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/intangible investments, such as software, design or training? We collect investment data for this wider intangible range for a panel of 7 UK industries 1992 -2007. Using the industry-level method in the R&D literature, Griliches (1973) for example, we regress industry TFP growth on lagged external knowledge stock growth, where the latter is outside industry knowledge stock growth 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. We expand our framework to allow for imperfect competition and non-constant returns and show our results are robust; 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, Mairesse, Mohnen (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 commercialising innovations. A framework for estimating a broader range of "intangible" investments is set out in Corrado, Hulten and Sichel (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 (1990) 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, UK software is not patentable, except under very special circumstances). Griliches' (1990) 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 Eberhardt, Helmers, Strauss (2013) and Hall, Mairesse and Mohnen (2009) 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

[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

spillovers. At a cross-country level, Corrado, Hulten, Hao and van Ark, (2009) and Corrado, Haskel, Iommi and Lasino (2012) find a correlation between TFP growth and intangible investment for a sample of countries. 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 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) labour transition flows between industries, constructed from the Labour Force Survey (LFS) (in robustness checks we also examine foreign R&D weighted by import purchases)[4].

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, Mairesse, Mohnen, 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, Hornbeck and Moretti, 2010 and Kantor and Whalley, 2013 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.

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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] Goodridge, Haskel and Wallis (2012) is based on 8 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).

[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 series observations, this work herein uses variation at the industry level. Economy-wide variables such as public R&D are subsumed into time dummies.

[4] We are extremely grateful to Richard Jones (ONS) for constructing these weights for us. They use labour 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.

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 8 two-digit UK manufacturing industries 1970-97 for example: her Table 1 lists the preceding most recent UK 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 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 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. 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. 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

2a. Model

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

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

where Y_t , L_t and K_t are output, labour input and tangible capital input 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):

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

In this section we assume perfect competition and constant returns to focus on spillovers. In the robustness section we extend the framework to 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, ΔlnA 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-minimising 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

$$\varepsilon_{X,it} = s_{X,it} + d_{X,it} \ , X = M_{it}, K_{it}, L_{it}, N_{it} \tag{4}$$

where $s_{x,it}$ 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:

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

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 "outside knowledge term", $\varepsilon_{\_N}\Delta\ln N_{\_it}$ in (2). Consider $\varepsilon_{\_N}$. 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 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 $\Delta\ln N_{\_it}$ for each industry n, 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:

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

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:

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

which has the following intuition. Measured industry TFP growth[5] 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_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 ΔlnTFP includes the contribution of industry-intangible capital. To interpret d_X as the excess return to industry-specific knowledge investment requires computing ΔlnTFP *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

[5] We allow for industries to have different output elasticities via the construction of TFP as in (5). But (7) does impose the same elasticities with respect to weighted outside intangibles, α_1. However, the effect of a unit increase in outside knowledge varies by industry, since this effect is α_1 times the sum of outside weights, and this sum varies by industry: see section 4b.

firms outside the industry. The first of these is measured in the d_i and the second is the outside term that we measure. If the coefficient on these outside spillovers depends upon firm characteristics, we will again omit a "mix" term. Thus we should be cautious in the interpretation of our outside industry terms as spillovers.

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.

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. However, this effect might be less when we use labour transition weights then 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, Schankerman and Van Reenen, 2012) 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) (and Bloom, et al, 2012, find positive spillover effects when controlling for firm prices, see their Table 5).

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 1: Industry Breakdown

SIC(2003)	Industry Description
ABC	Agriculture, Forestry and Fishing
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)

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. That said, Basu, Fernald and Kimball (2006) estimate 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).[6]

[6] 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

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.

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.

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 and robustness checks see Goodridge Haskel, and Wallis (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 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; 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 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

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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 ΔlnTFP from its industry and time means.

apply the newly acquired knowledge. It is therefore sensible to consider the data in these broader categories, as below.

Table 2: Intangible asset categories

Broad category of intangible asset	Includes
Computerised information	Computer software, computer databases
Intellectual property	Artsitic 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.

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 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 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. 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 capitalised 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% of industry gross output in 2005 (note that reported R&D in BERD is 0.01% of gross output in this industry).[7]

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 we subtract purchases of design made by and from the design industry itself, to avoid any possible double-counting when intra-industry outsourcing.

[7] 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 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 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.

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. Following CHS we subtract off 40% 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 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 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 labour force transitions (TR), estimated using Labour Force Survey (LFS) 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 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% of IC in industry X comes from within the industry, the weights for other industries will sum to 0.5.

4. Results

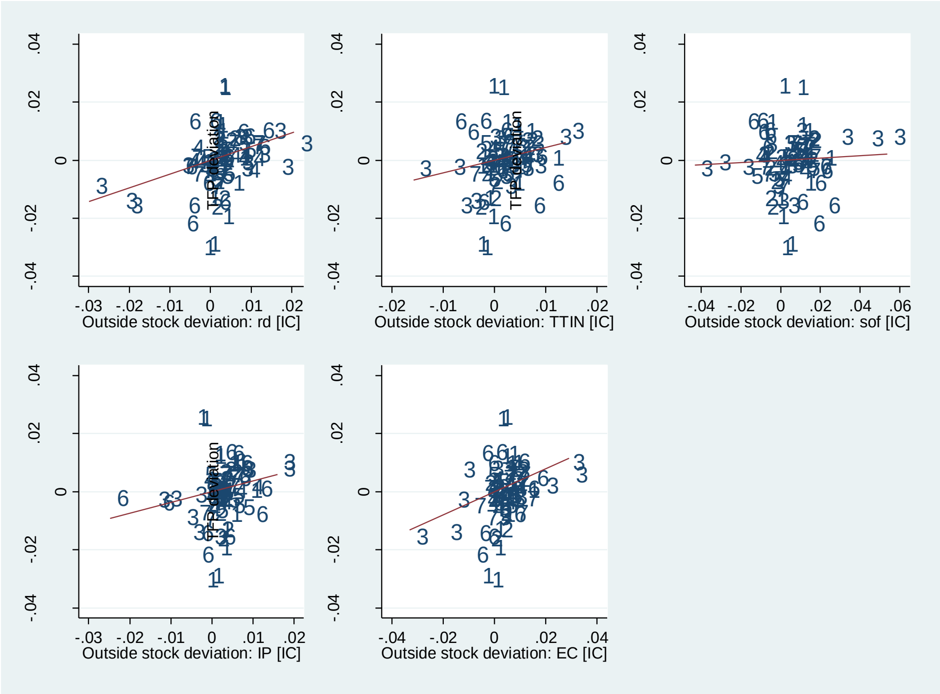
4a. Graphs and raw correlations

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. 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*, or *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 devation 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.

Figure 1: ΔlnTFP$_i$ against MΔlnN$_{_i}$ (outside industry ΔlnN, weighted by intermediate consumption of industry _i $_i$ by the industry i), all in deviation from industry and time mean terms, ΔlnTFP smoothed (t+2, t+1, t).



Notes to figure: outside ΔlnN are, clockwise from top left, rd = R&D; TTIN= total intangibles, sof= software and computerised databases; 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 organisational structures and business processes; and firm-provided training). . Aggregation of ΔlnN is by rental share of each intangible. Outside industry ΔlnN 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). All points are deviations from time and industry means.

Consider then the upper left panel for R&D. The points labelled “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 (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 labour transitions weighting scheme, as shown in the Appendix chart. Indeed for total innovative property and economic competencies the correlation appears negative.

4b. Regression results

To estimate (7) we proceed as follows. Even at these broader asset categorisations, the degree of collinearity 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 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 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.

Columns 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,[8] see penultimate row, are similar for each weighting scheme at 0.25 and 0.21: the survey paper by Hall et al (2009)

[8] 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: here 31%. Hence the coefficient that we then estimate is a coefficient on this "outside" DlnX variable, call it ∑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, ∑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%), 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 4d.

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).

Table 3: Fixed effects regression estimates of equation (7) (dependent variable, smoothed ΔlnTFP (t+2, t+1, t))

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ASSET	IC	TR	IC	TR	IC	TR	IC	TR	IC	TR	IC	TR
External R&D	0.43***	2.31**			0.38***	1.57**	0.44***	2.08**	0.38**	1.96***	0.25*	1.71**
	(4.61)	(3.05)			(7.42)	(2.52)	(5.91)	(3.05)	(2.76)	(3.85)	(2.14)	(2.52)
Internal R&D	0.043	0.074*			0.0027	0.036	0.037	0.052	0.034	0.063	0.041	0.070
	(1.86)	(1.95)			(0.15)	(0.83)	(1.22)	(1.03)	(1.78)	(1.89)	(1.29)	(1.65)
Total External Intangibles			0.52**	0.58								
			(2.97)	(0.59)								
Total Internal Intangibles			-0.20***	-0.18***								
			(-5.06)	(-5.64)								
Total External Intangibles excl. R&D					0.39*	0.070						
					(2.22)	(0.074)						
Total Internal Intangibles excl. R&D					-0.17***	-0.16***						
					(-5.26)	(-5.14)						
External Software							0.031	0.52				
							(0.18)	(1.01)				
Internal Software							-0.0030	0.012				
							(-0.054)	(0.29)				
External Innovative Property excl. R&D									0.17	-1.06		
									(1.78)	(-1.24)		
Internal Innovative Property excl. R&D									-0.024	-0.054		
									(-0.28)	(-0.73)		
External Economic Competencies											0.24*	-0.63
											(1.95)	(-0.84)
Internal Economic Competencies											-0.11**	-0.099*
											(-2.66)	(-2.23)
Observations	91	91	91	91	91	91	91	91	91	91	91	91
R-squared	0.185	0.147	0.287	0.228	0.372	0.273	0.187	0.161	0.204	0.170	0.304	0.226
Number of industries	7	7	7	7	7	7	7	7	7	7	7	7
Elasticity of external R&D	0.25	0.21	0.30	0.054	0.22	0.15	0.26	0.19	0.22	0.18	0.14	0.16
Elasticity of other external variable					0.22	0.0065	0.018	0.049	0.10	-0.098	0.14	-0.059

Notes to table: Dependent variable is dlnTFP smoothed, t+2, t+1, t. Independent variables are dated t, and are ∑mdlnK, 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 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 organisational structures and business processes; and firm-provided training).

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 too 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 the observation of rent spillovers as discussed above.

To explore further these variables, we entered them individually without the R&D term and found statistically significant effects for outside training and management, (coefficient 0.39 (t=4.91) and 0.33(t=2.05)) 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), 0.074(t=0.47), 0.076(t=1.08)), 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 ΔlnK 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.

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

4c. 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, 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. We may have insufficient cross-section variation to identify these effects.

Third, 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.

Fourth, we added controls for utilisation, following Basu, Fernald and Kimball (2006), $\Delta\ln(H/N)$, where H/N is hours per worker, into the industry spillover regressions. H and N are taken from KLEMS. Note that we control for utilisation somewhat by smoothing $\Delta\ln TFP$, using ex post factor shares (Berndt and Fuss, 1986, Hulten, 1986), and including time dummies. So we tried this utilisation term with unsmoothed $\Delta\ln TFP$ and dropping time dummies: the utilisation term was generally insignificant and the other effects unchanged.

Fifth, any other outside effects are relegated here to time dummies. To examine this further, we entered UK public R&D spending on the science budget, interacted with $(R/Y)_{it}$; this was statistically significant and the coefficient on outside R&D remains statistically significant and fell somewhat. We also entered $\Delta\ln K$ of foreign industry R&D, using country/industry R&D capital stocks from Helmers, Schulte and Strauss (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.

4d. Robustness to imperfect competition and non-constant returns

In the above, we supressed imperfect competition and non-constant returns into *d*. We now set out a more formal model, based on a stream of work by Basu, Fernald and Kimball (2006) and summarised in, for example, Basu and Fernald (2001). Consider (2). As they point out, profit maximising implies that

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

Where μ = a mark-up of output prices over marginal costs, if any and $s_{x,it}$ 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 monoposony power in the input market).

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

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

Combining (8) and (9) implies that

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

As they point out, mark-ups over marginal costs (μ>1) require increasing returns (γ>1) as e.g. in Chamberlinian/Robinson monopolistic competition. As it turns out we find, econometrically, that μ=γ=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, 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 labour 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 Tornquist 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 :

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

Adding these new terms to the substitutions in section 2, we may generalise 7 to read

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

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

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, 1998). 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% of revenue on their US industry data), and whilst their estimated μ varies it is on average very close to unity.

Table 4 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?

Table 4: Fixed effects regression estimates of equation (13) 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)
$(\Sigma\theta_N \Delta \ln N + \Sigma\theta_K \Delta \ln K)$ (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 to table: Dependent variable is dlnTFP smoothed, t+2, t+1, t. Independent variables are dated t, and are ∑wdlnK, 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 by fixed effects with time dummies. ***indicates significance at 1%, ** indicates significance at 5%, * at 10%. Memo items report point estimates and F tests on μ=1 and γ=1.

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 UK economy has no mark-up and constant returns? Romer (1990) argues that a feature of knowledge production is increasing returns. As Corrado, Goodridge and Haskel (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.

4d. 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

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

Where $s_{N,V}$ is share of R&D capital payments in market sector value added, 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 capitalised, is subsumed in ΔlnTFP and is given by the average income share of R&D in gross output 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 gross output for TFP, the effect on ΔlnV is the Domar-Hulten weighted sum of these effects. On our data, the Domar-Hulten weight is 2.26 and hence the effect of a $\Delta \ln N_i$(R&D) on ΔlnV is 0.10 or 0.17 based on the IC or TR weight coefficients from Table 3, columns 1 and 2.

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 0.48 and 0.36 respectively.

How do these compare with those in the literature? How do these compare with those in the literature? As mentioned, most studies do not capitalise R&D, and regress it on $\Delta \ln N_i$ and $\Delta \ln N_{\_i}$ generating "inside" and "outside" coefficients. Griliches (1990) in his survey suggests, an "inside" elasticity of 0.11 and an outside elasticity of twice[9] that, 0.22. Since most of the papers he reviews do not capitalise R&D, our equivalent elasticities are the sum of the first two terms in (14) and the last term, which using the TR weights are are 0.187 (= 0.017+0.17) and 0.36, almost exactly the ratio Griliches assumes (our IO weights give 0.117 (= 0.017+0.10) and 0.48). In the survey of more recent studies by Eberhardt, Helmers, and Strauss (2013) "outside" effects are smaller or larger than the own effects, see their Appendix Table A-1, Panel II.2).

In sum our estimates are economically significant and in line with other studies. It is interesting too that the outside effects with the labour transition weights are about 2/3rd the size of those with IC weights. If the IO weights have some pecuniary spillovers that the labour weights avoid, then the outside effect would be lower.

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?

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[9] 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).

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.

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

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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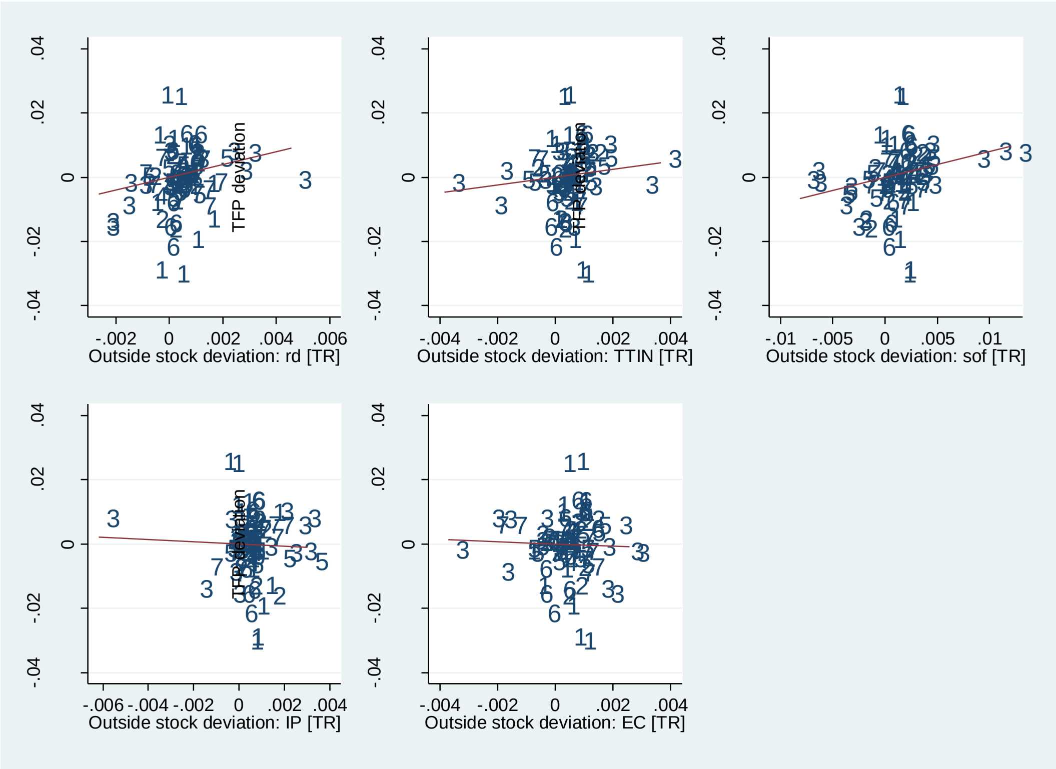
Appendix

Figure A1 shows scatters similar to Figure 1, but with labour transition weights, see text for details. Table A1 and A2 show robustness checks on key regressions, see section 4c for discussion.

Fig*ure A1: $lnTFP_i$ against $M\Delta lnN\_{i}$ (outside industry ΔlnN, weighted by labour transitions of industry $\_i_i$ by the industry i), all in deviation from industry and time mean terms, $\Delta lnTFP$ smoothed (t+2, t+1, t).*



Notes to figure: outside ΔlnN are, clockwise from top left, rd = R&D; TTIN= total intangibles, sof= software and computerised databases; 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 organisational structures and business processes; and firm-provided training). Aggregation of ΔlnN is by rental share of each intangible. Outside industry ΔlnN weighted using the labour transition-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). All points are deviations from time and industry means.

Table A1: Fixed effect regression estimates (dependent variable, smoothed ΔlnTFP (t+2, t+1, t))

	INCLUDING FINANCE (ind=6)		EXCLUDING FINANCE (ind=6)	
	(1)	(2)	(3)	(4)
ASSET	IC	TR	IC	TR
External R&D	0.32	1.31***	0.41*	1.40*
	(1.90)	(3.81)	(2.18)	(2.03)
Internal R&D	0.041	0.053	0.031	0.050
	(1.01)	(0.81)	(1.19)	(0.68)
External Software	0.11	0.77	0.31	0.98*
	(1.00)	(1.66)	(1.44)	(2.06)
Internal Software	0.029	0.045	0.070	0.071
	(0.73)	(1.57)	(1.16)	(1.90)
External Innovative Property excl. R&D	0.097	0.043	0.12	-0.084
	(0.94)	(0.040)	(0.43)	(-0.099)
Internal Innovative Property excl. R&D	0.016	0.00049	0.083	0.032
	(0.22)	(0.011)	(0.88)	(0.44)
External Economic Competencies	0.19*	-1.21	0.17	-2.16
	(1.96)	(-1.36)	(1.26)	(-1.99)
Internal Economic Competencies	-0.13*	-0.12*	-0.021	-0.016
	(-2.41)	(-2.38)	(-0.64)	(-0.56)
Observations	91	91	78	78
R-squared	0.329	0.264	0.395	0.270
Number of industries	7	7	6	6
Elasticity of external R&D	0.19	0.12	0.24	0.13
Elasticity of external software	0.11	-0.11	0.098	-0.20
Elasticity of external IP excl. R&D	0.061	0.072	0.18	0.091
Elasticity of external economic competencies	0.056	0.0040	0.072	-0.0078

Notes to table: Dependent variable is dlnTFP smoothed, t+2, t+1, t. Independent variables are ∑wdlnK, 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.

Appendix Table A2: Instrumental Variable estimation (dependent variable, smoothed ΔlnTFP (t+2, t+1, t))

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ASSET	IC	TR	IC	TR	IC	TR	IC	TR	IC	TR	IC	TR
External R&D	0.48**	3.52**			0.31**	2.30	0.49**	3.29*	0.34*	2.78**	0.28	1.54**
	(2.51)	(1.75)			(1.92)	(1.43)	(2.52)	(1.84)	(1.71)	(2.04)	(1.17)	(1.98)
Internal R&D	0.04	0.07*			0.01	0.04	0.03	0.05	0.04	0.07*	0.04	0.1
	(0.87)	(1.89)			(0.39)	(0.98)	(0.55)	(0.96)	(1.09)	(1.88)	(1.05)	(1.52)
Total External Intangibles			0.50**	0.17								
			(2.01)	(0.13)								
Total Internal Intangibles			-0.19***	-0.18***								
			(-3.76)	(-3.23)								
Total External Intangibles excl. R&D					0.33	-0.46						
					(1.43)	(-0.34)						
Total Internal Intangibles excl. R&D					-0.16***	-0.15***						
					(-3.34)	(-2.75)						
External Software							0.04	0.48				
							(0.46)	(0.89)				
Internal Software							-0.01	0.01				
							(-0.18)	(0.37)				
External Innovative Property excl. R&D									0.22	-0.73		
									(1.15)	(-0.62)		
Internal Innovative Property excl. R&D									-0.03	-0.03		
									(-0.65)	(-0.57)		
External Economic Competencies											0.10*	-1.04
											(1.89)	(-0.78)
Internal Economic Competencies											-0.13**	-0.13***
											(-3.07)	(-2.59)
Observations	91	91	91	91	91	91	91	91	91	91	91	91
R-squared	0.183	0.130	0.287	0.226	0.368	0.265	0.185	0.145	0.200	0.160	0.288	0.215
Number of industries	7	7	7	7	7	7	7	7	7	7	7	7
Sargan-Hansen Test of overidentifying restrictions	2.58	3.70	6.92	6.07	12.62	8.09	2.33	3.12	13.65	12.93	5.20	3.30

N**ote to table**: Instruments are lags 1 to 3 of external and internal capital stocks. Software estimates are not instrumented. Year dummies not shown. Chi-squared 4 degrees of freedom for columns 1 to 4 and 7 and 8. 8 degrees of freedom for all other columns. Dependent variable is dlnTFP smoothed, t+2, t+1, t. ***indicates significance at 1%, ** indicates significance at 5%, * at 10%. t-statistics reported in parentheses, using robust standard errors.

Appendix A3: calculations of inside and outside effects

Omitting fixed and time effects our model is,

$$\Delta \ln TFP_{it} = \sum_{X=L,K,N^{PRIV}} d_X \Delta \ln \mathrm{X} + \alpha_1 \left(M \Delta \ln N_{\_i,t} \right) \tag{15}$$

Let us focus on the case where the only spillover effects are from N and denote $d_{\_N}$ coefficient on outside industry spillovers. Thus we have

$$\Delta \ln TFP_i = d_N \Delta \ln N + d_{\_N} \left(M \Delta \ln N_{\_i} \right) \tag{16}$$

To aid intuition, let us write this out for a three-industry case, i=1,2,3 which gives, omitting time subscripts

$$\begin{aligned} \Delta \ln TFP_1 &= d_N \Delta \ln N_1 + d_{\_N} \left(\qquad m_{12} \Delta \ln N_2 + m_{13} \Delta \ln N_3 \right) \\ \Delta \ln TFP_2 &= d_N \Delta \ln N_2 + d_{\_N} \left(m_{21} \Delta \ln N_1 \qquad + m_{23} \Delta \ln N_3 \right) \\ \Delta \ln TFP_3 &= d_N \Delta \ln N_3 + d_{\_N} \left(m_{31} \Delta \ln N_1 + m_{32} \Delta \ln N_2 \qquad \right) \end{aligned} \tag{17}$$

Which in matrix form with our seven industries can be written

$$\begin{pmatrix} \Delta \ln TFP_1 \\ \vdots \\ \Delta \ln TFP_7 \end{pmatrix} = d_N \begin{pmatrix} \Delta \ln N_1 \\ \vdots \\ \Delta \ln N_7 \end{pmatrix} + d_{\_N} \begin{pmatrix} 0 & m_{12} \cdots & m_{17} \\ m_{21} & \ddots \cdots & m_{27} \\ \vdots & \vdots & \vdots \\ m_{71} & m_{72} \cdots & 0 \end{pmatrix} \begin{pmatrix} \Delta \ln N_1 \\ \vdots \\ \Delta \ln N_7 \end{pmatrix} \tag{18}$$

Let us now define aggregate ΔlnTFP as a weighted sum, with weights w to be defined later, of the industry $\Delta \mathrm{lnTFP}_i$

$$\Delta \ln TFP \equiv \sum_{i=1}^{I} w_i \Delta \ln TFP_i$$

$$=> \tag{19}$$

$$\Delta \ln TFP = d_N \sum_{i=1}^{I} w_i \Delta \ln N_i + d_{\_N} \sum_{i=1, i \neq j}^{I} w_i m_{ij} \Delta \ln N_j$$

From which we may derive a number of "inside" and "outside" elasticities as follows.

First, from (3) we note that the effect of $\Delta \mathrm{lnN}_i$ on $\Delta \mathrm{lnTFP}_i$, since TFP is capitalised including private returns, is a within-industry spillover. That is, it can be thought of as an inside effect, since it is an effect of own industry N on own TFP, but is a spillover since N is included in TFP. This elasticity is d_N.

Second, turning to "outside" effects, the effect of $\Delta \mathrm{lnN}_1$, R&D *in agriculture* for example, on *other industries,* can been seen by reading down the columns in 3 and will be

$$\frac{\partial \Delta \ln TFP_j}{\partial \Delta \ln N_i} = d_{\_\mathrm{N}} \sum\nolimits_{i=1 \ldots I.\, j \neq i} m_{ji} \tag{20}$$

Third, the effect of other ΔlnN, i.e. R&D *outside* agriculture, on TFP *in agriculture*, can be seen by reading across the columns in 3 and will be

$$\frac{\partial \Delta \ln TFP_i}{\partial \Delta \ln N_j} = d_{\_\mathrm{N}} \sum\nolimits_{i=1..I,\, j \neq i} m_{ij} \tag{21}$$

Finally, from (4), the total effect of ΔlnN on total ΔlnTFP consists of two effects, due to spillovers within the industry and outside the industry and given by summing up (4) which gives

$$\frac{\partial \ln TFP}{\partial \Delta \ln N} = d_N \sum\nolimits_{i=1..I} w_i + d_{\_N} \sum\nolimits_{i=1..I, i \neq j} w_i m_{ij} \tag{22}$$

Finally, the effect on overall market sector value added introduces in addition the effect of ΔlnN subsumed within TFP since its capitalised. We write this

$$\frac{\partial \Delta \ln V}{\partial \Delta \ln N} = s_{N,V} + d_N \sum\nolimits_{i=1..I} w_i + d_{\_N} \sum\nolimits_{i=1..I, i \neq j} w_i m_{ij} \tag{23}$$

Where since we use gross output in computing our TFP, the appropriate w_i in the second two terms are Domar-Hulten weights and the appropriate weight in the first term is the share of R&D capital payments in market sector value added, $s_{N,V}$ (Dal Borgo et al, 2013, equation 5).

In our data $S_{N,V}$=0.017, Σw_i=2.26 and $\Sigma w_i m_{ij}$=0.48 and 0.36 for the IC and TR weights respectively. Thus for the IC weights the numbers in (14) are 0.017, 0.10 and 0.48 based on d_N=0.04 and d_{N}=0.43. For the TR weights the numbers are 0.017, 0.17 and 0.36 based on d_N=0.07 and d_{N}=2.31.

A number of points are worth making. First, since we include ΔlnN in ΔlnTFP and we work with R&D capital stocks, the latter two terms in (14) correspond to net social returns, and have an elasticity of 0.58 and 0.53 based on IC and TR weights respectively.

How do these compare with those in the literature? As mentioned, most studies do not capitalise R&D, and regress it on $\Delta \ln N_i$ and $\Delta \ln N_{\_i}$ generating "inside" and "outside" coefficients. Griliches (1990) in his survey suggests these inside and outside elasticities are 0.11 and 0.22 respectively, with the latter based on a twice of the former. Our TR weights give inside and outside measures of 0.187 (= 0.017+0.17) and 0.36, almost exactly the ratio Griliches assumes (out IO weights give 0.117 (= 0.017+0.10) and 0.48). 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). Thus we conclude that our ratios are in line with those in the literature. (We note that Griliches, 1980, Table 11.1 compares ratios based on IO weighted industry studies to those based on patent flows and technology distances; in the latter, outside effects can be about 50% of within effects. In the survey of more recent studies by Eberhardt, Helmers, and Strauss (2013) "outside" effects are smaller or larger than the own effects, see their Appendix Table A-1, Panel II.2).

Third, our outside/insider ratios 4.4=.48/.117 and 2 = .22/.117 for our IC and TR weights respectively. As discussed above, the IC weights might include pecuniary spillovers due to mispriced intermediates (though our regressions are in terms of future TFP growth and lagged $\Delta \ln N_i$). Indeed, Ebhardt, Helmers and Strauss (2013) call the IO-based estimates "rent" spillovers If the TR weights are less prone to this we would expect the relative spillover impact to be less which it is.

Finally, what are the implied rates of return? Our data return estimates of elasticities. Making use of the standard relation between elasticities and rates of return we can write ρ=ε(V/N) where V is value added which we write since we are working with Domar-Hulten aggregated sectoral productivity. The ratio of real variables V/N is hard to interpret and thus we write $\rho=\varepsilon(P_V V/ P_N N)(P_N/P_V)$. Making use of the Hall-Jorgenson rental price formula $P_K=P_N(r+\delta-\pi)$ and noting that due to lack of data P_N $=P_V$ we can write

$$\rho = \varepsilon \frac{1}{(P_N \text{ N}/ P_V \text{ V})}(r + \delta - \pi) \tag{24}$$

Where all terms relate to R&D. Over this sample period $(P_N N/P_V V)$ =0.017. Over the same period the average value for r is 0.05. The standard estimate for δ in the case of R&D is 0.15. The rate of change in value-added prices is approximately 0.04. Therefore we can estimate (9) as (0.53/0.017)*(0.05+0.15-0.04)=4.99, suggesting a total rate of return including private returns of 500%. This is clearly very large, but it is worth our elasticities are in line with others who estimate elasticities and hence to the extent that they have similar R&D shares their implied rates of return are the same. So, for example, a private elasticity of 0.1, the central estimate quoted by Griliches (1980) would yield a private rate of return of around 100% and a social elasticity of 0.2 would imply a rate of return of 200%.

Consider, for example, Gullec and Van Pottelsberghe de la Potterie (1984). On their sample of 16 OECD countries, 1980-98, they regress ΔlnTFP' (i.e. TFP without capitalising R&D) on ΔlnN(private) and find a coefficient of 0.13 (p.365). The average $P^N N/P^V V$ in their sample is 2% (p.366), and hence ρ=0.13/0.02 = 6.5 or 650%.