Knowledge Spillovers, ICT and Productivity Growth

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Abstract

This paper looks at the channels through which intangible assets affect productivity. The econometric analysis exploits a new dataset on intangible investment (INTAN-Invest) in conjunction with EUKLEMS productivity estimates for 10 EU member states from 1998 to 2007. We find that (a) the output elasticity of intangible capital depends upon ICT intensity, consistent with complementarities between ICT and intangible capital; (b) non-R&D intangible capital has higher estimated output elasticities than its factor shares, as does (c) labour quality. The last two findings are consistent with spillovers from investments in knowledge-based/intangible capital and skills.

JEL: O47, E22, E01 Keywords: productivity growth, economic growth, intangible capital, intangible assets, ICT, spillovers

Knowledge Spillovers, ICT and Productivity Growth

The literature on the sources of economic growth devotes considerable attention to the accumulation of different types of capital: human capital, the special role of ICT capital, and in a newer strand of the literature, intangible capital. Work on intangible capital expands the core concept of business investment in national accounts by treating much business spending on "intangibles"—computerized databases, R&D, design, brand equity, firm-specific training, and organizational efficiency—as investment (e.g., see Corrado, Hulten, and Sichel, 2005). When this expanded view of investment is included in a sources-of-growth analysis, intangible capital is found to account for one-fifth to one-third of labour productivity growth in the market sector of advanced economies.[1]

This paper uses a cross-country econometric approach and a new database (INTAN-Invest) to study the direct and indirect (i.e., spillover) channels through which intangible capital affects productivity growth. The cross-country sources-of-growth literature finds a strong correlation between (a) the contribution of intangible capital deepening to a country's growth in output per hour and (b) the country's rate of growth of total factor productivity (TFP).[2] In light of previous evidence on spillovers from private R&D (e.g., Griliches, 1992; Griffith, Redding, and Van Reenen, 2004), it is perhaps unsurprising to find a correlation between intangible capital deepening and TFP growth consistent with spillovers to intangible capital. But private R&D stocks are only about one-third of the total private stock of intangible assets (according to INTAN-Invest estimates), suggesting a more thorough investigation of the relationship between non-R&D intangible capital and productivity growth is warranted.

Why might non-R&D intangible capital make a material difference in our understanding of productivity growth? First, microeconomic evidence demonstrates that the link from firm-level ICT adoption to productivity growth is complex, requiring for example co-investments in training and organizational change, to generate competitive advantage (e.g., Bresnahan, Brynjolfsson, and Hitt, 2002; Brynjolfsson, Hitt, and Yang, 2002). Corroborating evidence at the macroeconomic level is limited due to the heretofore lack of hard data on intangibles, however. Second, it is possible that the diffusion of knowledge created from non-R&D intangible investments, e.g., in design, marketing, and organizational change is a source of productivity spillovers. We are, we believe, the first to consider this question. Third, given that the production of intangibles is largely undertaken within firms by skilled workers and managers, a deeper understanding of the relative role of intangible vs. human capital in macro productivity data seems warranted in light of recent work that finds externalities to human capital formation using plant- and state-level data (Moretti 2004a,b).

As we shall shortly see, our work produces new findings on these topics: We (a) establish ICT-intangible capital complementarity in macro-level data, (b) find significant productivity

[1]The most recent report of this accounting is in Corrado, Haskel, Jona-Lasinio, and Iommi (2013). Corrado, Hulten, and Sichel (2009) and Marrano, Haskel, and Wallis (2009) first reported results of about one-fourth for the US and UK, respectively. The contribution in Japan (Fukao, Miyagawa, Mukai, Shinoda, and Tonogi, 2009) and in many EU countries (van Ark, Hao, Corrado, and Hulten, 2009), however, is lower.

[2]The most recent display of this finding is in (Corrado et al., 2013, figure 11) based on estimates from 1995 to 2007, whereas the finding first appeared in (van Ark et al., 2009, figure 8) based on estimates from 2001 to 2004.

spillovers to non-R&D intangible capital during our sample period, and (c) find externalities to labor composition (the usual channel through which human capital formation has an impact on productivity) and that they operate via a largely orthogonal channel, separate from that of intangible capital. We begin by presenting a general model that illustrates the effects of intangible capital accumulation on productivity growth (Section I). Then we describe the sources and main features of our data (Section II), set out our results (Sections III and IV) and conclude (Section V).

1 Model

This section sets out a model that describes how we believe that adding intangibles deepens our understanding of productivity and economic growth. We aim to show (a) what other models without intangibles have found and why this might be biased and (b) how adding intangibles affects results on spillovers and complementarities. Suppose that industry value added in country c, industry i and time t, $Q_{c,i,t}$ can be written as:

$$Q_{c,i,t} = A_{c,i,t}F_{c,i}(L_{c,i,t}, K_{c,i,t}, R_{c,i,t}) \tag{1}$$

On the right-hand side, L and K are labour and tangible capital services; likewise R is the flow of intangible capital services and A is a shift term that allows for changes in the productivity with which L, K and R are transformed into output. L, K and R are represented as services aggregates because in fact many types of each factor are used in production. We will introduce some key distinctions among factor types in a moment. Log differentiating equation (1) (per Solow, 1957) gives:

$$\Delta lnQ_{c,i,t} = \epsilon^L_{c,i,t}\Delta lnL_{c,i,t} + \epsilon^K_{c,i,t}\Delta lnK_{c,i,t} + \epsilon^R_{c,i,t}\Delta lnR_{c,i,t} + \Delta lnA_{c,i,t} \tag{2}$$

where ϵ^X denotes the output elasticity of an input X, which in principle varies by input, country, industry and time.

To empirically investigate the role of intangibles as drivers of growth starting from the existing literature, we take two steps. First, consider the ϵ terms. For a cost-minimizing firm we may write

$$\epsilon^X_{c,i,t} = s^X_{c,i,t},\ X = L, K, R \tag{3}$$

where s is the share of that factor's payments in value added. So this simply writes the first-order condition of a firm in terms of elasticities and assumes firms have no market power over and above their ability to earn a competitive return from investments in intangible capital.[3] Note that if equation (1) is, say Cobb-Douglas, then ϵ is constant over time and equation (2) might be transformed into a regression model with constant coefficients. If (1) were, say, CES, then ϵ would vary over time with all input levels, and so (2) might be written as a regression model with interactions between all the inputs.

[3] Omitting intangible capital therefore results in what may appear to be market power or excess returns to tangible capital. See Corrado, Goodridge, and Haskel (2011) for further discussion.

Now suppose a firm can benefit from the L, K or R in other firms, industries, or countries. Then, as Griliches (1979, 1992) notes the industry elasticity of ΔlnR on ΔlnQ is a mix of both internal and external elasticities so that we can write following Stiroh (2002)

$$\epsilon^X_{c,i,t} = s^X_{c,i,t} + d^X_{c,i,t}, \ \ X = L, K, R \tag{4}$$

which says that output elasticities equal factor shares plus d, where d is any deviation of elasticities from factor shares due to e.g., spillovers. Thus we write (2) as

$$\begin{aligned} \Delta lnQ_{c,i,t} = &(s^L_{c,i,t} + d^L_{c,i,t})\Delta lnL_{c,i,t} + (s^K_{c,i,t} + d^K_{c,i,t})\Delta lnK_{i,c,t} \\ &+ (s^R_{c,i,t} + d^R_{c,i,t})\Delta lnR_{i,c,t} + \Delta lnA_{i,c,t} \ \ . \end{aligned} \tag{5}$$

Second, consider the $\Delta lnQ_{c,i,t}$ terms. National accountants tend to treat spending on intangibles as intermediate inputs, not as investment in long-lived assets.[4] As a result, much spending on intangibles does not appear in conventional data on value added, denoted as V in what follows. To obtain a correct value added measure, denoted as Q, the additional real investment in intangible assets N must be added to V, in which case we can write

$$\Delta lnQ_{c,i,t} = (1 - s^N_{c,i,t})\Delta lnV_{c,i,t} + s^N_{c,i,t}\Delta lnN_{c,i,t} \tag{6}$$

where $s^N_{c,i,t}$ is the share of intangible investment in the value of output augmented to include intangibles. A standard accumulation equation is then used to generate net stocks of intangible assets from real investment N, and the flow of services R that enters (1) is derived from the net stocks.

Assume for simplicity balanced growth so that we have $\Delta lnR = \Delta lnN$ and also that the share of intangible investment in total output $s^N_{c,i,t}$ equals the factor share of intangible capital $s^R_{c,i,t}$ in total factor payments.[5] Inserting these assumptions into (6), substituting the result into (5), and writing the resulting expression in terms of $\Delta lnV_{c,i,t}$ yields the following:

$$\begin{aligned} \Delta lnV_{c,i,t} = &\frac{(s^L_{c,i,t} + d^L_{c,i,t})}{(1 - s^R_{c,i,t})}\Delta lnL_{c,i,t} + \frac{(s^K_{c,i,t} + d^K_{c,i,t})}{(1 - s^R_{c,i,t})}\Delta lnK_{c,i,t} \\ &+ \frac{d^R_{c,i,t}}{(1 - s^R_{c,i,t})}\Delta lnR_{c,i,t} + \Delta lnA_{c,i,t} \ \ . \end{aligned} \tag{7}$$

We are now in a position to make a number of points.

1.1 Data on intangibles available

Suppose one had data on intangibles. Looking at (5), with such data one can include intangibles in value added and measure the three inputs on the right plus their shares. Three approaches

[4]Exceptions are firms' spending on computer software, mineral exploration and creation of artistic originals, which are capitalized in national accounts. The most recent revision to guidelines for national accounts (European Commission, et al., 2009) also included R&D in the asset boundary. But this change came after the value added data used in this study were compiled.

[5]If balanced growth is along the optimal consumption path of a Golden Rule steady state, then capital income and investment shares are equal.

suggest themselves. First, to examine complementarities, one might suppose that the shares are functions of the inputs and regress ΔlnQ on interacted inputs. Second, to examine spillovers, that is $d > 0$, one might suppose that s and d are constant and regress ΔlnQ on the inputs and compare the estimated coefficients with input factor shares. Third, following Caves, Christensen, and Diewert (1982) one might note that a Divisia $\Delta lnTFP$ index can be constructed that is robust to an underlying translog production function such that we can write (5) as

$$\Delta lnTFP^{Q}_{c,i,t} = d^{L}_{c,i,t}\Delta lnL_{c,i,t} + d^{K}_{c,i,t}\Delta lnK_{c,i,t} + d^{R}_{c,i,t}\Delta lnR_{c,i,t} + \Delta lnA_{c,i,t} \tag{8}$$

where $\Delta lnTFP^{Q}_{c,i,t}$ is calculated as

$$\Delta lnTFP^{Q}_{c,i,t} = \Delta lnQ_{c,i,t} - s^{L}_{c,i,t}\Delta lnL_{c,i,t} - s^{K}_{c,i,t}\Delta lnK_{c,i,t} - s^{R}_{c,i,t}\Delta lnR_{c,i,t} \tag{9}$$

From (8) therefore, a regression of $\Delta lnTFP^{Q}$ on the inputs recovers the spillover terms.

1.2 Data on intangibles unavailable

In much of the literature, data on intangibles are not available. Consider then (7), in which ΔlnV is on the left hand side and the first term in the lower line is missing. A typical approach to considering spillovers is to estimate a relation between ΔlnV and ΔlnL and ΔlnK and compare the coefficients on ΔlnL and ΔlnK with conventionally calculated labour and capital shares. As (7) shows, the estimated coefficients potentially (a) reflect a combination of own (i.e, labour or capital) shares and spillovers and the factor share of intangibles, and (b) have an omitted variable bias depending on the correlation between ΔlnL and ΔlnK and ΔlnR. Note the sign of this bias is not obvious, partly because of the problem of omitted bias in multivariate equations, but also because when a regression includes time and fixed effects, the estimated coefficients on variables are in terms of deviations from their means and so might be negative if, for example, above average ΔlnR occurs at a time of below-average ΔlnK.[6]

Consider next constructing $\Delta lnTFP^{V}$ using ΔlnV and share-weighted ΔlnL and ΔlnK in an attempt to estimate d^L and d^K. This runs the risk of (a) using the wrong shares (b) recovering biased estimates of d^L and d^K, namely, $d^L/(1-s^R)$ and $d^K/(1-s^R)$. In the R&D literature, e.g. Schankerman (1981), this issue is handled by adjusting L and K to remove R&D workers. As may be seen from equation (7), $s^{K}_{c,i,t}$ and $s^{L}_{c,i,t}$ so calculated will eliminate this bias.[7]

1.3 Labour input

Before proceeding, it is worth noting that the term for the change on labour services ΔlnL can be written as the sum of two separate terms (a) labour services per worker hour $\Delta ln\Upsilon$, and (b)

[6] The coefficients in the regression also would be affected by endogeneity problems, as reviewed in Griliches and Mairesse (1998) and considered in the econometric work reported below.

[7] Note that because true value added (our Q) includes investment in knowledge capital (R), but measured value added (our V) excludes investment in R, a regression of V on K, L and R seems obviously biased because V excludes R. Although excluding R&D workers from L largely eliminates this bias, equation (5) gets around this problem more precisely by using Q, not V, as the regressand, i.e., by including R&D (the measured output of these workers) in output.

worker hours ΔlnH, i.e.,

$$\Delta lnL_{c,t} = \Delta ln\Upsilon_{c,t} + \Delta lnH_{c,t} \ . \tag{10}$$

The labour services per worker hour term accounts for differences in the marginal product of workers by type (e.g., according to skill level). In other words, labour input may be viewed as the product of hourly labour input and an index reflecting the composition of employment.The increase in Υ multiplied by labor's share is the direct channel whereby human capital accumulation contributes to economic growth [8].

Although equations (6) and (8) did not address the source of labour spillovers according to the terms in (10), externalities to labor composition are natural to consider as a potential source of spillovers supporting economic growth. Consider further that (a) changes in hours may be further decomposed into changes in total workers and changes in hours per worker and (b) changes in hours per worker are a proxy for changes in unobserved worker effort and capital utilization (Basu and Kimball, 1997) and (c) a large literature considers short-run increasing returns a propagation mechanism in business cycles. Equation (10) then suggests that the symmetry between the labour and capital terms in (6) and (8) likely requires modification in empirical work to be sure the short-run cyclical effects due to hours are appropriately disentangled from growth supporting externalities to labor composition.

1.4 Previous literature

Broadly, there are at least two strands of the literature on productivity, ICT, and intangibles: (a) estimating a production function, such as (2) and (b) estimating TFP such as (7). Regarding the first approach, Brynjolfsson, Hitt, and Yang, 2002 for example estimate the returns to ICT using a production function approach at the firm level, with no data on intangibles, and find a high estimated output elasticity relative to a plausible ICT income share. Typically this is rationalised as omitted variable bias where intangibles are omitted but are complementary to ICT, a rationale that we are able to justify, as shown below. An alternative approach is taken by Basu, Fernald, Oulton, and Srinivasan (2004). They use industry data and assume intangibles are related to ICT and then model the missing ΔlnR as a function of current and lagged ΔlnK^{ICT} and $s^{K^{ICT}}$. Acharya (2016) goes a step further and uses R&D as a proxy for all intangibles. A problem with the R&D proxy approach is that R&D is but one intangible and results are indeterminant; it may be a major source of spillovers (or the opposite, that another intangible assets is the major source and is highly correlated with R&D). We go beyond these works by introducing explicit data on all intangible asset types.

[8] Suppose for example there are skilled and unskilled workers, then we can write this as

$$\Delta lnL = \frac{W^U H^U}{\Sigma WH}\Delta ln(H^U/H) + \frac{W^S H^S}{\Sigma WH}\Delta ln(H^S/H) + \Delta lnH$$

Both returns to "learning-by-doing" (via experience and thus higher wages) and to schooling (again through higher wages) are embedded in this term. If labour types are paid their marginal products then this index (times the labour share) captures entirely the per hour contribution of skill changes and hence does not affect TFP (since TFP is calculated by subtracting off this from output growth). The capital per hour terms are analagous: growth in different capital types per hour, weighted by their rental shares.

Regarding spillovers, many papers study the spillover effects of R&D on productivity: Eberhardt, Helmers, and Strauss (2013) and Hall, Mairesse, and Mohnen (2009) are recent surveys of country- and industry-level work. Such studies usually regress conventional real output or TFP (i.e., ΔlnV or $\Delta lnTFP^{V}$) on "own" R&D and "outside" R&D, where own R&D might be, for example, the country (or industry) R&D-to-output ratio and outside R&D the same ratio for other industries (countries) weighted by a trade matrix. They typically find large own effects (i.e., elasticities exceeding R&D factor shares). The typical own elasticities exceed 0.2 with outside effects being smaller or larger depending on the own effects and whether adjustments for R&D capitalization are made. Very similar findings on an earlier generation of studies are in Griliches (1992, p. S44); for example, he settled on an own and outside elasticity of 0.1 and 0.2 respectively.

Finally, on labour spillovers, emerging micro evidence finds such evidence using plant or state-level data (see e.g., Moretti 2004a,b), but strong evidence on excess returns to human capital accumulation in the macro data is hard to find. Krueger and Lindahl (2001) find little role for such spillovers in cross-country growth regressions and argue they are obscured by measurement error. Using improved and more disaggregate data, Inklaar, Timmer, and van Ark (2008) still find no relation between skilled hours shares and TFP growth when including labor composition effects in the calculation of $\Delta lnTFP$ (i.e., no excess returns to skill upgrading).

1.5 Preview of approach and contributions

We make, we believe, a number of contributions in this paper. First, we use new data on intangible investment (INTAN-Invest). Using these new measures we are able to construct the variables in (5), in particular ΔlnQ and ΔlnR and the congruent shares and thereby calculate $\Delta lnTFP^{Q}$ as in (9). In other words, we can capitalize intangible investment in output and include intangible capital as an input to the production function and thereby generate unbiased estimates of output elasticities. Second, we can estimate equations such as (5) to explore complementarities between R and K, in particular ICT-capital. Third, we can estimate (8) to investigate spillovers and contrast these estimates with the conventional approach, based on estimates of (7) without intangibles.

2 Data

As previously indicated, this paper uses the INTAN-Invest harmonized measures of intangible investment. These estimates can be found on the INTAN-Invest website www.intan-invest.net, which also reports estimates of capital and nominal and real value added including intangibles. The construction of these data are reviewed inn the appendix to this paper and discussed and summarized in Corrado, Haskel, Jona-Lasinio, and Iommi (2013).

INTAN-Invest provides cross-country data for the full range of intangible assets as set out in Corrado et al. (2005, 2009). The estimates cover market sector intangibles for EU27 member countries, plus Norway and the United States from 1995 to 2005; the EU15 economies, the US, and the Czech Republic and Slovenia are covered through 2010. Market sector intangibles refers to investment by all of private industry except health, education, real estate and private households.[9]

The framework of the previous section is set in the country-industry-time dimension although it applies equally to the country-time, or market sector, dimension. We therefore proceed by working with *two datasets*. The first is the EUKLEMS (Timmer, O'Mahony, Inklaar, and van Ark, 2010) industry-level estimates of output and capital inputs for 26 market sector industries and 10 countries (March 2011 update, assessed June 2012). The second is a country-level market sector productivity dataset that includes the full range of intangibles that we have built ourselves using EUKLEMS methods. Further information on this dataset is in an appendix to this paper.

The geographical coverage of both datasets is as follows: Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden and the United Kingdom. Data for the United States are used as instruments in instrumental variable regressions. The period covered by annual growth rates for output and productivity is 1996 to 2007 in both datasets (the intangibles data start in 1995, and we do not include years affected by the global financial crisis). In our econometric analysis below we absorb two periods with lags, yielding rates of growth for output and productivity from 1998 to 2007 (10 years) for our empirical analysis.

To include intangible capital in a country-level productivity analysis we must, as the framework in section I showed, (a) capitalize intangible investment into value added; (b) include intangible capital as an input and (c) ensure that the factor shares are congruent with the additional capital. To do this, we take the existing EUKLEMS investment in tangible assets (March 2011 update) and our investment in intangible assets and rebuild all capital stocks via a perpetual inventory method and then solve for capital shares such that total capital payments exhaust value added adjusted for intangibles less labour payments in each period. Labor input is measured following the methodology of EUKLEMS using updated data from WIOD (released May 2012, accessed September 2013). Cross-country data on hours and compensation of all persons engaged in market sector production for three skill groups are used to construct a marginal-product weighted labor services aggregate L.

Table 1 sets out values (country-time averages) for growth rates and factor shares for some key variables in this dataset. The first four rows of the table show growth rates for real value added and TFP based on data with and without intangibles, i.e., before and after adjusting for the capitalization of intangibles. As may be seen these values differ by a nontrivial amount in compound growth rate terms. The remaining rows of column show the average rate of growth for the other variables in our analysis. (For market sector growth accounting results, see Corrado et al. (2013)). As may be seen, we distinguish between non-ICT capital and ICT capital. ICT capital includes computers, computer software, and communication equipment, and non-ICT covers all other published assets types except mineral exploration and artistic and entertainment originals, which are classified in currently published data as intangibles.[10]

Regarding our tangible vs. intangible asset grouping, note the following: (1) Following most of the ICT macro-productivity literature (and EUKLEMS), ICT *includes* computer software.

[9] NACE sectors A through K, excluding real estate, plus sector O. The market sector in EUKLEMS is similar except that it includes private households (sector P).

[10] Note that R&D has been capitalized in the European national accounts during the time of this writing. So were not able to include ESA2010 national account R&D estimates in our database.

Table 1: Rates of growth and factor shares for the market sector of 10 EU countries, 1998 to 2007[1,2]

	Variable (X)	$\Delta ln(X)$ (1)	$s(Q)^X$ (2)	$s(V)^X$ (3)
1.	Q	3.00		
2.	TFP^Q	.77		
3.	V	2.89		
4.	TFP^V	.86		
5.(a)	K^{NonICT}	2.23	22.5	25.9
5.(b)	K^{ICT}	12.40	4.9	5.5
6.	R	4.05	9.5	
6.(a)	$R^{R\&D}$	4.89	2.3	
6.(b)	$R^{NonR\&D}$	3.73	7.2	
7.	L	1.29	63.1	68.6
7.(a)	H	.89		
7.(b)	Υ	.40		

NOTES—Country-time averages for Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden and the United Kingdom.
1. Growth rates and shares are shown in percent.
2. K^{ICT} on line 5(b) *includes* computer software whereas intangible capital R on line 6 *excludes* it.

As a result, our variable for intangible capital R *excludes* computer software. (2) The two published intangible asset types that we exclude from K^{NonICT} are rather small for most European countries, with the result that while our K^{NonICT} variable literally is non-ICT equipment and structures, in practice it is little different from the non-ICT capital aggregate in EUKLEMS. (3) When we further disaggregate intangible capital into R&D and non-R&D intangibles, the latter consists of organizational capital, firm-specific human capital, brand and reputation, and new product development not included in R&D (design, new financial product development, artistic and entertainment originals, and mineral exploration), i.e., it does *not* include computer software but it *does* include the two other, smaller published asset types.

The columns of the table show factor shares with and without capitalization of intangibles. Referring to the second column, where all intangibles are capitalized, non-ICT capital has a share of 22.5 percent for our sample of 10 EU countries, ICT capital 4.9 percent, and intangible capital 9.5 percent—higher than ICT. Within intangible capital, the R&D share is 2.3 percent, while other intangibles collectively average 7.2 percent. We would expect to recover these values via econometric estimation of a production function (1) for Q—if, of course, the assumptions used to generate them (cost-minimizing firms, competitive factor and product markets) hold true. The labor share is 63.1 percent when all intangibles are capitalized, compared with 68.6 percent when they are not.[11]

[11]The capitalization of intangibles produces a "new" labor share that is lower than the "old" share by the fraction $\frac{P^V V}{(P^V V+P^N N)}$ where each $P^X X$ $(X = V, N)$ is a nominal value (V = value added excluding intangibles, N = intangible investment). The lower labor share reflects the fact that income shares sum to one, and, as a matter of arithmetic, newly accounting for the return to intangible capital lowers other factor shares.

2.1 Plots and Preliminaries

Figures 1–3 provide additional insights into the data (figures 1 and 2 show time averages in order to display countries, whilst 3 shows all points used in our double difference regresssions below). The Y-axis of figure 1 plots the contribution of intangible capital deepening to market sector growth in output per hour; the X-axis shows the contribution for ICT capital. The figure shows a positive relation between $s^R \Delta lnR/H$ and $s^{ICT} \Delta lnK^{ICT}/H$, suggesting complementarity between the two types of capital.

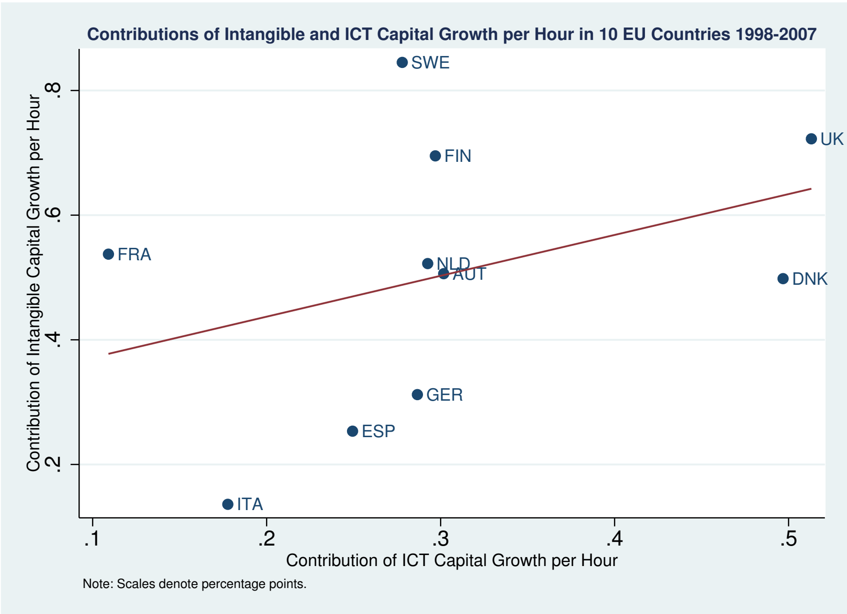

Figure 1: Contributions of Intangible and ICT Capital Deepening in 10 EU Countries 1998-2007

Figure 2 includes four panels, each with market sector $\Delta lnTFP^Q$ plotted on the Y-axis. Moving clockwise, the X-axis of the panels first show growth rates for our three major capital types (non-ICT capital, ICT capital, and intangible capital). The final panel shows labour services. Interestingly, the lower left panel show a positive relation between TFP growth and intangible capital growth, consistent with a spillover relationship. The other panels suggest this is not spuriously due to some common factor boosting all factors and growth. Indeed there is, if anything, a negative relation between $\Delta lnTFP^Q$ and, respectively, ΔlnK^{NonICT} and $\Delta ln(L)$. Finally, as we shall shortly see in our econometric analysis, we end up modeling both productivity change and its *acceleration* (or deceleration), i.e, we also look at the first difference of productivity growth. Figure 3 shows our country-level data after transforming them to reflect accelerations (or decelerations) in productivity change. As may be seen, roughly the same relationships, including the potential for productivity spillovers to intangible capital show through.

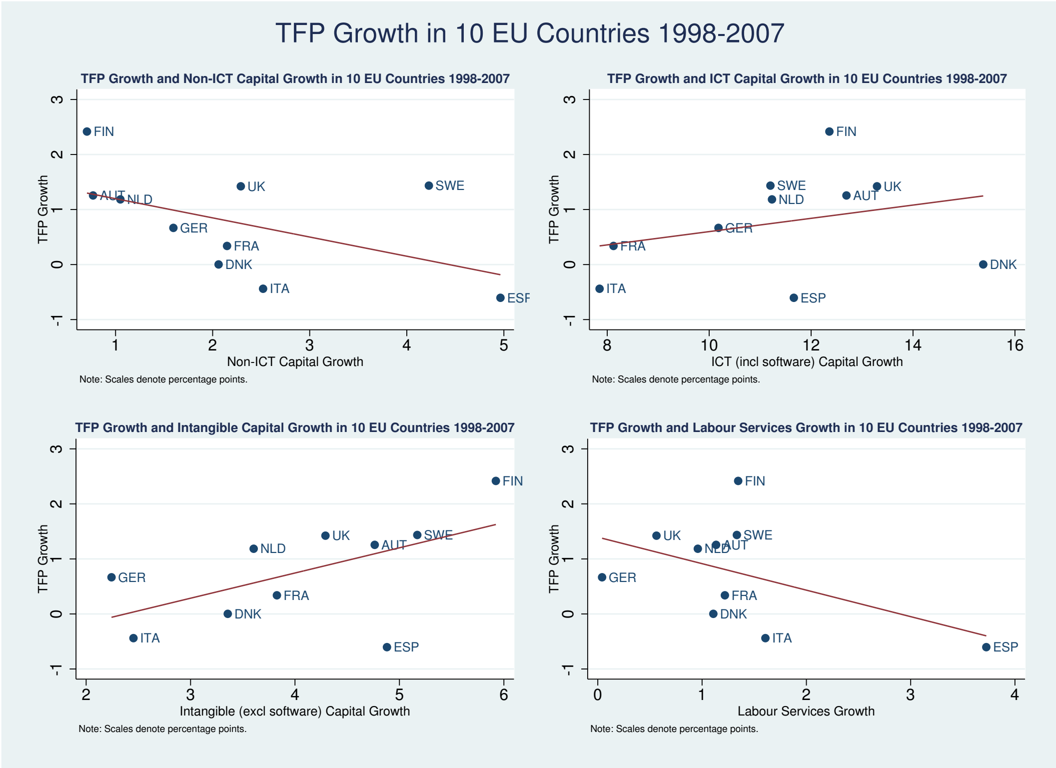

Figure 2: Market Sector TFP Growth in 10 EU Countries 1998-2007

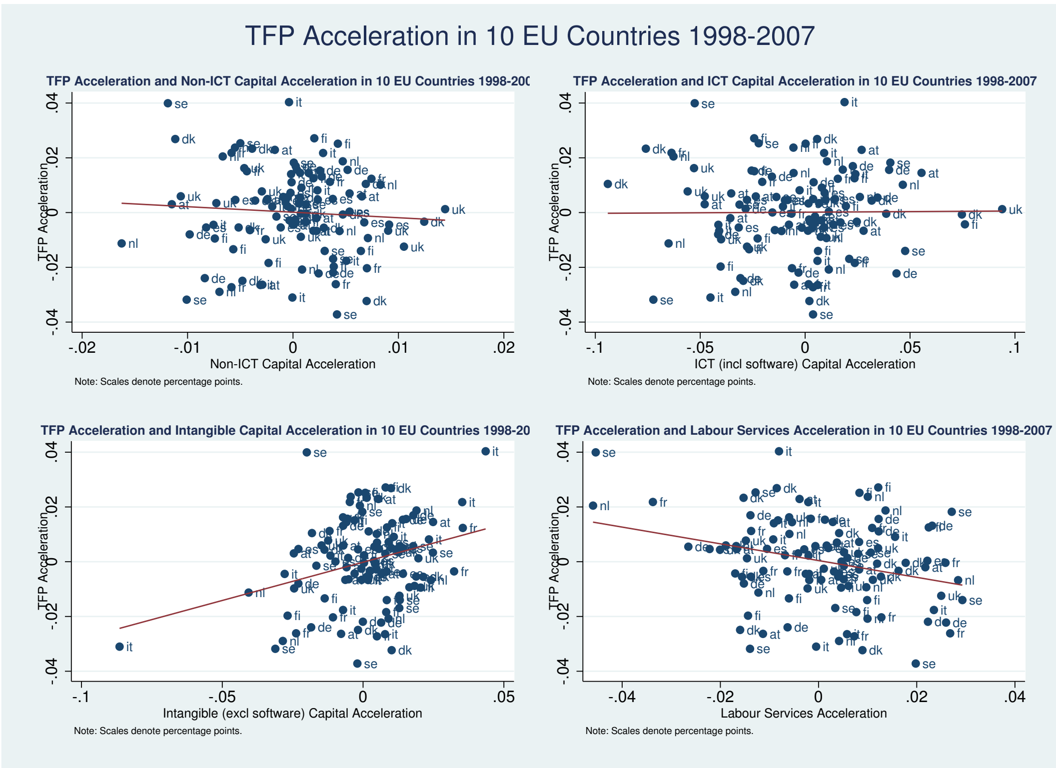

Figure 3: Market Sector TFP Growth Acceleration in 10 EU Countries 1998-2007

3 Intangible Capital and ICT Complementarity

Do countries that accumulate intangible capital at a relatively faster rate experience stronger productivity growth in ICT-intensive industries? We would expect an affirmative answer if intangible capital complements ICT capital in the production function, which is to say that for firms to realize the benefits from investments in ICT, investments in additional assets such as new organizational processes and better trained workers are necessary. As previously indicated, this mechanism is implicit in Bresnahan, Brynjolfsson, and Hitt (2002), who argue that the productivity gains from installing ICT hardware (tangible capital) would only be reaped with organizational change (which in our terms is installing intangible capital).

We use a difference-in-differences approach and evaluate the extent to which the growth contribution of intangible capital depends on the intensity of ICT capital. The approach is based on Rajan and Zingales (1998) who proposed an estimation model with country-industry interactions to test the impact of financial development on economic growth. The Rajan and Zingales approach has been widely adopted because it addresses the problem of reverse causality and reduces the omitted variable bias that frequently affects cross-country growth regressions.

Rajan and Zingales considered the question of whether financial development was a catalyst for growth, specifically, whether industries that rely relatively heavily on external finance grow faster in countries with more developed financial markets. They did this by interacting a measure of the importance of external finance in industry i with a measure of financial development of country c. We apply similar logic: To consider whether a country's accumulation of intangible capital is a catalyst for growth via increasing the competitive advantage of industries who rely more heavily on ICT, we measure the importance of ICT to industry i by the industry's average ICT intensity across all EU countries in our sample and time, and we interact this with growth in intangible capital in country c. We then use the U.S. ICT intensity of industry i to check the robustness of our results with an exogenous (to our sample) measure of ICT intensity.[12]

We model the change in industry-level productivity as:

$$\Delta lnA_{c,i,t} = \lambda_c + \lambda_i + \lambda_t + \eta_{c,i,t} \tag{11}$$

where the λ's are unobserved country, industry, and time effects. We then estimate the following variant of equation (7):

$$\begin{aligned} \Delta ln(V_{i,c,t}/L_{i,c,t}) = {} & \alpha_1 \Delta ln(K^{ICT}_{i,c,t}/L_{i,c,t}) + \alpha_2 \Delta ln(K^{NonICT}_{i,c,t}/L_{i,c,t}) \\ & + \alpha_3 \Delta ln(R_{c,t}/L_{c,t}) + \alpha_4 \Delta ln(R_{c,t}/L_{c,t}) * \overline{ln(K^{ICT}/L)_{c,t,i}} \\ & + \alpha_5 \overline{ln(K^{ICT}/L)_{c,t,i}} + \lambda_i + \lambda_c + \lambda_t + \eta_{i,c,t} \ . \end{aligned} \tag{12}$$

$\overline{ln(K^{ICT}/L)_{c,t,i}}$ denotes industry i's average (log) ICT intensity over countries and time, the term we use to capture the differential impact of intangibles on productivity growth in ICT

[12] This move also is from Rajan and Zingales: their industry importance term was a time average of the measured importance of external finance for industry i in the United States.

intensive sectors. Note the following. First, the industry dummies control for the possible correlation between specific industry characteristics and our measure of ICT intensity. Second, if our proxy for ICT intensity in equation (12) is at all correct, we should find $\alpha_4 > 0$, indicating that within each country industries that are more ICT intensive grow faster when ICT stocks are complemented by higher intangible capital accumulation. Third, we obtained our best results using average log ICT-intensity which has economic meaning: the implied output elasticity of R rises as ICT-intensity rises, but at a diminishing rate. Finally, note this equation is designed to be illustrative of these complementarities because the αs are constrained to be constant and we do not have complete industry-level intangible data to adjust V_i.[13]

Table 2 reports estimates of equation (12). Because of well known endogeneity issues that arise when estimating production functions, both OLS and IV results are shown. Robust (heteroskedasticity-adjusted) standard errors are reported for all coefficients; outlier-robust regression methods produce very similar results.[14] Correction for first-order serial correlation is not required., i.e., the Wooldridge F-statistic for the regression shown in column 1 is F(1,188) - .609 Prob>F=.4361. Columns 1 and 2 of the table show that both ΔlnK^{NonICT} and ΔlnK^{ICT} are statistically significantly associated with growth in labour productivity. The inclusion of ΔlnR in columns 3 and 4 reduces their coefficients, however. Columns 5 and 6 and 7 and 8 introduce the main terms of interest, namely interactions between ΔlnR and ICT intensity, using OLS and IV, respectively. Note that we use both U. S. values and own lags for instrumenting the capital terms. This is done because, in the presence of country dummies, the identifying variation for the capital terms is its deviation from its country-level mean. An increase in ΔlnK relative to its country mean might be caused by an unobservable technological opportunity that also raises ΔlnV, such as the discovery of a new technology. On the assumption that the United States is the frontier economy, U.S. values are used as instruments. The estimated IV coefficients are similar to OLS for $\Delta lnR/L$ but rather larger for the other terms. To summarise, all interaction effects are positive and statistically significant (i.e., $\widehat{\alpha}_4 > 0$), whether using EU ICT intensities in columns 5 and 6, or the U.S. ones in columns 7 and 8. This suggests that labour productivity growth in above-average ICT intensive industries was faster in countries experiencing higher increases in ΔlnR, or that ICT capital and intangible capital are complements in production[15].

4 Intangible Capital and Productivity Spillovers

Having investigated intangible capital and ICT in the production function, we are now in the position to test for knowledge spillovers using a more structured specification based on using $\Delta lnTFP$ as the dependent variable, per equation (8).

[13]Eberhardt et al. (2013) further point out that estimated input elasticities might be biased if they are incorrectly restricted to be constant across countries and industries over time.

[14]Estimates with clustered standard errors to take into account the possible impact of clustered correlation both by country and by country-industry did not affect the interaction results. Clustered correlation by country estimates generated slightly reduced ICT and NonICT coefficients. However, given the small number of countries (10), it is likely that clustered estimates are affected by few-cluster biased standard errors (Cameron, Gelbach, and Miller (2008)), so that we do not put much emphasis on them.

[15]We also interacted industry-level ICT intensity with country ΔlnR for major intangible sub-aggregates. All were statistically significant (in separate equations for each, as the combination of all in one equation was too collinear). This again suggests complementarity. For further evidence, see Corrado, Haskel, and Jona-Lasinio (2016).

Table 2: $\Delta ln(V/L)_{i,c,t}$ Regressions with Interactions, 1998 to 2007

	Estimation Technique:							
	OLS	IV[1]	OLS	IV	OLS	IV	OLS	IV
Variable[2]	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta ln(K_{i,c,t}^{NonICT}/L_{i,c,t})$	0.292***	0.248***	0.0715***	0.104*	0.0803***	0.104**	0.0789***	0.126**
	(0.0222)	(0.0565)	(0.0241)	(0.0548)	(0.0240)	(0.0518)	(0.0241)	(0.0509)
$\Delta ln(K_{i,c,t}^{ICT}/L_{i,c,t})$	0.0473***	0.0927***	0.0267**	0.00596	0.0236**	-0.0268	0.0248**	-0.00500
	(0.0123)	(0.0273)	(0.0117)	(0.0264)	(0.0116)	(0.0258)	(0.0117)	(0.0248)
$\Delta ln(R_{c,t}/L_{i,c,t})$			0.476***	0.477***	0.636***	0.699***	0.434***	0.398***
			(0.0293)	(0.0723)	(0.0456)	(0.0916)	(0.0338)	(0.0509)
$\overline{ln(K^{ICT}/L)_{c,t,i}}$					0.123***	0.101*		
					(0.0253)	(0.0518)		
$\overline{(lnK^{ICT}/L)_{c,t,i}}$*$(\Delta lnR_{c,t}/L_{i,c,t})$					0.108***	0.145***		
					(0.0263)	(0.0451)		
$\overline{(lnK^{ICT}/L)_{US,t,i}}$							0.115***	0.108***
							(0.0272)	(0.0258)
$\overline{(lnK^{ICT}/L)_{US,t,i}}$ *$(\Delta lnR_{c,t}/L_{i,c,t})$							0.0938***	0.136***
							(0.0282)	(0.0431)
Observations	2,268	1,890	2,268	1,890	2,268	2,079	2,268	2,079
R-squared	0.325	0.219	0.382	0.283	0.390	0.291	0.388	0.293

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

NOTES—Robust (heteroskedasticity-adjusted) standard errors in parentheses. All specifications include country and time fixed effects (coefficients not reported). For list of countries, see note to table 1.

1. For all columns using IV, instrumented variables: $\Delta lnK^{NonICT}, \Delta lnK^{ICT}, \Delta lnR$ (where applicable).

2. For all columns using IV, list of instruments: $\Delta lnK_{US}^{NonICT}, \Delta lnK_{t-1}^{NonICT}, \Delta lnK_{t-1}^{ICT}$. ΔlnR_{US} and ΔlnR_{t-1} where applicable.

Using $\Delta lnTFP$ as the dependent variable, rather than estimating production functions, is advantageous since it mitigates bias due to (a) endogeneity of inputs, (Griliches and Mairesse, 1998) and (b) varying output elasticities (Eberhardt et al., 2013). To use $\Delta lnTFP^{Q}$ requires working with our market sector dataset, however, where we can (a) adjust output (b) include all inputs and (c) therefore use the appropriate regressand.

4.1 Estimation Results

Our framework encompasses the possibilities of spillovers to all major factors of production, and we look at evidence for each after first examining results for intangible capital. Initially we model $\Delta A_{c,t}$ as in equation (11), from which we obtain our basic estimating equation for productivity spillovers

$$\text{(13)} \qquad \Delta(\Delta lnTFP^{Q}_{c,t}) = \beta_1\Delta(\Delta lnK^{NonICT}_{c,t}) + \beta_2\Delta(\Delta lnK^{ICT}_{c,t}) + \beta_3\Delta(\Delta lnR_{c,t}) + \beta_4\Delta(\Delta lnL_{c,t}) + \lambda_t + \eta_{c,t} \; .$$

In terms of the model set out in section 1, the estimated coefficients are: $\beta_1 = d^{NonICT}$, $\beta_2 = d^{ICT}$, $\beta_3 = d^{R}$, and $\beta_4 = d^{L}$. Because spillovers might take time, we experiment with lags and then consider disaggregation of R and L into components shown in table 1. Notice we have double-differenced (13) and so implicitly allow for country effects [16]. We report random effects (and some IV estimates) below: OLS and RE results are very similar.

The results of estimating equation (13) are shown in table 3. All regressions contain time effects and have robust standard errors and are in $\Delta(\Delta)$ form, so the dependent variable is $\Delta(\Delta lnTFP^{Q})$ or $\Delta(\Delta lnTFP^{V})$ as indicated (thus we drop the λ_c: this is statistically acceptable) [17] .

Column 1 of table 3 sets out estimates using conventional productivity data: the regressand is $\Delta(\Delta lnTFP^{V})$ and regressors conventional capital and labour inputs, $\Delta(\Delta lnK^{Non-ICT})$ and $\Delta(\Delta lnK^{ICT})$, along with $\Delta(\Delta lnL)$. The estimated spillover coefficients on capital inputs are insignificant while the coefficient on labor services is negative and significant.

Column 2 includes intangibles, so the regressand is now $\Delta(\Delta lnTFP^{Q})$ and regressors add $\Delta(\Delta lnR)$, which is statistically (and economically, see below) significant. As previously discussed, $\Delta(\Delta lnL)$ represents a combination of a term capturing changes in the composition of the workforce $\Delta(\Delta ln\Upsilon)$ and hourly labour input $\Delta(\Delta lnH)$. [18] The rest of the table explores this, beginning in column 3, which simply lags $\Delta(\Delta lnL_{c,t})$ and obtains a positive coefficient.

[16] Statistical analysis suggests that residuals in our differenced equation are autocorrelated (Wooldridge autocorrelation test: F(1,9)=24.64, Prob>F=.0008) and that fixed effects are more efficient than random effects (a Hausman test gives χ^2=29.75, Prob> χ^2=.003). However, we cannot adopt Newey-West with fixed effects since the small size of our sample would generate inefficient estimation results. Thus we resort to second differences that allows to eliminate the country fixed effect and to account for serial correlation in a consistent framework.

[17] We tested our model with the Common Correlated Effect estimator (CCEP) to check for biases induced by unobserved common factors and found very similar results. We thank a referee for this suggestion.

[18] It might be felt that a negative relation between $\Delta(\Delta lnTFP^{Q})$ and $\Delta(\Delta lnL)$ goes against the classic notion of procyclical productivity. However, recent papers have documented the decline and/or reversal of procyclical productivity in recent years and countries, particularly in the US (see e.g. Gali and van Rens, 2010), which might in turn be due to changes in labour market flexibility and/or different effects of technology and demand shocks. So our findings are in line with this change.

Column 4 enters lags: $\Delta(\Delta ln\Upsilon_{c,t-1})$ and $\Delta(\Delta lnH_{c,t-1})$. Only $\Delta(\Delta lnH_{c,t-1})$, worker hours, is significant likely because it captures unmeasured utilisation, which may be magnified in a $\Delta(\Delta lnTFP)$ equation. But when the disaggregated terms are lagged twice, as in column 5, which would likely reduce the utilisation effect, the coefficient on $\Delta(\Delta ln\Upsilon_{c,t-2})$ becomes highly significant while that on $\Delta(\Delta lnH_{c,t-2})$ is no longer significant. Furthermore, the significance of the estimated spillover coefficient for $\Delta(\Delta\Upsilon_{c,t-2})$ is independent of the inclusion of intangible capital in the model and data (column 3). Finally, in column 6, we change the dependent variable to $\Delta(\Delta lnTFP^V)$ and get the same result, indicating this finding is not a quirk of the intangibles-incorporated data. In what follows therefore we stick with this specification as our baseline spillover equation.

Table 4 disaggregates intangibles into two components, R&D and nonR&D intangibles; recall, software is included with ICT, and thus non-R&D intangibles consists of non-scientific innovative property and economic competencies such as brand, organizational structure, and firm-specific human capital (i.e., training). In column 1 $\Delta(\Delta lnR^{NonR\&D}_{c,t})$ is significant while $\Delta(\Delta lnR^{R\&D}_{c,t})$ is not. Column 2 adds lags to explore if intangible spillovers take time, and column 3 drops insignificant terms and is the preferred specification. In the regression shown in column 3, the spillover coefficient on $\Delta(\Delta lnR^{NonR\&D})$ remains significant with a value very similar to before. The spillover coefficient on $\Delta(\Delta lnR^{R\&D}_{c,t-1})$ is borderline significant, but interestingly, its value is in line with the coefficient on external R&D of 0.2 assumed by Griliches (1992, p.S44). Column 4 then shows a regression using a version of the data where R&D is the only intangible asset that is capitalized produces the same coefficient.

The final column of Table 4 experiments with IV. Since we use $\Delta(\Delta lnTFP)$ as a regressor, we are not estimating private output elasticities and avoid the classic Andrews-Marshack simulteneity problem, but we may still have problems of e.g. measurement error (which can be magnified in differenced data). We are however mindful of the limitations of IV due to e.g., biases from poor instruments especially in a short panel. This is a topic for more future work: for the moment, column 5 shows representative results from using lagged differences as instruments for the contemporaneous variables $\Delta lnR^{NonR\&D}_{c,t}$, ΔlnK^{ICT}_t and ΔlnK^{NonICT}_t. Our main conclusions around intangibles are unaffected: the magnitude of the $\Delta(\Delta lnR^{NonR\&D}_{c,t})$ and $\Delta(\Delta lnR^{R\&D}_{c,t-1})$ terms both rise, and they are statistically significant. In addition, there is also borderline statistical significance of the $\Delta(\Delta lnK^{ICT}_t)$ term, which also might be a subject for future exploration.

Table 3: $\Delta(\Delta lnTFP_{c,t})$ Spillover Regressions, 1998 to 2007

	Dependent Variable:					
	$\Delta(\Delta lnTFP^{V}_{c,t})$	$\Delta(\Delta lnTFP^{Q}_{c,t})$				$\Delta(\Delta lnTFP^{V}_{c,t})$
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta(\Delta lnK^{NonICT}_{c,t})$	-0.127	-0.061	-0.648*	-0.676*	-0.477	-0.612
	(0.401)	(0.351)	(0.347)	(0.359)	(0.372)	(0.426)
$\Delta(\Delta lnK^{ICT}_{c,t})$	-0.026	-0.020	-0.009	-0.013	-0.074	-0.076
	(0.056)	(0.051)	(0.063)	(0.065)	(0.077)	(0.086)
$\Delta(\Delta lnR_{c,t})$		0.176***	0.253***	0.251***	0.208***	
		(0.050)	(0.046)	(0.048)	(0.054)	
$\Delta(\Delta lnL_{c,t})$	-0.638***	-0.573***				
	(0.080)	(0.082)				
$\Delta(\Delta lnL_{c,t-1})$			0.196**			
			(0.078)			
$\Delta(\Delta ln\Upsilon_{c,t-1})$				0.124		
				(0.148)		
$\Delta(\Delta lnH_{c,t-1})$				0.236***		
				(0.080)		
$\Delta(\Delta ln\Upsilon_{c,t-2})$					0.316***	0.319**
					(0.107)	(0.132)
$\Delta(\Delta lnH_{c,t-2})$					-0.073	-0.057
					(0.143)	(0.152)
Observations	100	100	100	100	90	90
R^2	0.649	0.672	0.527	0.529	0.554	0.511

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

NOTES—Robust (heteroskedasticity-adjusted) standard errors in parentheses. All columns use random effects (RE) estimation. For list of countries, see note to table 1.

1. All specifications have been tested both with Random Effect and OLS estimators. OLS and RE results are largely coincident.

Table 4: $\Delta(\Delta lnTFP_{c,t})$ Spillover Regressions, 1998 to 2007

	Dependent Variable: $\Delta(\Delta lnTFP^{Q})$				
	RE				IV[1,2]
Variable	(1)	(2)	(3)	(4)	(5)
$\Delta(\Delta lnK^{NonICT}_{c,t})$	-0.506	-0.550		-0.535	
	(0.364)	(0.474)		(0.377)	
$\Delta(\Delta lnK^{ICT}_{c,t})$	-0.083	-0.041		-0.054	
	(0.076)	(0.080)		(0.073)	
$\Delta(\Delta lnR^{NonR\&D}_{c,t})$	0.192***	0.150*	0.169***		0.319***
	(0.037)	(0.078)	(0.057)		(0.107)
$\Delta(\Delta lnR^{R\&D}_{c,t-1})$		0.230*	0.245*	0.197*	0.426**
		(0.129)	(0.126)	(0.115)	(0.207)
$\Delta(\Delta ln\Upsilon_{c,t-2})$	0.352***	0.348***	0.314***	0.308***	0.330*
	(0.109)	(0.108)	(0.105)	(0.110)	(0.173)
$\Delta(\Delta lnH_{c,t-2})$	-0.059	-0.061			
	(0.127)	(0.112)			
$\Delta(\Delta lnR^{NonR\&D}_{c,t-1})$		-0.175			
		(0.114)			
$\Delta(\Delta lnR^{R\&D}_{c,t})$	-0.095	-0.098			
	(0.090)	(0.089)			
$\Delta(\Delta lnK^{NonICT}_{c,t-1})$		-0.140			
		(0.285)			
$\Delta(\Delta lnK^{ICT}_{c,t-1})$		0.099**	0.060		0.139*
		(0.042)	(0.066)		(0.073)
Observations	90	90	90	90	70
R^2	0.559	0.599	0.545	0.530	0.519

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

NOTES—Robust (heteroskedasticity-adjusted) standard errors in parentheses. Columns 1, 2, 3, 4 show random effects estimation (RE) results, while column 5 shows instrumental variable (IV) estimates. Note that in column 4 only R&D is capitalized. For list of countries, see note to table 1.

1. Instrumented variables: $\Delta lnK^{ICT}, \Delta lnR^{NonR\&D} and \Delta lnR^{R\&D}$. Instruments used: $\Delta lnK^{ICT}_{t-2}, lnK^{ICT}_{t-2}, \Delta lnR^{NonR\&D}_{t-2}, lnR^{NonR\&D}_{t-2}, \Delta lnR^{R\&D}_{t-2}$, $lnR^{R\&D}_{t-2}$

2. F-tests on first stage regressions and Cragg-Donald test reject the null that the instruments underlying column 5 are weak

4.2 Economic significance

To judge the economic significance of our findings, we look first at the projected effects on $\Delta lnTFP^Q$ using column 5 of Table 3. These results imply a contribution of improvements in workforce skills to productivity of 0.12 percentage points per year, on average (.32 * .40 = .12). The contribution from investments in intangible capital is a good bit larger: 0.85 percentage point per year (.21 * 4.05) based on the actual change shown in Table 1. These are statistically and economically significant contributions. They are, however, very large as actual $\Delta lnTFP^Q$ = 0.77 percent per year.

Might these estimates be upward biased? A number of points are worth making. First, the elasticity of $\Delta lnR^{R\&D}$ is in line with other estimates. Second, we would usually expect that differencing raises measurement error and, to the extent it is classical, produces estimates that are biased downwards (and note we have double differencing here). Third, double differencing might lead to outlier observations but robust estimation techniques are always used and there is no reason to believe our estimates are affected by a small number of influential observations (see Figure 3).

Fourth, our production function specification assumes that ΔlnQ or $\Delta lnTFP$ in country c is affected by (changes in) the stock of knowledge R in country c. There is of course a body of literature on cross-border knowledge flows in the case of R&D (for a summary of the macro- and industry-level evidence see Hall et al., 2009). The exploration of non-R&D intangible capital knowledge flows is essentially nonexistent, however. Whether such flows are mediated by trade, the absorptive capacity of industries, or other mechanisms is not known, and advancing the state of knowledge in this area would be a useful line of work, requiring of course additional data. That said, *if* such international spillovers can be represented by a country-specific trend in the $\Delta lnTFP$ equations, they are removed by double differencing. It is possible however, that international knowledge spillovers are not sufficiently controlled for by this and that the $\Delta(\Delta lnR_{c,t})$ terms are correlated with global knowledge increases that raise productivity, thus exaggerating the coefficient on country $\Delta(\Delta lnR_{c,t})$.

Fifth, we know all too well that we are very early in the game of measuring non-R&D intangibles. As a result, there is a possibility that the data we use suffer from nonclassical (i.e., systematic) measurement error.[19] One culprit that springs to mind is systematic error in the price deflator used to obtain real stocks of intangible assets, i.e., the deflator could systematically understate the change in "quality" (or value in use).[20] Again, we believe these effects should be largely removed by double-differencing.

[19]Note the following: Let $y = \beta x + \epsilon$. Suppose x is measured with error such that $x^m = x + u$. Then the standard attenuation bias formula is $\hat{\beta} = cov(x^m, y)/var(x^m) = cov(x+u, \beta x + \epsilon)/var(x+u)$, or $\hat{\beta} = \beta \frac{(\sigma_x^2 + \sigma_{x,u})}{(\sigma_x^2 + \sigma_u^2 + 2\sigma_{x,u})}$. With classical measurement error $\sigma(x, u) = 0$ and the expression reduces to standard formula indicating downward bias. However, if $\sigma(x, u) \neq 0$ then the bias can negative or positive.

[20]Corrado, Goodridge, and Haskel (2011) study, for example, the case of R&D, and find that its contribution to productivity warrants using a deflator for R&D that falls faster than the deflator that is conventionally used.

5 Conclusions

This paper uses a cross-country econometric approach and a new database (www.INTAN-Invest.net) to study the channels through which intangible capital affects productivity growth in the market sector of 10 major European countries, 1998-2007. The intangible capital we study is the knowledge capital resulting from investments in R&D, design, brand equity, firm-specific training and organizational change. In our country-level work, we adjust value added, factor shares and TFP accordingly with the addition of such investment. We cannot do this in our country-industry work, and so focus instead on complementarities with ICT capital inputs. We think that we go beyond many previous studies, where comprehensive data on intangible investment data was not available and connections with economic growth investigated either via R&D or inferred from assumed correlations with ICT investment.

We have three key findings. First, using our country-industry-time data, we find that the estimated output elasticities of ICT capital are reduced when intangibles are introduced, suggesting that, as conjectured in much of the pre-intangible *data* literature, returns to ICT depend crucially on the presence of "unmeasurable" intangibles. Indeed, we believe we demonstrate that ICT and intangibles are complements in production. That is, we find positive contributions to $\Delta lnQ/H$ from interaction effects between ΔlnR and industry ICT intensity, suggesting that returns to a country's investments in intangible capital are stronger in its ICT-intensive industries.

Second, we find evidence of productivity spillovers to increases in intangible capital and, third, we also find evidence of spillovers to growth in workforce skills. Our finding of growth spillovers to intangible capital is robust to whether R&D is included or excluded and with IV. In other words, we believe our results showing a significant (positive) coefficient on intangible capital are consistent with an underlying mechanism producing a growth "dividend" to investments in non-R&D intangibles.

What do we make of our finding of productivity spillovers from workforce skills? This finding seems orthogonal to the size and significance of the spillover coefficient we estimate for intangible capital, suggesting that intangible capital of firms and human capital of workers play distinct roles in generating externalities in production. That said, the inescapable conclusion of our work is that a country's "knowledge economy" plays a special role in generating favorable productivity and growth outcomes.

Despite these encouraging results, advocating policy-makers to take the indirect effects of non-R&D intangibles into consideration when framing innovation and ICT/digital policies requires additional research and validation. Advances in measurement are on the horizon (industry-level intangibles, public sector intangibles), and soon it will be possible to revisit the issues traversed in this paper with better and richer data.

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