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Carol Corrado
Jonathan Haskel
Cecilia Jona-Lasinio

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Carol Corrado

The Conference Board and Georgetown University

Jonathan Haskel

Imperial College, CEPR and IZA

Cecilia Jona-Lasinio

ISTAT and LLEE

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

Knowledge Spillovers, ICT and Productivity Growth ^{*}

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 marginal impact of ICT capital is higher when it is complemented with intangible capital, and (b) non-R&D intangible capital has a higher estimated output elasticity than its conventionally-calculated factor share. These findings suggest investments in knowledge-based capital, i.e., intangible capital, produce productivity growth spillovers via mechanisms beyond those previously established for R&D.

JEL Classification: O47, E22, E01

Keywords: productivity growth, economic growth, intangible capital, intangible assets, ICT, spillovers

Corresponding author:

Jonathan Haskel
Imperial College Business School
South Kensington Campus
Tanaka Building, Room 296
Exhibition Road
London SW7 2AZ
United Kingdom
E-mail: j.haskel@ic.ac.uk

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Knowledge Spillovers, ICT and Productivity Growth

Carol Corrado, Jonathan Haskel, and Cecilia Jona-Lasinio

A large body of work on the sources of economic growth considers the accumulation of capital: human capital, the special role of ICT capital, and in a newer strand of the literature, intangible capital. The literature 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 the US and EU 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. Why might 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, however, due to the heretofore lack of hard data on intangibles.

A second reason stems from the fact that the production of intangibles is largely undertaken within firms by skilled workers and managers, and recent micro literature finds externalities to human capital formation using plant- and state-level data (Moretti 2004a,b). Again, corroborating evidence based on macro- or industry-level data is very limited; after controlling for the direct effect of human capital accumulation on output through private rates of return, most researchers have found no evidence of an additional effect through externalities (e.g., Inklaar, Timmer, and van Ark, 2008).

Finally, 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

¹The 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.

²The 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.

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 that suggests spillovers to intangible capital. But private R&D stocks are only about one-third of total private net stocks of intangibles, suggesting a more thorough investigation of the relationship is warranted.

As we shall shortly see, our work produces new findings on these topics: We (a) establish ICT-intangible capital complementarity, (b) find significant productivity spillovers to non-R&D intangible capital, and (c) find that externalities to labor “quality” 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).

I. Model

This section sets out a model that describes how we believe that adding intangibles deepens our understanding of 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:

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

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) gives:

$$(2) \quad \Delta \ln Q_{c,i,t} = \epsilon_{c,i,t}^L \Delta \ln L_{c,i,t} + \epsilon_{c,i,t}^K \Delta \ln K_{c,i,t} + \epsilon_{c,i,t}^R \Delta \ln R_{c,i,t} + \Delta \ln A_{c,i,t}$$

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

$$(3) \quad \epsilon_{c,i,t}^X = s_{c,i,t}^X, \quad X = L, K, R$$

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.

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 $\Delta \ln R$ on $\Delta \ln Q$ is a mix of both internal and external elasticities so that we can therefore write following Stiroh (2002)

$$(4) \quad \epsilon_{c,i,t}^X = s_{c,i,t}^X + d_{c,i,t}^X, \quad X = L, K, R$$

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.⁴ All this suggests that we may write (2) as

$$(5) \quad \begin{aligned} \Delta \ln Q_{c,i,t} = & (s_{c,i,t}^L + d_{c,i,t}^L) \Delta \ln L_{c,i,t} + (s_{c,i,t}^K + d_{c,i,t}^K) \Delta \ln K_{i,c,t} \\ & + (s_{c,i,t}^R + d_{c,i,t}^R) \Delta \ln R_{i,c,t} + \Delta \ln A_{i,c,t} \end{aligned}$$

Second, consider the $\Delta \ln Q_{c,i,t}$ terms. As Griliches (1980) and Schankerman (1981) pointed out, if R&D inputs are included in the conventional L and K terms and a regression model is used to determine the R&D output elasticity, the results will be biased. The flip side to this argument is that, to the extent that intangibles (such as R&D) are long-lasting assets and not intermediate inputs, the spending must be capitalised as investment and included in value-added (as in Corrado et al., 2005, 2009).

Denoting conventional value added (in which intangibles are treated as intermediates) as V , we can then write:

$$(6) \quad \Delta \ln Q_{c,i,t} = (1 - s_{c,i,t}^R) \Delta \ln V_{c,i,t} + s_{c,i,t}^R \Delta \ln N_{c,i,t}$$

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

⁴Equation (4) can be justified using the Griliches (1979, 1992) example: Suppose the production function for firm 1 in industry i can be written $Y_{1i} = R_{1i}^\epsilon R_{ai}^d$ where R_{1i} is the firm's specific knowledge capital and R_{ai} is aggregate knowledge in the industry and all other factors are omitted for simplicity. The firm's first-order condition can be written $\epsilon = s^R$. If all firms are optimising and face identical factor prices the industry production function relating $\sum Y$ and $\sum R$ can be written $Y_i = R_i^{\epsilon+d} = R_i^{s^R+d}$ (non-identical firms will introduce additional mix terms).

where N is real intangible investment and we have approximated the share of intangible investment costs in nominal Q as s^R , the share of intangible rental payments in nominal Q . Substituting (6) into (5) gives

$$(7) \quad \begin{aligned} \Delta \ln Q_{c,i,t} &= (1 - s_{c,i,t}^R) \Delta \ln V_{c,i,t} + s_{c,i,t}^R \Delta \ln N_{c,i,t} \\ &= (s_{c,i,t}^L + d_{c,i,t}^L) \Delta \ln L_{c,i,t} + (s_{c,i,t}^K + d_{c,i,t}^K) \Delta \ln K_{c,i,t} \\ &\quad + (s_{c,i,t}^R + d_{c,i,t}^R) \Delta \ln R_{c,i,t} + \Delta \ln A_{c,i,t} \end{aligned}$$

and when this expression is written in terms of $\Delta \ln V_{c,i,t}$, it becomes

$$(8) \quad \begin{aligned} \Delta \ln V_{c,i,t} &= \frac{(s_{c,i,t}^L + d_{c,i,t}^L)}{(1 - s_{c,i,t}^R)} \Delta \ln L_{c,i,t} + \frac{(s_{c,i,t}^K + d_{c,i,t}^K)}{(1 - s_{c,i,t}^R)} \Delta \ln K_{c,i,t} \\ &\quad + \frac{d_{c,i,t}^R}{(1 - s_{c,i,t}^R)} \Delta \ln R_{c,i,t} + \Delta \ln A_{c,i,t} \end{aligned}$$

where for simplicity we have assumed that $\Delta \ln R = \Delta \ln N$ (as in the "maximal consumption" steady state). We are now in a position to make a number of points.

A. Data on intangibles available

Suppose one had data on intangibles. Looking at (7), with such data one can include intangibles in value added and measure the three inputs on the right plus their shares. Three approaches suggest themselves. First, to examine complementarities, one might suppose that the shares are functions of the inputs and regress $\Delta \ln Q$ on interacted inputs. Second, to examine spillovers, that is $d > 0$, one might suppose that s and d are constant and regress $\Delta \ln Q$ 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 $\Delta \ln TFP$ index can be constructed that is robust to an underlying translog production function such that we can write (7) as

$$(9) \quad \Delta \ln TFP_{c,i,t} = d_{c,i,t}^L \Delta \ln L_{c,i,t} + d_{c,i,t}^K \Delta \ln K_{c,i,t} + d_{c,i,t}^R \Delta \ln R_{c,i,t} + \Delta \ln A_{c,i,t}$$

where $\Delta \ln TFP_{c,i,t} = \Delta \ln TFP_{c,i,t}^Q$ and $\Delta \ln TFP_{c,i,t}^Q$ is calculated as

$$(10) \quad \Delta \ln TFP_{c,i,t}^Q = \Delta \ln Q_{c,i,t} - s_{c,i,t}^L \Delta \ln L_{c,i,t} - s_{c,i,t}^K \Delta \ln K_{c,i,t} - s_{c,i,t}^R \Delta \ln R_{c,i,t}$$

From (9) therefore, a regression of $\Delta \ln TFP_{c,i,t}^Q$ on the inputs recovers the spillover terms.

It is apparent that these approaches have advantages and disadvantages. Estimating a production function potentially uncovers complementarities that are suppressed in TFP . Against

this, estimation of production functions gives rise to well-known econometric problems: for example, the coefficients on the inputs are endogenous because shocks to A affect input choices, as is implicit in the first-order condition (3).

B. Data on intangibles unavailable

In much of the literature, data on intangibles are not available. Consider then (8), in which $\Delta \ln V$ is on the left hand side and the first term in the lower line is missing. Now consider estimating a relation between $\Delta \ln V$ and $\Delta \ln L$ and $\Delta \ln K$ and comparing the coefficients on $\Delta \ln L$ and $\Delta \ln K$ with s_L and s_K . The coefficients would have the endogeneity problems just mentioned and in addition would potentially (a) reflect a combination of shares and (b) have an omitted variable bias depending on the correlation between $\Delta \ln L$ and $\Delta \ln K$ and $\Delta \ln R$. 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 $\Delta \ln R$ occurs at a time of below-average $\Delta \ln K$. We explore this below.

Consider next constructing $\Delta \ln TFP^V$ using $\Delta \ln V$ and share-weighted $\Delta \ln L$ and $\Delta \ln K$ 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 $d^K/(1 - s^R)$.

Two other approaches are worth noting. One is to assume that missing intangibles are correlated with an available variable e.g., $\Delta \ln K_{t-k}^{ICT}$ (ICT capital, perhaps lagged k periods, as in Basu *et al.* 2004), or to use R&D as a proxy for all other intangibles. A problem with a latter approach is that while R&D is but one intangible, it may be the major source of spillovers (or the opposite, namely that another intangible asset is the major source and is highly correlated with R&D). We cannot know of course unless we have gathered data for all intangibles, the position we find ourselves in this paper.

II. Data

This paper uses the INTAN-Invest harmonized measures of business intangible investment, intangible capital, and nominal and real value added including intangibles (Corrado, Haskel, Jona-Lasinio, and Iommi, 2012) along with multifactor productivity estimates congruent with these data.

INTAN-Invest provides data across countries 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 US 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.⁵ The INTAN-Invest data and documentation are available at www.intan-invest.net. INTAN-Invest data at the industry level are under development but not available as of this writing.⁶

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 build ourselves using EUKLEMS methods and EUKLEMS, INTAN-Invest, and World-Input-Output Database (WIOD; see Timmer, 2012) data.

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.

A. Country-Level Dataset Construction

To include intangible capital in a country-level productivity analysis we must, as the framework in section I showed, (a) capitalise 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

⁵NACE 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)

⁶See Corrado, Haskel, Jona-Lasinio, and Iommi (2014, forthcoming), scheduled for presentation at the 3rd World KLEMS Conference, Tokyo, May 19–20, 2014, for further information.

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 . This allows us to express changes in labor input as the sum of two terms:

$$(11) \quad \Delta \ln L_{c,t} = \Delta \ln H_{c,t} + \Delta \ln \Upsilon_{c,t}$$

where H is total hours worked and Υ adjusts hours by the effectiveness of each hour (i.e., $L = H * \Upsilon$). The term Υ is often referred to as “labor quality,” and its increase (multiplied by labor’s share) is the direct channel whereby human capital accumulation contributes to economic growth.

Table 1 sets out values (country-time averages) for growth rates and factor shares for some key variables in this dataset.⁷ 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. 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, both of which are classified in currently published data as intangibles.⁸

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

⁷Market sector growth accounting results using INTAN-Invest data have been analyzed previously (Corrado, Haskel, Jona-Lasinio, and Iommi, 2013).

⁸As of the writing of this paper (April 2014), R&D is not capitalized in the national accounts of European countries although doing so is scheduled for later this year.

Three points must then be borne in mind about our tangible vs. intangible asset grouping. (1) Following most of the ICT macro-productivity literature (and EUKLEMS), ICT *includes* computer software. 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 our K^{NonICT} variable literally is non-ICT equipment and structures but in practice 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.

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)	E	.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.

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.⁹

B. Plots and Preliminaries

Figures 1–3 provide additional insights into the data. 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 $s^R \Delta \ln R / H$ and $s^{ICT} \Delta \ln K^{ICT} / H$, suggesting complementarity between the two types of capital.

⁹The 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.

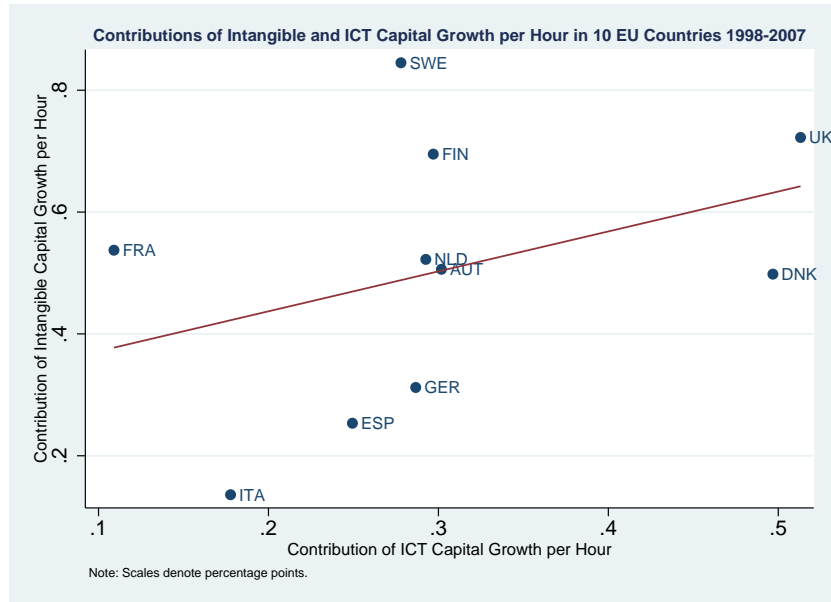


FIGURE 1. CONTRIBUTIONS OF INTANGIBLE AND ICT CAPITAL DEEPENING IN 10 EU COUNTRIES 1998-2007

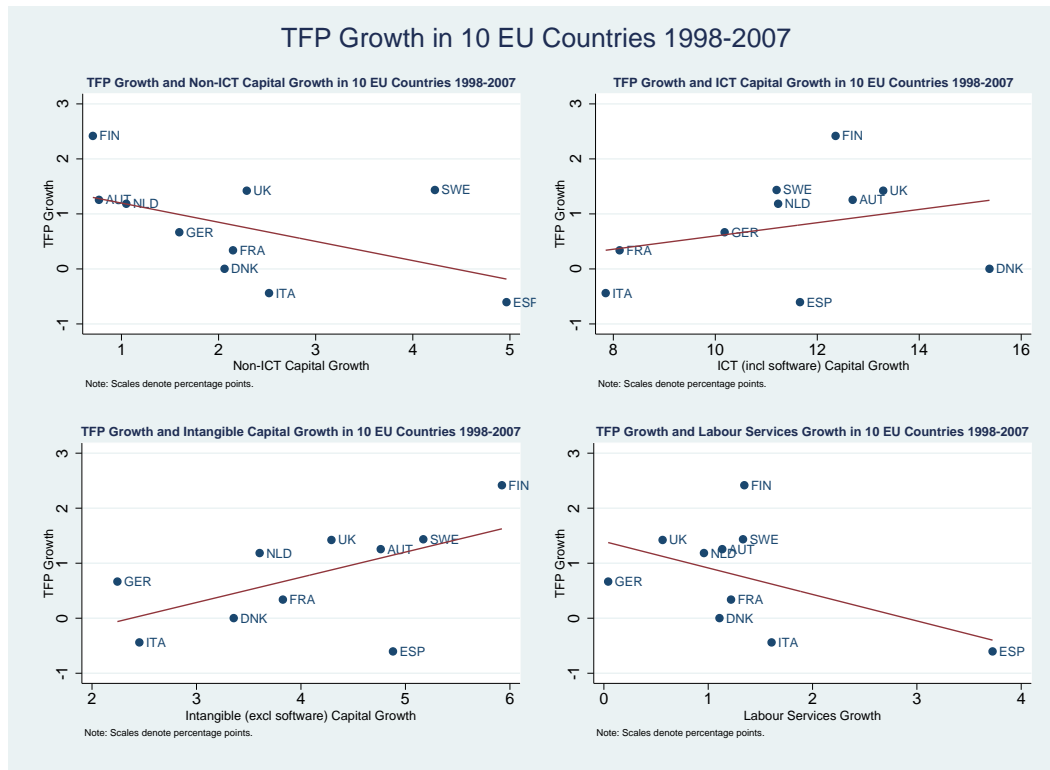


FIGURE 2. MARKET SECTOR TFP GROWTH IN 10 EU COUNTRIES 1998-2007

Figure 2 includes four panels, each with market sector $\Delta \ln TFP^Q$ 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 $\Delta \ln TFP^Q$ and, respectively, $\Delta \ln K^{NonICT}$ 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.

We now turn to presenting our econometric results, beginning with a discussion of how we test for complementarity between intangible capital and ICT.

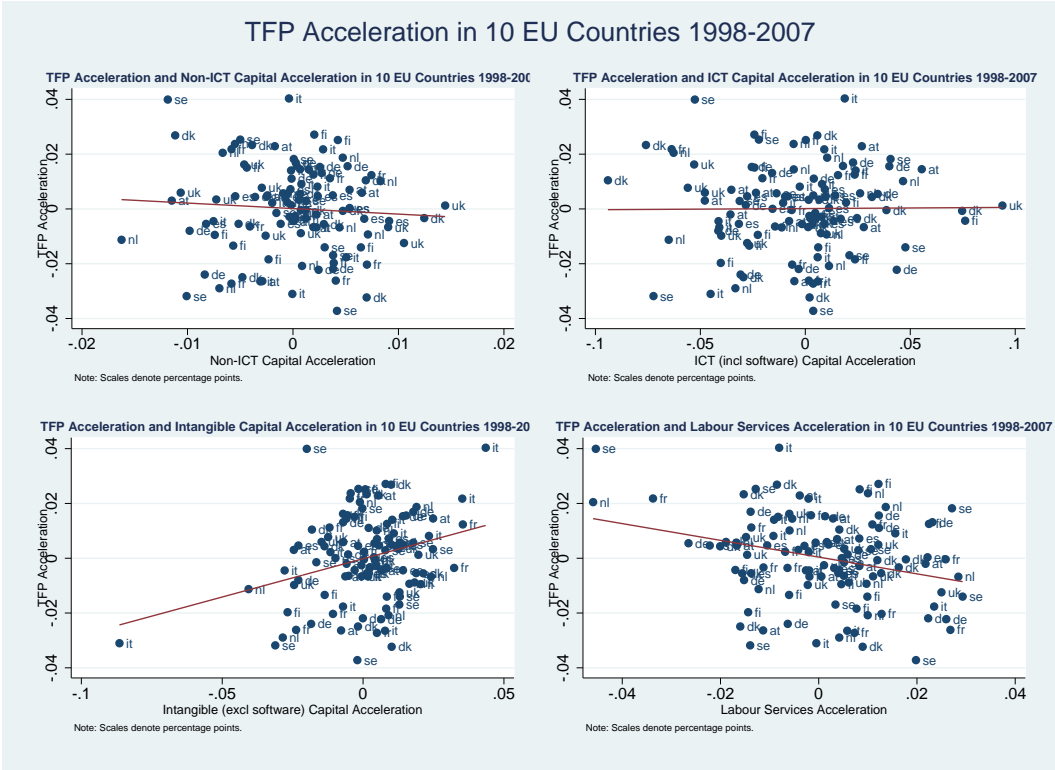


FIGURE 3. MARKET SECTOR TFP GROWTH ACCELERATION IN 10 EU COUNTRIES 1998-2007

III. Intangible Capital and ICT Complementarity

Do countries that accumulate intangible capital at a relatively faster rate experience stronger productivity growth in ICT-intensive industries? That is the question we investigate in this section. 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 US ICT intensity of industry i to check the robustness of our results with an exogenous (to our sample) measure of ICT intensity.¹⁰

We model the change in industry-level productivity as:

$$(12) \quad \Delta \ln A_{c,i,t} = \lambda_c + \lambda_i + \lambda_t + \eta_{c,i,t}$$

¹⁰The latter 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.

where the λ 's are unobserved country, industry, and time effects. We then estimate the following variant of equation (8):

$$(13) \quad \begin{aligned} \Delta \ln(V_{i,c,t}/L_{i,c,t}) = & \alpha_1 \Delta \ln(K_{i,c,t}^{ICT}/L_{i,c,t}) + \alpha_2 \Delta \ln(K_{i,c,t}^{NonICT}/L_{i,c,t}) \\ & + \alpha_3 \Delta \ln(R_{c,t}/L_{c,t}) + \alpha_4 \Delta \ln(R_{c,t}/L_{c,t}) * \overline{(K^{ICT}/L)}_i \\ & + \alpha_5 \overline{(K^{ICT}/L)}_i + \lambda_i + \lambda_c + \lambda_t + \eta_{i,c,t} . \end{aligned}$$

$\overline{(K^{ICT}/L)}_i$ denotes an industry's average ICT intensity, the term we use to capture the differential impact of intangibles on productivity growth in ICT intensive sectors. Note that the industry dummies control for the possible correlation between specific industry characteristics and our measure of ICT intensity. If our proxy for ICT intensity in equation (13) 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.

Table 2 reports estimates of equation (13). 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. Correction for first-order serial correlation is not required, i.e., the Wooldridge F-statistic for the regression shown in column 1 is $F(1,188) = .609$ $\text{Prob} > F = .4361$. Columns 1 and 2 of the table show that both $\Delta \ln K^{NonICT}$ and $\Delta \ln K^{ICT}$ are statistically significantly associated with growth in labour productivity. The inclusion of $\Delta \ln R$ 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 $\Delta \ln R$ and ICT intensity, using OLS and IV, respectively. Note that we use both US 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 $\Delta \ln K$ relative to its country mean might be caused by an unobservable technological opportunity that also raises $\Delta \ln V$, 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 $\Delta \ln R/L$ but rather larger for the other terms. We do not set too much store at this stage by the size of the coefficients, however, because they implicitly impose constant output elasticities over countries and time.

As the Table shows, all interaction effects are positive and statistically significant (i.e., $\hat{\alpha}_4 > 0$), 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 $\Delta \ln R$, or that ICT capital and intangible

capital are complements in production.¹¹ The finding also suggests a mechanism whereby intangible capital (especially non-R&D intangible capital) might be expected to generate productivity spillovers.

As to the size of these impacts, consider an industry with an ICT intensity at the 75th percentile (Transport equipment) and an industry at 25th percentile (Food and beverages). The estimates in table 2 suggest that the annual labor productivity growth differential between these industries is 0.4 - 0.5 percentage points higher in a country with an accumulation rate of intangible assets at the 75th percentage (Sweden) than it is in a country at 25th percentile (France).¹² Based on the implied average annual change in output per hour shown in table 1 (line 3 less line 7a, or 2.1 percent per year), these effects are consequential.

¹¹We also interacted ICT intensity with $\Delta \ln R$ for major intangible sub-aggregates (not shown). All were statistically significant (in separate equations for each, as the combination of all in one equation was too collinear). This again suggests complementarity.

¹²We further note, as per previous footnote, that the estimated differential effect is stronger for design (0.5) and training (0.4) as compared to R&D (0.35) and organizational capital (0.3).

TABLE 2— $\Delta \ln(V/L)_{i,c,t}$ REGRESSIONS WITH INTERACTIONS, 1998 TO 2007

Variable ²	Estimation Technique:							
	OLS (1)	IV ¹ (2)	OLS (3)	IV (4)	OLS (5)	IV (6)	OLS (7)	IV (8)
$\Delta \ln(K^{NonICT}/L)$	0.292*** (0.0222)	0.248*** (0.0565)	0.0715*** (0.0241)	0.104* (0.0548)	0.0803*** (0.0240)	0.104** (0.0518)	0.0789*** (0.0241)	0.126** (0.0509)
$\Delta \ln(K^{ICT}/L)$	0.0473*** (0.0123)	0.0927*** (0.0273)	0.0267*** (0.0117)	0.00596 (0.0264)	0.0236** (0.0116)	-0.0268 (0.0258)	0.0248** (0.0117)	-0.00500 (0.0248)
$\Delta \ln(R/L)$			0.476*** (0.0293)	0.477*** (0.0723)	0.636*** (0.0456)	0.699*** (0.0916)	0.434*** (0.0338)	0.398*** (0.0509)
$\overline{(K^{ICT}/L)}_{EU}$					0.123*** (0.0253)	0.101* (0.0518)		
$\overline{(K^{ICT}/L)}_{EU} * (\Delta \ln R/L)$					0.108*** (0.0263)	0.145*** (0.0451)		
$\overline{(K^{ICT}/L)}_{US} * (\Delta \ln R/L)$							0.115*** (0.0272)	0.108*** (0.0258)
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: $\Delta \ln K^{NonICT}$, $\Delta \ln K^{ICT}$, $\Delta \ln R$ (where applicable).

For all columns using IV, list of instruments: $\Delta \ln K_{US}^{NonICT}$, $\Delta \ln K_{t-1}^{NonICT}$, $\Delta \ln K_{t-1}^{ICT}$, $\Delta \ln R_{t-1}$ where applicable.

2. The overbar in the variables used in columns 5—8 denotes a time average.

IV. Intangible Capital and Productivity Spillovers

We cannot adjust industry-level output to include intangibles and thus cannot place too much emphasis on the magnitude of the output elasticities estimated via equation (13). But having accounted for the importance of intangible capital in the production function, we are now in the position to test for knowledge spillovers using a more structured specification based on equation (9), the equation that uses productivity $\Delta \ln TFP$ as the dependent variable.

Using $\Delta \ln TFP$ as the dependent variable is advantageous because doing so mitigates many of the endogeneity issues that arise when estimating production functions (Griliches and Mairesse, 1998). To fully exploit growth accounting estimates of factor shares 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. These are of course very great advantages, but against this, the sample size is drastically reduced compared with that used to estimate equation (13) and gives rise to certain econometric issues, discussed below. Before we present these estimation results, we first review previous literature that has searched for spillovers in the productivity data.

A. Previous literature

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 the many country- and industry-level studies available on the topic. Such studies usually regress conventional real output or TFP (i.e., $\Delta \ln V$ or $\Delta \ln TFP^V$) 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.

A much more recent literature has attempted to study the effects of intangibles on productivity, encouraged in particular by the ICT revolution. Some papers 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 (e.g., Brynjolfsson, Hitt, and Yang, 2002). 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 above. 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 $\Delta \ln R$ as a function of current and lagged $\Delta \ln K^{ICT}$ and $s^{K^{ICT}}$. Acharya and Basu (2010) go a step further and include R&D in the analysis. We go beyond these works by introducing explicit data on all intangible asset types.

Regarding 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 recent data, Inklaar et al. (2008) still find no relation between skilled hours shares and TFP growth when including labor composition effects in the calculation of $\Delta \ln TFP$ (i.e., no excess returns to skill upgrading).¹³

B. Estimation Results

Our framework encompasses all of the above-mentioned spillover dimensions, and we look at each after first examining results for overall intangible capital. Initially we model $\Delta A_{c,t}$ as in equation (12) (without industry effects of course), from which we obtain our basic estimating equation for productivity spillovers:

$$(14) \quad \begin{aligned} \Delta \ln TFP_{c,t}^Q &= \beta_1 \Delta \ln K_{c,t}^{NonICT} + \beta_2 \Delta \ln K_{c,t}^{ICT} + \beta_3 \Delta \ln R_{c,t} \\ &+ \beta_4 \Delta \ln L_{c,t} + \lambda_c + \lambda_t + \eta_{c,t} . \end{aligned}$$

In terms of the model set out in section I, 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.

The results of estimating equation (14) are shown in table 3. The regressions in columns 1 and 2 suggest that the only input that has a positive and significant spillover coefficient (at the 99 percent level) is intangible capital. Labour input shows a negative coefficient in column 1, so we lag it, and significance disappears (column 2). The results shown in column 2 are problematic for econometric reasons, however. First, the equation's residual errors are rather autocorrelated (Wooldridge test for autocorrelation in panel data produces the F-statistic: $F(1,9)=24.64$, $\text{Prob}>F=.0008$). Second, random effects estimation is rejected in favor of fixed effects (Hausman test on the regression produces the χ^2 -statistic, $\chi^2=29.75$, $\text{Prob}>\chi^2=.003$).

¹³In contrast, Vandebussche, Aghion, and Meghir (2006) found a positive effect of the high-skilled hours share on TFP growth calculated using hourly labor input.

The first best solution with a large dataset would be to apply the Newey-West correction (columns 3 and 4) and run fixed effects. But in small samples, as ours, Newey-West with fixed effects is not efficient because it relies on asymptotics. An alternative approach is to experiment with first differences (FD of $\Delta \ln TFP$, columns 5 and 6) where the fixed country effect λ_c is eliminated from the model.

TABLE 3— $\Delta \ln TFP_{c,t}^Q$ SPILLOVER REGRESSIONS, 1998 TO 2007

Variable	Estimation Technique:					
	RE		RE with Newey-West		RE (on FD)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln K^{NonICT}$	-0.215 (0.159)	-0.380* (0.196)	-0.217* (0.117)	-0.369** (0.159)		
$\Delta \ln K^{ICT}$	-0.0118 (0.0665)	0.00100 (0.0724)	-0.0115 (0.0466)	0.00181 (0.0566)		
$\Delta \ln R$	0.294*** (0.101)	0.298*** (0.0979)	0.324*** (0.0774)	0.324*** (0.0849)		
$\Delta \ln L$	-0.462*** (0.145)		-0.460*** (0.117)			
$\Delta \ln L_{t-1}$		-0.125 (0.195)		-0.148 (0.163)		
$\Delta(\Delta \ln K^{NonICT})$					-0.0613 (0.351)	-0.648* (0.347)
$\Delta(\Delta \ln K^{ICT})$					-0.0199 (0.0512)	-0.00913 (0.0631)
$\Delta(\Delta \ln R)$					0.176*** (0.0499)	0.253*** (0.0463)
$\Delta(\Delta \ln L)$					-0.573*** (0.0820)	
$\Delta(\Delta \ln L_{t-1})$						0.196** (0.0781)
Observations	100	100	100	100	100	100
R-squared	0.561	0.473	0.562	0.474	0.671	0.527

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

NOTES—Robust (heteroskedasticity-adjusted) standard errors in parentheses. RE=random effects estimation. Newey-West=Newey-West correction for autocorrelation of equation errors. FD=first difference specification (of $\Delta \ln TFP^Q$). For list of countries, see note to table 1.

Looking at table 3 therefore, the main message is that $\Delta \ln R$ or $\Delta(\Delta \ln R)$ is consistently positive and statistically significant. A second is that econometric reasons compel working with the differenced specification (the double-difference, or productivity acceleration, specification), which produces a sizable spillover coefficient (.25). Still, our story on knowledge spillovers remains incomplete: First, the estimation of equation (14), even in “double-difference” form, can be affected by structural identification problems related to measurement error, multicollinearity, and simultaneity biases. As previously mentioned, we believe by working with

TFP we have minimized the latter, but we still need to employ IV to mitigate coefficient bias due to classical measurement error, which can be magnified in differenced data. Second, we need to (a) search more deeply for the source of the significant spillover coefficient on intangible capital and (b) factor the significance of the labor term into our discussion: What is its source, and why does it surface with the acceleration specification? Finally, we are mindful of the rather sizeable (and marginally significant) negative spillover coefficient on non-ICT capital.

The next stage of our results is presented in table 4. All regressions contain time effects and have robust standard errors. Here, although the dependent variable in all columns is $\Delta(\Delta \ln TFP)$, sometimes the regressions use conventional data where $\Delta(\Delta \ln V)$ is used to construct $\Delta(\Delta \ln TFP^V)$; at other times, $\Delta(\Delta \ln TFP^Q)$ is used. We do this both to fully implement the model set out in section I and also to determine whether the significance of the labor term has to do with the inclusion of intangible capital.

Column 1 of the table sets out estimates using conventional productivity data and conventional capital inputs, $\Delta(\Delta \ln K^{Non-ICT})$ and $\Delta(\Delta \ln K^{ICT})$, along with $\Delta(\Delta \ln L)$ as regressors. As the column shows, the estimated spillover coefficients on capital inputs are insignificant while the coefficient on labor services is negative and significant. But, as already mentioned and seen above, spillovers might take time and so column 2 lags the labor term. This makes a substantial difference: the coefficient on $\Delta(\Delta \ln L_{t-1})$ is statistically significant and positive. This result then is independent of the inclusion of intangible capital in the production function (or the data); indeed the size of the estimated spillover coefficient for labor services in column 2 of table 4 is virtually identical to that shown in the last column of table 3.

Consider now intangibles, where note that their inclusion affects both inputs and outputs so both our regressors and our dependent variable change. We have already seen that adding intangibles produces a sizable spillover coefficient (column 6 of table 3), and that the underlying mechanisms for this are independent (in a statistical sense) from the sizable spillover coefficient we obtain for the labor term (column 2 of table 4). Columns 3 and 4 show the results of applying instrumental variable estimation techniques to these two equations, and the lower panel reports the P-Value of the Hansen J test for them. All told, and as readily seen, the main spillover story does not change: $\Delta \ln R$ remains statistically significant, as does $\Delta \ln L_{t-1}$. Moreover, the very large marginally significant coefficient on non-ICT capital loses significance. Note also that the value of the IV-estimated coefficients on $\Delta \ln L_{t-1}$ are lower than their OLS counterparts, but this is an expected result. On the other hand, the coefficient on intangibles increases a bit when IV is applied (from .253 in table 3, column 6, to .269 in

TABLE 4— $\Delta(\Delta \ln TFP_{c,t})$ SPILLOVER REGRESSIONS, 1998 TO 2007

Variable	Estimation Technique:					
	RE		GMM ¹		RE	
	Dependent Variable:					
	$\Delta(\Delta \ln TFP^V)$			$\Delta(\Delta \ln TFP^Q)$		
	(1)	(2)	(3)	(4)	(5)	(6) ²
$\Delta(\Delta \ln K^{NonICT})$	-0.127 (0.401)	-0.769* (0.407)	-0.498 (0.381)	-0.327 (0.343)	-0.593 (0.362)	-0.651 (0.427)
$\Delta(\Delta \ln K^{ICT})$	-0.026 (0.056)	-0.001 (0.076)	-0.047 (0.066)	-0.081 (0.061)	-0.013 (0.059)	0.009 (0.071)
$\Delta(\Delta \ln L)$	-0.638*** (0.080)					
$\Delta(\Delta \ln L_{t-1})$		0.204*** (0.071)	0.183** (0.085)	0.157** (0.078)	0.184** (0.080)	0.184*** (0.066)
$\Delta(\Delta \ln R)$				0.269*** (0.095)		
$\Delta(\Delta \ln R^{NonR\&D})$					0.234*** (0.039)	
$\Delta(\Delta \ln R_{t-1}^{R\&D})$					0.176* (0.095)	0.173* (0.102)
Observations	100	100	99	99	100	100
R-squared	0.649	0.477	0.466	0.507	0.538	0.493
Hansen J (P-Value)			0.861	0.263		

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

NOTES—Robust (heteroskedasticity-adjusted) standard errors in parentheses. RE=random effects estimation. GMM=Generalized method of moments. For list of countries, see note to table 1.

1. Instrumented variables: $\Delta \ln K^{NonICT}$, $\Delta \ln K^{ICT}$, $\Delta \ln K^R$.

Instruments used: $\Delta \ln K_{t-1}^{NonICT}$, $\Delta \ln K_{t-1}^{ICT}$, $\Delta \ln K_{t-1}^R$, and $\ln K_{t-1}^{ICT} * \Delta \ln R_{t-1}$.

2. Output and TFP are adjusted for R&D only.

table 4, column 4), which may signal nonclassical measurement error, a subject to which we return below.¹⁴

The final two columns present a major novelty of our results. Column 5 repeats column 4, but breaks out $\Delta \ln R$ into $\Delta \ln R^{NonR\&D}$ and $\Delta \ln R_{t-1}^{R\&D}$ (we obtained the most statistically significant results using a lagged term for R&D). The spillover coefficient on $\Delta \ln R^{NonR\&D}$ remains significant with a value very similar to before. The spillover coefficient on $\Delta \ln R_{t-1}^{R\&D}$ 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), as mentioned above. Finally, column 6 reports the same coefficient from a regression using a version of the data where R&D is the only intangible asset that is capitalized.

¹⁴ICT capital is instrumented with the interaction between the rate of growth of intangible capital and the ICT capital stock. The idea is that, when intangibles are not capitalized, the interaction instrument accounts for the underlying complementarities between ICT and intangible capital that can only affect TFP through ICT generating positive excess returns. This does not produce a spillover term on ICT, but neither does the use of this instrument for ICT drive down the size or significance of the intangible capital spillover coefficient when intangibles are included in the regression.

C. Labor Externalities

We find a significant (positive) spillover coefficient on increases in labor services when we shift from modeling the rate of productivity growth to modeling its rate of acceleration but this is not surprising if changes in the workweek of labor are associated with unmeasured cyclical effects in TFP growth as suggested by Basu, Fernald, and Kimball (2006). That said, it is worthwhile digging a little deeper to determine whether our results for labor services may also reflect an underlying mechanism supporting economic growth.

As previously seen (equation 11), our labor term $\Delta \ln L$ represents a combination of a composition (“labor quality”) term $\Delta \ln \Upsilon$ and hourly labor input $\Delta \ln H$. We can further regard hours as the combination of average hours worked Ψ and number of workers employed E (i.e., $H = \Psi * E$ where $\Psi = H/E$). This allows us to write

$$(15) \quad \Delta \ln L_{c,i,t} = \Delta \ln \Upsilon_{c,i,t} + \Delta \ln \Psi_{c,i,t} + \Delta \ln E_{c,i,t} .$$

Now, when considering economic growth, it seems natural to assume

$$(16) \quad d_{c,i,t}^L \Delta \ln L_{c,i,t} = d_{c,i,t}^L \Delta \ln \Upsilon_{c,i,t} .$$

which says that if $d_{c,i,t}^L$ is found to be > 0 , i.e., when returns beyond the private returns paid to labor input are detected, the underlying mechanism is externalities to upgrading the skills of the workforce. An extra kick from “working smarter,” if you will.

The empirical literature on cyclical variation in productivity change suggests “working harder” also generates externalities, however. Setting aside the term in E for the moment, if there are short-run externalities to “working harder,” the coefficient on $\Delta \ln \Psi_{i,c,t}$ will not $= 0$ as is implicit in (16). This is because the usual approach to capturing this influence is to posit that changes in “effort” are positively correlated with changes in average hours per worker. Short-run changes in the workweek of labor also arguably proxy for changes in capital utilization, and thus overall factor utilization as well (Basu and Kimball, 1997). In either case we are compelled to write

$$(17) \quad d_{c,i,t}^L \Delta \ln L_{c,i,t} = \phi_{c,i,t}^L \Delta \ln \Upsilon_{c,i,t} + \omega_{c,i,t} \Delta \ln \Psi_{c,i,t}$$

where ϕ^L is the coefficient of interest when searching for spillovers from human capital formation on economic growth. We will not recover this coefficient without using $\Delta \ln \Upsilon_{c,i,t}$ as a separate regressor. Finally, consider the $\Delta \ln E_{i,c,t}$ term. The term is obviously included when

TABLE 5— $\Delta(\Delta \ln TFP_{c,t})$ AND $\Delta \ln TFP_{c,t}$ SPILLOVER REGRESSIONS, 1998 TO 2007

Variable ¹	Estimation Technique:				
	RE		RE with Newey-West		
	Dependent Variable:				
	$\Delta(\Delta \ln TFP^Q)$	$\Delta(\Delta \ln TFP^V)$	$\Delta \ln TFP^Q$	$\Delta \ln TFP^Q$	$\Delta \ln TFP^Q$
	(1)	(2)	(3)	(4)	(5)
$\Delta \ln K^{NonICT}$	-0.676* (0.359)	-0.477 (0.372)	-0.612 (0.426)	-0.367** (0.164)	-0.365*** (0.134)
$\Delta \ln K^{ICT}$	-0.013 (0.065)	-0.074 (0.077)	-0.076 (0.086)	0.00184 (0.0568)	-0.00557 (0.0538)
$\Delta \ln R$	0.251*** (0.048)	0.208*** (0.054)		0.324*** (0.0870)	0.356*** (0.0918)
$\Delta \ln \Upsilon_{t-1}$	0.124 (0.148)			-0.121 (0.199)	
$\Delta \ln H_{t-1}$	0.236*** (0.080)			-0.155 (0.182)	
$\Delta \ln \Upsilon_{t-2}$		0.316*** (0.107)	0.319** (0.132)		0.311* (0.178)
$\Delta \ln H_{t-2}$		-0.073 (0.143)	-0.057 (0.152)		-0.240 (0.149)
Observations	100	90	90	100	100
R-squared	0.528	0.553	0.510	0.475	0.500

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

NOTES—Robust (heteroskedasticity-adjusted) standard errors in parentheses. RE=random effects estimation. Newey-West=Newey-West correction for autocorrelation of equation errors. For list of countries, see note to table 1.

1. In columns 1-3, variables are double-differenced, i.e., the variable denoted $\Delta \ln R$ in the row label is $\Delta(\Delta \ln R)$ in the regressions.

estimating a production function; less obviously, the same holds for a TFP spillover regression to allow for increasing returns.

We are interested in whether $\phi^L > 0$, not identification of short-run mechanisms associated with changes in the labor workweek. As a result, we ran regressions in which $\Delta \ln L$ was decomposed into $\Delta \ln \Upsilon$ and $\Delta \ln H$. This was done using both forms of $\Delta \ln TFP$, i.e., as itself and also as its FD, productivity growth acceleration $\Delta(\Delta \ln TFP)$. We also experimented with lags. First, we found that when $\Delta \ln L_{t-1}$ is disaggregated in the regression shown in column 6 of table 3, only the hours term is significant (column 1 of table 5). But when the disaggregated terms are lagged twice, the coefficient on $\Delta \ln \Upsilon_{t-2}$ becomes highly significant while that on hours is no longer significant (column 2). Furthermore, the significance of the estimated spillover coefficient for $\Delta \Upsilon_{t-2}$ is independent of the inclusion of intangible capital in the model and data (column 3). Finally, when the regression is specified in terms of productivity change, i.e., we do not “double-difference,” $\Delta \ln \Upsilon_{t-2}$ surfaces as significant at

the 90 percent level but externalities to $\Delta \ln H$ do not emerge (columns 4 and 5).¹⁵ This suggests the estimated hours effect in column 1 is a short-run cyclical mechanism as in Basu et al. (2006).

All told then, it would appear we have detected spillovers to “working smarter” And, as in tables 3 and 4, the significance (and size) of the estimated spillover coefficient on intangible capital is materially unchanged with changes in the specification of the labor term. Indeed, the significance of spillovers to intangible capital appears to reflect mechanisms largely independent of the usual channel whereby human capital formation influences economic growth (i.e., via the labor “quality” term).

D. Economic significance

To judge the economic significance of our findings, we look first at the projected effects on $\Delta \ln TFP^Q$ using column 2 of table 5. These results imply that, above and beyond the estimated direct contribution of improvements in workforce skills to productivity (0.4 percentage points per year according to table 1), there has been an additional small boost—.12 percentage points per year, on average (.32 * .40 = .12)—due to externalities. The dividend 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 $\Delta \ln TFP^Q = 0.77$ percent per year.

Might these estimates be upward biased? A number of points are worth making. First, the elasticity of $\Delta \ln R^{R\&D}$ 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.

Fourth, our production function specification assumes that $\Delta \ln Q$ or $\Delta \ln TFP$ 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-

¹⁵The column 4 and 5 regressions report very significant negative coefficients on $\Delta \ln K^{NonICT}$, but we already have seen significance of this variable come and go with changes in specification. Although not shown, this also happens with $\Delta \ln K^{ICT}$. A *positive* spillover coefficient on $\Delta \ln K^{ICT}$ is obtained using GMM with $\Delta \ln TFP^Q$ as the regressand in a regression similar to column 2 of table 3, whereas GMM estimation of columns 2 and 3 of table 5, where $\Delta(\Delta \ln TFP)$ is the regressand, produces a significant *negative* coefficient on $\Delta(\Delta \ln K^{ICT})$. In these regressions, the coefficients on labor quality and intangible capital remain essentially the same. In view of the rigorous findings for ICT based on industry-level data as reported in table 2, the instability in separately estimated country-level ICT effects is not a very great concern to us.

and industry-level evidence see Hall et al., 2009). The exploration of non-R&D intangible knowledge flows is in its infancy, 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 require more work and more data. That said, our estimates can be thought of as follows: *If* such international spillovers (and anything else, for that matter) can be represented by a country-specific trend in the $\Delta \ln TFP$ 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 $\Delta(\Delta \ln R_{c,t})$ terms are correlated with global knowledge increases that raise productivity, thus exaggerating the coefficient on country $\Delta(\Delta \ln R_{c,t})$.

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. 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).¹⁶ Again, we believe these effects should be largely removed by double-differencing. Beyond that, ameliorating such a matter is outside the scope of the econometric analysis conducted in this paper.¹⁷

Finally, we may of course be writing down the wrong production function—the direct implication of our finding that ICT and intangible capital are complements in production. This mechanism leads to a situation in which industries (countries) that rely on intangible capital have systematically higher productivity than those that don’t, and this is in all likelihood a major source of the spillovers that we find.

V. 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. 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.

¹⁶Corrado, 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.

¹⁷But we can add 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 be negative or positive.

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 output 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 $\Delta \ln Q/H$ from interaction effects between $\Delta \ln R$ 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* workforce skills. Our finding of growth spillovers to intangible capital is robust to whether we model the rate of TFP growth or its acceleration. It also is robust to whether R&D is included or excluded and to whether techniques that control for endogeneity and classical measurement error are applied. 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. An aspect of that mechanism seems to be complementarity of intangible capital with ICT.

What do we make of our finding of productivity spillovers from upgrades to workforce skills? This finding seems orthogonal to the size and significance of the spillover coefficient we estimate for intangible capital, suggesting that intangible capital and human capital 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, and possibly better models, too. That said, we believe this paper offers strong evidence, indeed the strongest to date, that investments in non-R&D intangibles play a significant role in economic growth.

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