if μ=1, because if μ=1 output elasticities are measured by their factor shares (Hall, 1988). Note that it is a coefficient on the share-weighted input sum since μ is common to all inputs. The third line goes to 0 if γ=μ and so controls for the fact that we have imposed constant returns in order to measure our unknown (two) capital inputs residually. Basu and Fernald (2001, their equation 9) have the second line but not the first or third. The first is absent because they do not analyse spillovers. The third is absent because they calculate returns to capital ex ante and hence do not need to impose constant returns. For them, therefore, μ is calculated econometrically using the second line as a regressor and then γ is calculated from (10) since the shares are known ex ante. As a matter of data however, they report that the revenue shares, in practice, sum to very near one (the residual sum is at most 3 percent of revenue on their U.S. industry data), and whilst their estimated μ varies it is on average very close to unity.

Table 6 therefore runs our key specifications with these two new terms. In column 1 we have the R&D terms and column 2 the R&D and the non-R&D intangible terms. What do we find?

First, the R&D and non-R&D terms are very similar in sign and significance to those reported above. So the results above are robust to non-constant returns and imperfect competition. Second, we find point estimates, in column 1 for example, of μ=0.986 and γ=0.786. We find in both columns that we can reject the hypothesis that either μ or γ are significantly different from one.

Does this mean the U.K. economy has no mark-up and constant returns? Romer (1990) argues that a feature of knowledge production is increasing returns. As Corrado *et al*. (2011) point out however, in his two sector model, increasing returns are in his upstream knowledge producing sector; the downstream sector that rents knowledge is perfectly competitive. If this is right, there are a number of possibilities. First, especially with much knowledge production in-house, each firm/industry has within it a knowledge-producing and knowledge-using sector. Available data thus merges the two together and cannot detect a mark-up. Second, analyses without intangibles implicitly assigns knowledge costs to the returns on tangible capital, which might look like mark-ups because they have omitted rental payments to knowledge. Third, we impose the same μ and γ across industries: with more data we might be able to relax this reliably.

4.5. *Economic Significance*

What is the effect of R&D, $\Delta \ln N_i$(R&D) on market sector value added, denoted ΔlnV? As Appendix 3 sets out, there are three effects which might be set out as

$$\frac{\partial \Delta \ln V}{\partial \Delta \ln N} = s_{N,V} + d_N \sum\nolimits_{i=1..I} w_i + d\_N \sum\nolimits_{i=1..I, i \neq j} w_i m_{ij} \tag{14}$$

TABLE 6

Regression Estimates of Equation (13) with Industry Fixed Effects and Aggregate Year Dummies, Incorporating Imperfect Competition and Returns to Scale (Dependent Variable, Smoothed ΔLNTFP (T+2, T+1, T))

	(1)	(2)
VARIABLES	Smoothed TFP	Smoothed TFP
$\Sigma s_X \Delta \ln X$ (coeff μ-1)	−0.014	−0.043
	(−0.22)	(−0.69)
$(\Sigma 0_N \Delta \ln N + \Sigma \theta_K \Delta \ln K)$ (coeff γ-μ)	−0.20**	−0.12
	(−2.73)	(−1.54)
Internal R&D stock	0.0075	−0.0014
	(0.31)	(−0.071)
External R&D Stock	0.40*	0.44**
	(2.20)	(3.47)
Internal Stock of Total Intangibles excl. R&D		−0.10*
		(−2.06)
External Stock of Total Intangibles excl. R&D		0.44*
		(2.09)
Observations	91	91
R-squared	0.383	0.461
Number of ind	7	7
Memo:		
Point estimate of μ	0.986	0.957
Test that μ=1	F(1, 6) = 0.05	F(1, 6) = 0.47
	Prob > F = 0.8330	Prob > F = 0.5183
Point estimate of γ	0.786	0.837
Test that γ=1	F(1, 6) = 3.57	F(1, 6) = 1.77
	Prob > F = 0.1076	Prob > F = 0.2315

Notes: Dependent variable is dlnTFP smoothed, t+2, t+1, t. Independent variables are dated t, and are $\sum$wdlnN, 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) weights. Estimation using industry fixed effects with aggregate time dummies (not reported). ***indicates significance at 1 percent, ** indicates significance at 5 percent, * at 10 percent. Memo items report point estimates and F tests on μ=1 and γ=1.

Where $s_{N,V}$ is the share of R&D capital payments in market sector value added, $d_{\_N}$ the coefficient on internal industry $\Delta \ln N_i$(R&D), w_i the Domar-Hulten weight, m_{ij} the relevant weight in the outside weighting matrix, and $d_{\_N}$ the regression coefficient on the outside $\Delta \ln N_{\_i}$(R&D).

Looking at, (14), first, there is the private elasticity of $\Delta \ln N_i$(R&D) on ΔlnV, which, since R&D is capitalized, is given by the average income share of R&D in market sector value-added which is 0.017.

Second, there are any within-industry spillovers from $\Delta \ln N_i$(R&D) on industry i. These are captured by the effect of $\Delta \ln N_i$(R&D) on $\Delta \ln TFP_i$ and since we use industry gross output for TFP, the effect on ΔlnV is the Domar-Hulten weighted sum of these effects. On our data, the sum of the Domar-Hulten weights is 2.26 and hence the effect of a $\Delta \ln N_i$(R&D) on ΔlnV is (0.043*2.26=)0.10 or (0.074*2.26=)0.17 based on the IC or TR weight coefficients from Tables 4 and 5, column 1.

Finally, there are outside-industry spillovers from $\Delta \ln N_{\_i}$(R&D) on industry I, which again have to be Domar-Hulten weighted and multiplied by the relevant outside weighting matrix element. Since $\Sigma w_i m_{ij}$=0.48 and 0.36 for the IC and TR weights respectively, these elasticities are (0.43*0.48 =)0.21 and (2.31*0.36 =)0.83 respectively.

How do these compare with those in the literature? As mentioned, most studies do not capitalize R&D, and regress it on $\Delta\ln N_i$ and $\Delta\ln N_{\_i}$ generating "inside" and "outside" coefficients. Griliches (1992) in his survey suggests, an "inside" elasticity of 0.11 and an outside elasticity of twice[11] that, 0.22. Since most of the papers he reviews do not capitalize R&D, our equivalent elasticities are the sum of the first two terms in (14) and the last term. That is the sum of the private contribution (which we have effectively excluded from TFP by capitalizing R&D within our growth-accounting), plus any excess contribution internal to the industry, plus any excess contribution external to the industry. Using the IC weights these are 0.117 (= 0.017 + 0.10) and 0.21, almost exactly the ratio Griliches assumes (our TR weights give 0.187 (= 0.017 + 0.17) and 0.83), a ratio of around four to one (outside to inside). In the survey of more recent studies by Eberhardt *et al*. (2013) "outside" effects are smaller or larger than the own effects, see their Appendix Table A-1, Panel II.2). Appendix A3 fully sets out how we estimate inside and outside effects.

In sum our estimates are economically significant and in line with other studies.

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 seven U.K. 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 labor 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.

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.

[11]Terleckyji (1980) finds coefficients in the ratio (outside to inside) of 1.6 and 2.7 (Table 6.3, last two rows) using IO coefficients and R&D intensities. Sveikauskas (1980) using a similar method finds ratios of 3.5 and 2.1 (his Table 2, rows 4 and 6).

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.

Third, regarding internal industry intangible capital, we find some, but less, evidence of within industry spillovers, or excess returns over and above those already accounted for in the estimation of industry TFP. We do generate negative and statistically significant internal coefficients in some cases, although this effect is removed when the financial services industry is dropped.

Fourth, we have extended the framework to test for non-constant returns and imperfect competition: our results are robust. Likewise they are robust to controlling for utilization and international R&D and to using instrumental variable methods.

What can we say about spillovers from these correlations? First, note of course that correlation does not imply causation. Second, our correlations are consistent with spillovers of R&D but might of course reflect assumptions such as constant returns/perfect competition or our use of aggregate data. On returns/competition we have tried to test for these and found our results robust. On the use of aggregate data, we cannot of course account for the considerable heterogeneity at the firm level. The firm-level model we have set out suggests that to the extent we have not picked up the "mix" effects that come from unobserved heterogeneity in the industry or time dummies, which are correlated with outside spillover terms, we have bias to our spillover terms. Without assumptions on heterogeneity in the firm-level spillovers term, the biases are unknown.

Third, we have been unable to estimate any absorptive capacity effects. To identify them we likely need more cross-section variation e.g. between big and small industries/firms, and so this may just be an artefact of our available data. Future work with longer and wider data sets is no doubt needed.

Fourth, whilst we have a correlation with either broad non-R&D intangibles, or economic competency intangibles (the sum of training, marketing and management) we have not been able to find significant correlations within each component. This may be statistical since the elements of intangible investment are very collinear with R&D (which is as it should be if there are complementarities). Or it might be economic: spillovers arise from the bundle of outside non-R&D intangible investments not just each element. Again, future work on wider and longer datasets might help shed light on this conclusion.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Figure A1: DlnTFPi against MDlnN_i (outside industry DlnN, weighted by labour transitions of industry _i i by the industry i), all in deviation from industry and time mean terms, DlnTFP smoothed (t+2, t+1, t).

Table A1: Regression estimates using industry fixed effects and aggregate year dummies (dependent variable, smoothed ΔlnTFP (t+2, t+1, t))

Table A2: Instrumental variable estimation using industry fixed effects and aggregate year dummies (dependent variable, smoothed ΔlnTFP (t+2, t+1, t))

Appendix A3: Calculations of inside and outside effects