Deliverable 5.5

Innovation-driven productivity growth: the role of ICT capital and effective labour

Due date of deliverable: 2021/2/28

Submission date: 2021/1/12

Actual Submission date: 2022/10/03

Globalinto Identifier:	WP5
Deliverable Number	WP5 / D 5.5
Deliverable Title	Innovation-driven productivity growth: the role of ICT capital and effective labour
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Innovation-driven productivity growth: the role of ICT capital and effective labour [♣]

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Abstract: In this paper we assess the importance of information and communication technology (ICT) and other intangible capital (IC), such as research and development (R&D) and organizational capital (OC) for labour productivity. For this purpose, we use a rich employer–employee panel data set of Norwegian firms covering the period 2008–2019, including detailed occupational data. To operationalize the concepts of R&D capital and OC, we apply novel GLOBALINTO measures of investments in R&D and OC that are based on firm-level wage costs related to specific occupations. We further explore the interactions between ICT capital and labour skills by incorporating intangible-work biased technical change (IBTC) – a concept originally proposed by Piekkola (2020) – as a factor in a neo-classical production function. The analysis is provided for selected industries in manufacturing and services. Overall, all three types of intangible capital seem to be important for productivity, with ICT having clearly the highest impact. We estimate positive interaction effects between (a high level of) ICT capital and (high) shares of workers engaged in either R&D-, organizational- or ICT-related activities at the firm level. The estimates, however, vary widely across industries.

Keywords: Intangible capital, ICT, R&D, organizational capital, firm performance, productivity
JEL classification: C33, C52, D24, O38

[♣]This paper is part of Globalinto project and we acknowledge financial support from the European Union Horizon 2020 program "The mechanisms to promote smart, sustainable and inclusive growth" through the grant 822259 (GLOBALINTO).
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1. Introduction

Business innovation is regarded as a potentially important driver of productivity growth, both at the micro and macro level, by increasing international competitiveness, economic growth and real per capital incomes. It is therefore of great interest to businesses and policy-makers to identify the factors that stimulate innovation and to understand how these factors interact. R&D is an important factor behind innovations, but it is not the only one. Today, firms invest in a wide range of intangible assets, such as information technologies, software, patents, designs, trademarks, new organisational processes and firm-specific skills. Within the GLOBALINTO project, these non-physical assets are referred to as a firm's intangible assets or capital, IC (see Bloch et al., 2022).

According to Corrado et al. (2018), the growth rate of investments in intangibles has been greater than that of tangible capital during 2000-2013 in the countries that they analyse (17 EU countries and the US). It is a paradox that this development has been accompanies by a slowing of productivity growth in the most developed (OECD) economies during the last 10-15 years. This phenomenon is sometimes referred to as the great productivity slowdown.[1] A lack of proper accounting and measurement of intangible assets is seen as a possible reason explaining the seemingly poor productivity performance of developed countries. Arguably, there are several aspects of intangible assets which make it harder to measure their contributions to production and value added (such as GDP) than tangible inputs, such as physical capital, hours worked and material inputs. For example, productivity growth is measured by means of output deflators that are weighted averages of price increases of existing goods, but fails to take into account new goods and varieties, which have no base-year prices (Diewert and Feenstra 2019). Brynjolfsson and Oh (2012) and Brynjolfson et al. (2018) make the case that welfare is growing faster than (measured) economic output due to free digital services, such as payment services and social media networks, and Brasch and Raknerud (2022) estimate that new intermediate goods through net entry of firms contribute about 0.5 percentage point annually to labour productivity growth in Norwegian manufacturing.

While there is a long tradition for including R&D measures in national accounting, in recent years more and more attention has been devoted to the role of Information and Communication Technology (ICT) and organizational and managerial capital (OC) as enablers of innovation (see Vincenzo, 2011 and Bloch et al., 2022). ICT, in particular, is a dynamic area of investment, as well as a very pervasive technology.[2] One aspect of ICT is automation or robotization, which is related to intangible investments in software for artificial intelligence and statistical learning algorithms (Acemoglu and Restrepo 2020, 2018; Autor and Salomons 2018; Leduc and Liu 2019).

[1] For all the OECD countries combined, the trend growth in annual labour productivity – real output per hour worked – declined steadily from 1.8 percent in 2000 to 0.4 percent in 2014. Also in the US, the growth in labour productivity – real output per hour worked – slowed markedly around 2005. During the previous ten years, labour productivity in the business enterprise sector had risen at an annual average pace of more than 3 percent (1994–2004); it then slowed to about 2 percent annually during 2005-2010 and then dropped to just 0.5% during 2011-2016. For Norway, it was found that productivity growth in the mainland business sector declined after 2005 compared to 1996-2005 (cf. the official reports: NOU 2015: 1 and NOU 2016:3 (in Norwegian)).

[2] ICT is often referred to as a modern general purpose technology, GPT (see Bresnahan and Trajtenberg 1995, for a definition of GPT, and Castiglione 2012, for an investigation of GPT features of ICT).

The possible benefits of ICT to a firm include, among others, increased input efficiency, general cost reductions and greater flexibility in the production process. This technology can also stimulate innovation activity in a firm, leading to higher product quality or the creation of new products or services. Its use has the potential to increase innovation by improving possibilities for communication and speeding up the diffusion of information through networks. For example, technologies that allow staff to effectively communicate and collaborate across wider geographic areas will encourage strategies for less centralised management, leading to organisational innovation. Previous analyses confirm that ICT plays an important role in firm performance, *e.g*. Brynjolfsson and Hitt (2000, 2003), OECD (2004), Gago and Rubalcaba (2007), Crespi *et al.* (2007) and van Leeuwen (2008). These studies evaluate the effects of ICT use and innovation on productivity. A few studies, i.e. Hall *et al.* (2013), Vincenzo (2011), Polder *et al.* (2009) and Rybalka (2015), focus on the direct link between ICT and innovation.

Because of the inherent unique and novel nature of intangible assets, e.g. the development of a new patent, trademark or design, an important motivation for intangible investments is to reduce competition and extract a monopoly profit: for example, a patent grants the holder a temporary monopoly, which in return are obliged to make the technical details public. Granting of patents for narrow claims of innovation are negative consequences of the IP system (Kang and Bekkers 2015, Berger et al. 2012, Peeperkorn 2003). Patents granted for narrow claims do not necessarily extend the technological frontier but contribute to protecting existing monopolies.[3]

Similarly, more horizontal product differentiation leads to more trademarking, but not necessarily the creation of (genuinely) new products and services (e.g. Mangani, 2007). A number of recent studies have argued that rising market power among firms has crowded out labour's share of income (De Loecker and Eeckhout, 2017; Eggertsson, Robbins and Wold 2018; Gutierrez and Philippon 2017, Bergholt et al. 2019). These studies find evidence of declining competition and increasing market concentration. The claim is that trends in firms' market power have spurred profit growth at the expense of labour income, and, consequently, have led to increased inequality.

In addition to accumulated intangible investments (which we will refer to as IC), increased quality of workers is a potential source of productivity growth. The GLOBALINTO project uses the term *intangible-work biased technological change* (IBTC) to characterize the impact of labour quality improvements on output growth (Bloch et al., 2022). Piekkola (2020) makes a distinction between R&D-labour input, OC-labour input and other labour inputs, and constructs a measure of labour quality based on the share of labour in each category and their relative wages. This labour quality term is referred to as IBTC. The classification of workers used to construct IBTC is obtained by linking workers' professional codes with matched worker-firm data, and hence require detailed and complex data for the relevant population of workers and firms.

Our approach applies – and, in key aspect, extends – the methodology of Piekkola (2020) to Norwegian registry data from 2008-2019, covering the whole population of workers and firms, with detailed information about individuals' wages, employer-employee relations, education and professional codes, and detailed information on firms' investments (including investments in purchased hard- and software and own-accounted software). We extend the productivity measure of Piekkola in two ways. First, we obtain

[3] 'Patent thickets' is the term given to overlapping patents over similar technologies that may have negative welfare effects by limiting the ability of competitors to launch new products (Hall et al. 2013).

a more complete classification of workers' role in the firm than Piekkola (2020) by including professional codes related to ICT-tasks, in addition to R&D and OC. Secondly, we generalise the Cobb-Douglas aggregator (which assumes that the elasticity of substitution equals one between the three types of IC) by using the CES-aggregator (allowing the elasticity of substitution to be any non-negative number). This generalisation has the obvious benefit that a firm is not required to have a positive stock of all three types of IC to produce positive output – an assumption that is overwhelmingly rejected by data. Instead, we require that a firm has a positive stock for at least one type of IC to be included in the estimation sample. Using economic index theory, we obtain a closed form expression for relative changes in the CES aggregator and an estimable form of the production function log-form.

2. Technology and structural estimation

2.1 The product function

We assume a constant return to scale Cobb-Douglas value-added production function in three aggregate inputs: labour (*L*), tangible capital (*K*) and intangible capital (*IC*). That is:

$$Y_t = A_t l(L_t, t)^{\beta_L} K_t^{\beta_K} IC_t^{\beta_{IC}} \tag{2.1}$$

where *Y* is value added and *t* refers to calendar year. Equation (2.1) can be considered a nested Cobb-Douglas model, where the terms $l(L_t, t)$ and IC_t are themselves aggregates of more primary input factors.

First, the term $l(L_t, t)$ is referred to as the effective labour supply by Piekkola (2020) and depends on the allocation of labour input into different occupational categories. We separate here between four categories: $L = (L_R, L_{OC}, L_{ICT}, L_Y)$, where L_R refers to number of man-years by employees in R&D occupations (*R&D capital formation*), L_{OC} to number of man-years by employees in managerial occupations (*organizational capital formation*), L_{ICT} to number of man-years by employees in ICT occupations and L_Y is residual labour input. Following Piekkola (2020):

$$l(L_t, t) = a_{Rt} L_{Rt} + a_{OC,t} L_{OC,t} + a_{ICT,t} L_{ICT,t} + L_{Yt}, \tag{2.2}$$

where the coefficient a_{jt} represents the relative quality of one man-year spent on the formation of intangible assets of type *j* relative to one man-year spent on ordinary work ($a_{Yt} = 1$ by normalization).

We define total man-years as:

$$\overline{L}_t = L_{Rt} + L_{OC,t} + L_{ICT,t} + L_{Yt}$$

and corresponding labour shares: $s_{jt} = L_{jt} / \overline{L}_t$. We can then reformulate (2.2) as follows:

$$\begin{aligned} l(L_t,t) &= (a_{Rt}s_{Rt} + a_{OC,t}s_{OC,t} + a_{ICT,t}s_{ICT,t} + s_{Y,t})\overline{L}_t \\ &= ((a_{Rt}-1)s_{Rt} + (a_{OC,t}-1)s_{OC,t} + (a_{ICT,t}-1)s_{ICT,t} + 1)\overline{L}_t . \end{aligned}$$

Given the assumption of perfect substitutability implicit in (2.2), the wage, w_{jt}, of worker of type *j* must be proportional to efficiency in equilibrium. That is: $w_{jt} \propto a_{jt}$ for all *j*, which motivates the following estimator of relative quality of labour-type *j*:

$$\hat{a}_{jt} = w_{jt} / w_{Yt} \text{ for } j \in \{R, OC, ICT\}.$$

Furthermore, we use the approximation $\ln(1+x) \simeq x$ for "small" *x* to obtain:

$$\begin{aligned} \ln(l(L_t,t)) &= \ln((a_{Rt}-1)s_{Rt} + (a_{OC,t}-1)s_{OC,t} + (a_{ICT,t}-1)s_{ICT,t} + 1)) + \ln(\overline{L}_t) \\ &\simeq (\frac{w_{Rt}}{w_{Yt}}-1)s_{Rt} + (\frac{w_{OC,t}}{w_{Yt}}-1)s_{OC,t} + (\frac{w_{ICT,t}}{w_{Yt}}-1)s_{ICT,t} + \ln(\overline{L}_t) \\ &= IBTC_t + \ln(\overline{L}_t). \end{aligned} \tag{2.3}$$

The sum of the three first terms ($IBTC_t$) represents (approximately) the log of relative efficiency of labour input when the share allocated to group $j \in \{R, OC, ICT, Y\}$ is s_{jt} – compared to a (hypothetical) situation where all workers are non-IC workers (i.e., $s_{Yt} = 1$). A change in $IBTC_t$ reflects changes both in the allocation of labour across the four groups and the change in the relative efficiency of the three IC groups relative to the non-IC group, as approximated by $w_{jt} / w_{Yt} - 1$.

The allocation of workers does, however, not only affect IBTC, but also intangible capital formation, IC_t:

$$IC_t = \left(\sum_{j \in \{ICT, R, OC\}} \gamma_j X_{jt}^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)}, \tag{2.4}$$

Where $X_{ICT,t}$, $X_{OC,t}$ and $X_{R,t}$ refer to ICT-, organizational- and R&D capital stock, respectively. The two latter variables are intrinsically related to labour input, i.e. they cannot meaningfully be separated from the workers (managers and researchers, respectively) who possess the given knowledge. In contrast, $X_{ICT,t}$ represents investments in hardware and software – purchased or own-account – that by nature are distinct from firm- and occupation-specific labour inputs (see Section 3 for variable constructions and discussions).

The knowledge capital stock reduces to a Cobb-Douglas aggregate in the limiting case $\sigma \to 1$. As an approximation, we may assume that the composition of IC_t satisfies cost-minimization: for given value of IC_t, the allocation of X_{jt} on $j \in \{ICT, R, OC\}$ minimizes cost given input factor prices. Then

$$\Delta \ln(IC_t) \simeq \sum_{j \in \{ICT,R,OC\}} \omega_{jt} \Delta \ln(X_{jt}) \tag{2.5}$$

where the weights ω_{jt} sum to one and each of them are proportional to the logarithmic average[4] of the user cost shares of total IC user costs. The remarkable property of equation (2.5) is that it does not require knowledge about σ or γ_j. Therefore, these parameters can be firm-specific without causing an incidental parameter problem. In fact, equation (2.5) is consistent to second order with any exact, twice differentiable aggregator function and exact in the case of the CES aggregator function (see Diewert 1978, and Brasch and Raknerud 2022).

On log-level form, the aggregate IC variable can be approximated as:

$$\ln(IC_t) \simeq \sum_{j \in \{ICT,R,OC\}} \left(\omega_{jt} \ln(X_{jt}) + \sum_{s=1}^{t-1} (\omega_{js} - \omega_{j,s+1}) \ln X_{is} \right) \tag{2.6}$$

By differencing, it is easy to check that (2.6) satisfies (2.5), equipped with the initial condition:

$$\ln(IC_1) = \sum_{j \in \{ICT,R,OC\}} \omega_{j1} \ln(X_{j1}) \ \text{ (where } \omega_{j1} \ln(X_{j1}) = 0 \text{ if } \omega_{j1} = 0).$$

The initial value X_{j1} is calculated following the approach of Hall and Mairesse (1995) (see Section 3). Based on the above assumptions and approximations, we derive the following equation:

$$\begin{aligned} \ln(Y_{it}) = \beta_K \ln(K_{it}) + \beta_{IC} \ln(IC_{it}) + \beta_L \ln(\overline{L}_{it}) \\ + \sum_{j \in \{R,OC,ICT\}} \beta_{Lj} (\frac{w_{jit}}{w_{Yit}} - 1) s_{jit} + \ln A_{it}, \end{aligned} \tag{2.7}$$

where the last term can further be expressed as:

$$\ln(A_{it}) = \beta_0 + \beta_1 Z_{it} + u_i + e_{it}. \tag{2.8}$$

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[4] The logarithmic mean of (non-negative) numbers y and z is defined as $M(y,z)=0$ if $y=0$ or $z=0$, $M(y,z) = y$ if $y = z$ and $M(y,z)=(y-z)/(\ln(y)-\ln(z))$ otherwise.

Here Z_{it} is a vector of dummies for industry (at 2-digit Nace-code level) and time dummies; β_1 is a vector with the corresponding coefficients; u_i is a firm–specific term that captures different non–observed time-invariant firm characteristics affecting productivity (i.e., management ability, organisational culture, etc.); and the error term e_{it} comprises measurement errors and idiosyncratic productivity shocks.

From (2.7), the elasticity of Y_{it} with respect to K_{it} and IC_{it} are β_K and β_{IC}, respectively. The elasticity with respect to labour is more complicated, because there are several types (qualities) of labour. Furthermore, we need to take into account that investments in IC_{it} are proportional to labour costs. To proceed, we first note that by definition:

$$El_{L_{jit}} Y_{it} = \frac{L_{jit} \partial \ln(Y_{it})}{\partial L_{jit}}.$$

Therefore:

$$\frac{\partial \ln(Y_{it})}{\partial L_{jit}} = \frac{\beta_L}{\bar{L}_{it}} + \beta_{Lj} \left(\frac{w_{jit}}{w_{Yit}} - 1\right) \frac{1}{\bar{L}_{jit}} + \beta_{IC,j} \frac{\omega_{jit}}{L_{jit}} \frac{\partial \ln X_{jit}}{\partial \ln L_{jit}}.$$

Where the last term reflects that IA-labour costs of type *j* is also an investment in IC of the same type (i.e., an investment in the stock variable X_{jit}). In fact, except for $X_{ICT,t}$, we have $X_{jit} \propto L_{jit}$, because IC investments are proportional to labour costs by construction (see Section 3). Therefore, $\partial \ln X_{jit} / \partial \ln L_{jit} = 1$ and

$$El_{L_{jit}} Y_{it} = \left(\beta_L + \beta_{Lj} \left(\frac{w_{jit}}{w_{Yit}} - 1\right) \right) s_{jit} + \beta_{IC} \omega_{jit} \text{ for } j \in \{R, OC, ICT\}, \tag{2.9}$$

where $\omega_{ICT,it} = 0$ and

$$El_{L_{Yit}} Y_{it} = \beta_L s_{Yit}. \tag{2.10}$$

We further define labour productivity as output (value added) per man-years, $Y_{it} / \bar{L}_{it}$. Since

$$\frac{L_{jit} \partial \ln(\bar{L}_{it})}{\partial L_{jit}} = \frac{L_{jit}}{\bar{L}_{it}} = s_{jit}$$

we conclude that

$$El_{L_{jit}} (Y_{it} / \bar{L}_{it}) = L_{jit} \left(\frac{\partial \ln Y_{it}}{\partial L_{jit}} - \frac{\partial \ln \bar{L}_{it}}{\partial L_{jit}} \right) = El_{L_{jit}} (Y_{it}) - s_{jit} \text{ for } j \in \{R, OC, ICT, Y\}.$$

A partial increase in a specific type of labour will increase labour productivity if the (partial) output elasticity exceeds the labour share of the given type of labour.

2.2 Interaction effects

Several recent studies claim that differences in the skills of the workforce are particularly important for the usage of ICT capital. For example, the study on ICT and Economic Growth for 13 countries (see OECD, 2003) demonstrated that the use of ICT contributes to improved business performance, but only when it is complemented by other investments and actions at the firm level, such as changes in the organisation of work and changes in workers' skills (see also Caroli and Van Reenen, 1999 and Bresnahan et al., 2002). To test for complementarity between ICT capital and composition of the workforce in the firm, we consider a translog extension of the (nested) Cobb-Douglas model, where we add three interaction terms to the equation (2.7):

$$\begin{aligned}\ln(Y_{it}) &= \beta_K \ln(K_{it}) + \beta_L \ln(\overline{L}_{it}) + \beta_{IC} \ln(IC_{it}) + \sum_{j\in\{ICT,R,OC\}} \beta_{Lj}(\frac{w_{jit}}{w_{Yit}} - 1)s_{jit} \\ &+ \beta_{R\times ICT} s_{Rit} \ln X_{ICT,it} + \beta_{OC\times ICT} s_{OC,it} \ln X_{ICT,it} + \beta_{ICT\times ICT} s_{ICT,it} \ln X_{ICT,it} + \ln A_{it},\end{aligned} \tag{2.11}$$

where $\beta_{j\times ICT}$ for $j \in \{R, OC, ICT\}$ are interaction coefficients to be estimated. If these coefficients are positive, we can conclude that the intensity of ICT use and specific skills are complementary and that productivity of ICT is increasing with the share of the corresponding type if innovation labour input, and vice versa. If negative, then the ICT and the given type of labour are substitutes.

To see the effect of the interaction terms on the elasticities of output (or, equivalently, labour productivity) with respect to IC work, we obtain:

$$El_{L_{jit}} Y_{it} = \left(\beta_L + \beta_{Lj}(\frac{w_{jit}}{w_{Yit}} - 1) \right) s_{jit} + \beta_{j\times ICT} s_{jit} \ln(X_{ICT,it}) \text{ for } j \in \{R, OC, ICT\}.$$

3. Data and variable description

3.1 Data sources

Our primary data source is the Structural statistics from Statistics Norway.[5] These data are register data which are based on general financial statements in the tax returns and are collected annually since 1995. Since 2002, these data have comprised information about annual investments in hardware (purchased) and software (both purchased and on own-account).

[5] The Structural statistics are organised according to the Standard Industrial Classification (SIC 2007) and are collected for the following industries: Mining, oil and gas extraction, Manufacturing, Information and communication, Professional, scientific and technical services, Building and construction, Wholesale and retail trade and Hotels, restaurants and catering. See Rybalka (2009) for more details.

We merge these data with the Register of employers and employees (REE) and the National education database (NED) to obtain information about employer-employee relations. All employers are obliged to send information to the REE about all employees' contract start and end, working hours, overtime and occupation, whereas the NED gathers all individually based statistics on education from primary to tertiary education and has been provided by Statistics Norway since 1970. The occupational codes used in this paper are available since 2008. Hence our estimation sample consists of Norwegian firm level-data for 2008-2019.[6]

3.2 Variable description

Value added (Y_{it}) is defined as in the official statistics, i.e. the 'Production value' (turnover adjusted for changes in stocks of finished goods, goods in process and goods and services purchased for resale) minus 'Intermediate consumption' (value of the goods and services consumed as inputs in the production process, excluding fixed assets whose consumption is recorded as consumption of fixed capital**)**. Public subsidiaries are added and special taxes are subtracted. This variable was deflated using the National Account price index for GDP.

Total man-years, $\overline{L}_{it}$, is the sum of all individually contracted man-years worked by employees (one man-year is 1950 hours worked during the calendar year). The variable $\overline{L}_{it}$ is distributed across four labour groups, according to the occupational codes listed in Piekkola et al. (2021, Box 1).

The variables $X_{R,it}$ and $X_{OC,it}$ – stocks of intangible R&D capital (R&D) and organizational capital (OC), respectively – are calculated using GLOBALINTO occupation-based approach as described in Piekkola et al. (2021, Section 2.2) and Bloch et al. 2022. The underlying main assumption is that investments in R&D capital is proportional to wage costs of R&D workers and that investments in OC are proportional to wage costs of managers. For example, the Norwegian official R&D statistics show that about 63 percent (68 percent) of total R&D expenditures (total R&D current costs) are labour costs on own R&D employees. [7] It is further assumed that only part of working time goes to intangible investment. The share of labour costs dedicated to the production of intangible goods is 0.7 in R&D occupations and 0.4 in OC related (management and marketing occupations). For a listing of the GLOBALINTO intangible assets occupations see Bloch et al. (2021) and for the details regarding the accumulation of labour costs into corresponding IC stocks see Piekkola et al. (2021).[8]

The variable $X_{ICT,it}$ is ICT capital services, which are calculated from the information on the firm investments in hardware and software (purchased and own-account). While the assumption behind using wage costs of individuals in certain occupations as proxies for investments in R&D and OC may be attractive in the absence of direct data – since these IC-types are inherently related to individuals' knowledge and abilities – we measure ICT capital differently for two reasons. First, we have register

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[6] While estimation period covers 2008-2019, we use all available data from annual 2002–2019 Structural statistics for ICT and tangible capital construction.

[7] See https://www.ssb.no/en/statbank/table/07963.

[8] Piekkola et al. (2021) uses the perpetual inventory method (PIM) with a depreciation rate of 15% for R&D capital and 20% for OC. The initial value problem is solved by assuming that the initial stock is the result of an infinite investment series, where the annual investments are equal to the initial investment adjusted using a geometrically decreasing growth rate *backwards* in time.

data for ICT expenditures and therefore do not have to rely on (*ad hoc*) factor multipliers to convert firm- and occupation-specific wage costs into ICT capital investments. Secondly, ICT investments comprise both hardware and software, which can be either purchased or own-account expenditures. Therefore, it is not reasonable to assume that there is proportionality between (occupation-specific) wage costs and ICT expenditures.

Since 2002, Statistics Norway has collected micro level information on investment expenditures on ICT, i.e., on purchased hardware, I_{1t}, and purchased and own account software, I_{2t} and I_{3t}, respectively. As deflators for obtaining real expenditures, we use the National Account price indices of the corresponding investments. Further, we construct the capital stocks for each type of asset separately and then aggregate them to a total ICT capital stock. The (real) ICT capital stock of type *k* at the beginning of a given year *t*, ICT_{kt}, is computed by the PIM method using a constant rate of depreciation, δ_k:

$$ICT_{kt} = (1-\delta_k)ICT_{k,t-1} + I_{k,t-1},\ k = 1,2,3 \text{ and } t = 1,2,...$$

Relying on available data on depreciation rates for IT–hardware and software capital from the U.S. (Fraumeni 1997, Moulton et al. 1999), we use depreciation rates of 31% for IT–hardware, 55% for purchased software and 33% for own–account software.[9] The total ICT capital services are calculated as:

$$X_{ICT,t} = \sum_{k=1,2,3} (r+\delta_k)ICT_{kt}\ ,$$

where *r* is 3.5%, which is the average real return on 10-year government bonds for the period 2002–2019.[10]

Finally, the variable K_{it} is the tangible capital services, which are calculated from the information on the firm investments in tangible assets by PIM-method.[11] These two variables were deflated using the National Account price indices for tangible investments, respectively.

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[9] Similar to the construction of R&D capital and OC (see Footnote 8), the initial ICT capital stock of type *k* at the beginning of the observation period for a given firm is calculated as if it was the result of an infinite ICT investment series, with a fixed pre-sample growth rate, g_k. To make the estimator more robust, we set the initial value equal to the firm's average *detrended* – using g_k – investment value over the whole observation period. The estimates of the pre-sample growth rates g_k are: 24% for real hardware investment, 8% for real purchased software capital and 26% for own account software capital. These estimates are obtained using all available data from 2002–2019.

[10] For the further details of the construction procedure for the ICT capital measure and sensitivity of the results with respect of the choice of different parameters see Rybalka (2009).

[11] All tangible assets have been divided into two types: equipment (denoted by the superscript *e*) which include machinery, vehicles, tools, and transport equipment; and buildings and land (denoted by the superscript *b*). Then capital services are $K_t = \sum_{j=e,b} (r+\delta_j)K_{jt}$, where the applied in GLOBALINTO depreciation rates, δ_j, are 13 % (versus 20 % in our earlier studies, e.g. Raknerud et al., 2007, and Rybalka, 2009) for equipment and 5% for buildings (also 5 % Raknerud et al., 2007, and Rybalka, 2009), while the real rate of return, *r*, is set to 4 %.

3.3 Sample and descriptive statistics

We follow Piekkola et al. (2021) and limit our sample to firms with at least 5 employees on average divided into nine industry groups differing by technology level (see Bloch et al. 2021, Section 5 for definition of the nine industry groups). In addition, we exclude agriculture and forestry (Nace A), mining (Nace B), water supply (Nace E), construction (F), financial intermediation and insurance (Nace K), health (Nace Q), education (Nace P) and public administration (Nace O) and non-profit sectors (Nace Q, S, T, U, X). Due to the lack of information on ICT investment for electricity and gas supply (Nace D), this industry is also excluded from our analysis. Table 3.1 reports descriptive statistics about the main variables in the model.

Table 3.1 Summary statistics for key variables in the production function

Variable	Mean	Q1	Median	Q3	Std	N
Y/L	91.4	47	68.9	101	398	336745
L	32.6	6.73	10.5	20.3	169	336758
X_{OC}/L	48.2	13.7	27.4	51.5	349	161779
X_R/L	173	26.8	73.6	224	494	87419
X_{ICT}/L	1.99	0.45	1.07	2.36	9.35	309092
K/L	36.8	2.03	5.11	14.6	776	336758

Note: Value added (*Y*) and stock variables $(X_{ICT}, X_{OC}, X_R, K)$ measured in EUR 1000 (fixed 2015 prices). *L* is number of man-years.

Table 3.2 reports the average ICT intensity with respect to labour input for the total ICT capital services and by the type of ICT asset (i.e. purchased hardware, purchased software and own-accounted software) over 2008-2019 by nine technology types. Not surprisingly, ICT services are the most ICT intensive with respect to ICT capital intensity including hardware and own-account software intensity. They are followed by R&D services and KIS (knowledge-intensive services). It is interesting that management services are the most ICT intensive with respect to the purchased software asset per employee.

Table 3.2 Total ICT capital services and different ICT assets per labour input by industry group

Industry group	Nace-codes	ICT/L	Hard-ware/L	Purchased soft-ware/L	Own ac-count soft-ware/L
Hightech	21, 26	2.89	3.65	2.14	1.02
Medium-hightech	20, 27-30	1.88	2.70	1.17	0.71
Medium-lowtech	19, 22-25, 33	1.21	1.80	0.81	0.33
Lowtech	10-18, 31-32	1.35	2.01	0.86	0.41
KIS	50-51, 58-66, 69-75, 78, 80, 84-93	3.15	4.56	1.93	1.11
ICT services	62-63	4.60	6.61	2.53	2.10
R&D services	71-72	3.10	4.38	2.33	0.61
Management services	69-70, 73	2.97	3.56	2.77	0.32
Low KIS	45-47,49,52-53,55-56,68, 77,79,81-82,94-96,97-99	1.61	2.38	1.19	0.22

Figure 3.1 shows the evolution of employment shares, s_{jit} , for each type of intangible labour (i.e., for $j \in \{ICT, R, OC\}$ for Norway from 2008 to 2019. We see that the share of ICT employees (in full-time equivalents) has been increasing through the whole period from 4.3 % in 2008 to 5.3 % in 2019, while the share of managers has stagnated at the level of 8 % after an increase in the start of the period of our analysis. The share of R&D employees was rapidly increasing until 2015, but then decreased until 2018, probably because many R&D suppliers to the oil industry were affected by low oil-prices after 2015, and then increased again in 2019.

Figure 3.1. Employment shares within each intangible type for Norway. 2008-2019

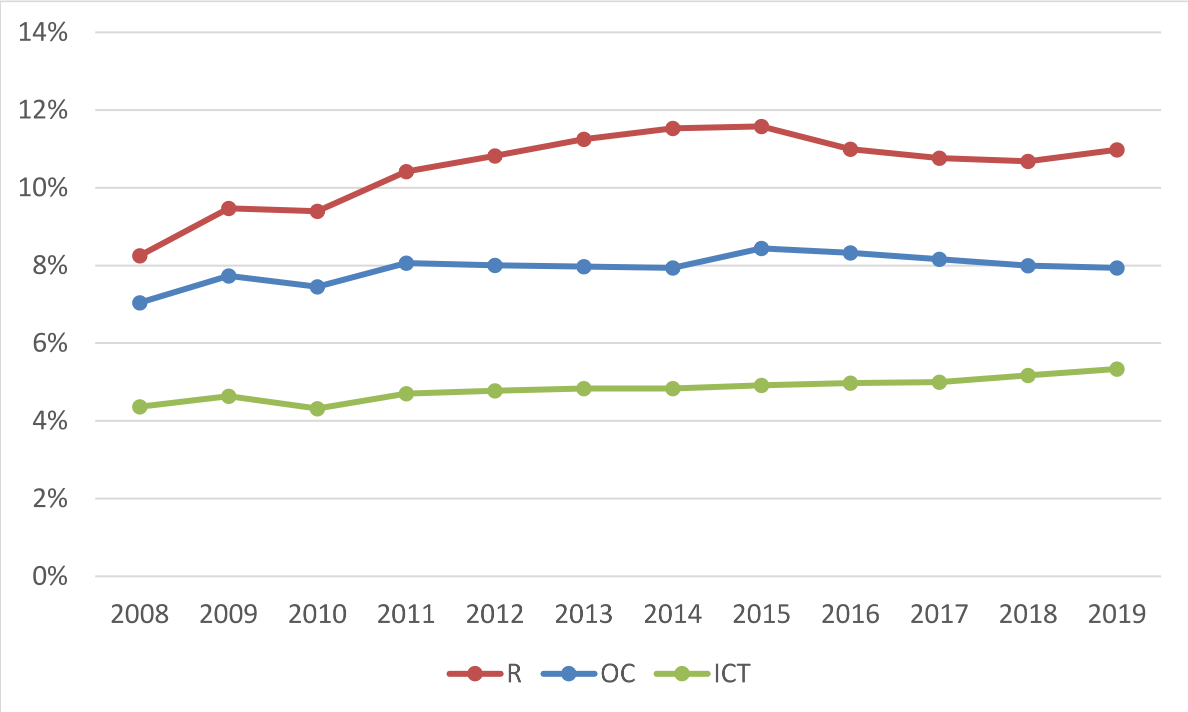

Table 3.3 reports the average shares for different types of labour over 2008-2019 by nine technology types. Not surprisingly, R&D services are the most R&D intensive with respect to use of R&D employees (in full-time equivalents), ICT services are the most ICT intensive with respect to use of ICT employees, and management services are the most OC intensive with respect to use of OC employees. High-tech and medium-high-tech manufacturing industries are also highly R&D intensive. They also use relatively high shares of organisational employees, while KIS use relatively high shares of ICT employees.

4. Estimation results

We estimate the model in equation (2.11), i.e. the full model including interaction terms, on a sample of firms in Norwegian market industries: both manufacturing and services, using data for 2008-2019. The industries are divided into: high/high-middle tech manufacturing; low-middle tech manufacturing; low tech manufacturing, knowledge intensive service industries & ICT; R&D services; and other services (see Table A.1 in Piekkola et al. 2021 for a complete listing of the corresponding industries at Nace2 level). While the sample in principle covers all firms in the mentioned industries, we have restricted the estimation sample to firms with at least 5 employees on average during the sample period and to firm-years (i.e., one firm observed in one year) with positive ICT capital stock and positive IC stock (that is, either positive OC *or* R&D*)*. Table 4.1 presents random effects parameter estimates and Table 4.2 presents fixed effects parameter estimates.

Table 3.3 Average employment shares within each intangible type by industry group

Industry group	Nace-codes	R	OC	ICT
Hightech	21, 26	39.0 %	11.4 %	4.9 %
Medium-hightech	20, 27-30	25.9 %	11.2 %	1.6 %
Medium-lowtech	19, 22-25, 33	11.7 %	8.4 %	1.1 %
Lowtech	10-18, 31-32	5.0 %	8.2 %	1.3 %
KIS	50-51, 58-66, 69-75, 78, 80, 84-93	7.1 %	6.9 %	7.5 %
ICT services	62-63	8.2 %	9.2 %	63.6 %
R&D services	71-72	64.2 %	8.5 %	3.2 %
Management services	69-70, 73	2.9 %	25.4 %	2.9 %
Low KIS	45-47,49,52-53,55-56,68, 77,79,81-82,94-96,97-99	2.6 %	5.7 %	1.2 %

The random effects model assumes that the error components e_{it} and u_i (see equation (2.8)) are uncorrelated with the input factors. While this is a strong assumption since factor inputs and (total factor) productivity is determined in a simultaneous system of equations (see Marschak and Andrews, 1944), the simultaneity problem may be alleviated by the fact that all stock variables are determined at the beginning of *t* (end of *t-1*), and hence may be uncorrelated with the idiosyncratic error term, e_{it}. The assumption that the input factors are uncorrelated with u_i may be more problematic. Therefore, we also estimate a fixed effects version of the model (see Table 4.2), which allows the fixed effect, u_i, to be correlated with any explanatory variable.[12]

We first focus on the coefficient of ICT capital, $\ln(X_{ICT})$. If there were no interaction effects in the model, this would be the elasticity of output (*Y*) with respect to ICT investments. The estimates are highly significant and stable across the industries, varying from 0.043 (the lowest) in low-tech manufacturing to 0.089 (the highest) in R&D services, with standard errors of 0.01 or less. The fixed effects estimate of this parameter is generally slightly lower, but still highly significant across industries, varying from 0.025 in low-tech manufacturing to 0.056 in R&D services, with standard errors of 0.01 or less.

We next turn to the coefficient (β_K) of $\ln(K)$, i.e. the elasticity of output with respect to tangible capital. The estimates are again stable across industries and highly significant: 0.07 for all firms, both in Table 4.1 (RE) and Table 4.2 (FE). The highest estimate is 0.118 in low-tech manufacturing (Table 4.2) and the lowest is 0.028 in High/High-middle tech manufacturing (Table 4.2).

[12] An alternative method to handle the problem of endogeneity and potential autocorrelation in the residuals, would be to a generalized method of moments (GMM) estimator, e.g. the estimator proposed by Arellano and Bond (1991), which uses lagged levels and first differences of the endogenous variables as instruments. However, since we find this estimator to be highly sensitive to the choice of instruments, we do not report GMM estimates here, but will explore this approach in future research.

The coefficient (β_L) of $\ln(\bar{L})$ can be interpreted as the elasticity of output with respect to ordinary (non-IA) labour input for firms with $s_Y = 1$ – i.e. firms that only employ non-IA labour (see (2.9)). The estimate of this elasticity is close to 0.80 for all industries, regardless of estimation method, except for high/high-middle tech manufacturing and R&D services, where the estimates are close to 0.95 in the FE model and – respectively – 0.90 and 0.95 in the RE model.[13]

The coefficient of the labour share, s_j, refers to the IBTC-terms, and reflects to what extent IC workers of type *j* (*j*=*R*, *ICT* or *OC*) has a *higher* output elasticity than non-IC workers (*j*=*Y*), i.e. a higher elasticity than $\beta_L s_j$ (see equations (2.9)-(2.10) – here we have dropped the subscript *it*). In Table 2 most of the estimates corresponding to s_j are positive, but they vary substantially across industries: R&D workers contribute positively to labour productivity growth (relative to non-IA workers), with highly significant estimates for IBTC-R (the coefficient of s_R), with p-value<0.01 in R&D services and other services. The corresponding results for IBTC-OC (the coefficient of s_{OC}) show one p-value<0.01 (in Knowledge intensive services & ICT) and even significant *negative* estimates in other services. The IBTC-ICT coefficient (the coefficient of s_{ICT}) is significantly positive in knowledge intensive services & ICT but negative in several other industries. The FE estimates vary even more widely than the RE estimates: there are few significant *positive* FE estimates and some significant negative ones. To sum up: the only robust finding is a positive estimate of IBTC-R in R&D services: the estimate is larger than 0.20 with a p-value below 0.01 in both tables.

We next turn to the interactions between $\ln(X_{ICT})$ and the IA-labour shares, s_j. The RE estimates in Table 4.1 reveal mostly significant and positive interaction effects. Although there again are huge variations across industries, the estimates for all firms are significant at the 1 percent level for the three interaction coefficients (varying between 0.02 and 0.05). The interaction terms also contribute substantially to the overall estimate of the elasticity of output with respect to *ICT*, which is estimated to 0.145 and is significantly higher than the estimate for tangible capital (0.07). The FE estimates in Table 4.2 show similar results for all firms: the three interaction effects are significant at the 1% level, with estimates between 0.028 and 0.034. The overall FE estimate of the elasticity of output with respect to *ICT* is 0.119, which again is much higher than the FE estimate of the elasticity with respect to tangible capital (0.072). If we look closer at industry-specific estimates, we find wide variations, with several negative estimates. Thus, there is considerable sampling uncertainty.

We finally comment on the estimates for OC, $\ln(X_{OC})$, and R&D capital, $\ln(X_R)$. Focusing on the results for all firms in Table 4.1 and 4.2, we find significant positive RE estimates at the 1% level in Table 4.1, but only at the 5% and 10% level in Table 4.2 (FE estimates). More importantly, in all cases

[13] Interestingly, these estimate are of the same magnitude as the wage cost shares in Norwegian market industries reported by Statistics Norway (wages costs as share of value added), which was about 85 percent on average during 2008-2018 in, for example, both Manufacturing and Professional, scientific and technical activities. See Table 3.8 and 3.3 respectively in https://www.ssb.no/nasjonalregnskap-og-konjunkturer/artikler-og-publikasjoner/_attachment/431075?_ts=17472ce3de8 (in Norwegian). It is well known that in a standard Cobb-Douglas model with constant returns to scale and homogenous input factors (labour and capital), the wage cost share relative total factor costs equal the elasticity of labour.

the coefficient estimates are <0.01, so that we can safely conclude that R&D capital and OC capital play a much smaller role for productivity growth than ICT capital.

Table 4.1. Random effects estimate of production function parameters[1)]

		Manufacturing			Services		
Coeff. of:	All firms[2)]	H-HM[3)]	LM[4)]	Low[5)]	KIS& ICT[6)]	R&D[7)]	Other[8)]
$\ln(X_{ICT})$	0.048***	0.046***	0.052***	0.043***	0.056***	0.089***	0.045***
	(0.001)	(0.009)	(0.005)	(0.004)	(0.003)	(0.010)	(0.001)
$\ln(K)$	0.070***	0.047***	0.061***	0.097***	0.058***	0.038***	0.075***
	(0.001)	(0.007)	(0.004)	(0.005)	(0.003)	(0.005)	(0.001)
$\ln(\bar{L})$	0.826***	0.949***	0.894***	0.852***	0.833***	0.968***	0.795***
	(0.002)	(0.014)	(0.009)	(0.009)	(0.004)	(0.010)	(0.002)
s_R	0.115***	0.099	0.218*	0.012	0.108*	0.365***	0.147***
	(0.019)	(0.100)	(0.095)	(0.084)	(0.043)	(0.053)	(0.042)
s_{OC}	0.013	0.427**	0.188*	-0.030	0.146***	0.210*	-0.092***
	(0.019)	(0.139)	(0.084)	(0.079)	(0.037)	(0.087)	(0.027)
s_{ICT}	0.136***	-0.430*	-0.297	-0.005	0.185***	-0.017	0.015
	(0.021)	(0.202)	(0.350)	(0.147)	(0.030)	(0.125)	(0.052)
$\ln(X_{ICT})\times s_R$	0.025***	0.005	0.022	0.062**	0.003	-0.046***	0.002
	(0.004)	(0.023)	(0.026)	(0.021)	(0.011)	(0.013)	(0.012)
$\ln(X_{ICT})\times s_{OC}$	0.052***	0.056	0.020	0.139***	0.025*	-0.008	0.055***
	(0.006)	(0.042)	(0.030)	(0.028)	(0.010)	(0.026)	(0.008)
$\ln(X_{ICT})\times s_{ICT}$	0.020***	0.110	0.268*	0.003	0.003	0.054	0.058***
	(0.005)	(0.059)	(0.126)	(0.042)	(0.007)	(0.038)	(0.017)
$\ln(X_R)$	0.007***	0.004	-0.003	0.008***	0.005**	-0.005	0.008***
	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)	(0.001)
$\ln(X_{OC})$	0.008***	-0.014**	-0.002	0.006*	0.006***	-0.011***	0.012***
	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)
Elast. wrt. *ICT*[9)]	0.145***	0.217***	0.362***	0.247***	0.087***	0.089***	0.160***
	(0.008)	(0.076)	(0.132)	(0.054)	(0.016)	(0.048)	(0.022)
Elasticity of scale [10)]	1.056***	1.203***	1.312***	1.210***	0.989***	1.079***	1.050***
	0.014	0.079	0.132	0.056	0.019	0.051	0.027
No. of obs.	326,692	10,892	17,883	21,673	58,282	15,413	202,549
R^2 - within	0.414	0.314	0.414	0.362	0.498	0.498	0.381
R^2 - between	0.798	0.830	0.859	0.827	0.758	0.754	0.774
R^2 - overall	0.782	0.829	0.836	0.818	0.763	0.761	0.759
σ_e^2 [11)]	0.429	0.498	0.382	0.409	0.469	0.473	0.405
σ_u^2 [12)]	0.481	0.543	0.389	0.465	0.569	0.542	0.467

Notes: [1)] Variables in first column refer to the explanatory variables of Equation (2.10) (subscript *i* and *t* suppressed). Fixed time effects are included but not reported. Robust standard errors in parenthesis; *, ** and *** refer to significant estimate at 10, 5 and 1 percent level (p-value<0.1,0.05 and 0.01), respectively. When the coefficient depends of firm-years, e.g. the coefficient $\beta_{L,R}(w_{Rit}/w_{Yit}-1)$ of the variable s_{Rit}, the reported estimate represents an average over all firm-years: $\beta_{L,R}(\bar{w}_R/\bar{w}_Y-1)$. [2)]All industries. [3)]High—High-middle technology manufacturing. [4)]Low-middle technology manufacturing. [5)]Low technology manufacturing. [6)]Knowledge intensive market industries in services and ICT services. [7)]R&D services. [8)]Other services. [9)] Elasticity with respect to *ICT*: $\beta_{ICT}+\bar{s}_R\beta_{R\times ICT}+\bar{s}_{OC}\beta_{OC\times ICT}+\bar{s}_{IC}\beta_{ICT\times ICT}$, where $\bar{s}_j$ refers to sample average. [10)]Estimate of elasticity of scale: $\beta_L+\beta_K+\beta_{ICT}+\beta_{KBC}+\bar{s}_R\beta_{R\times ICT}+\bar{s}_{OC}\beta_{OC\times ICT}+\bar{s}_{IC}\beta_{ICT\times ICT}$, where $\bar{s}_j$ refers to sample average. [11)] Variance of idiosyncratic error term. [12)] Variance of random effect.

Table 4.2. Fixed effects estimate of production function parameters [1)]

Coeff. of:		Manufacturing			Services		
	All firms[2)]	H-HM[3)]	LM[4)]	Low[5)]	KIS&ICT[6)]	R&D[7)]	Other[8)]
$\ln(X_{ICT})$	0.028***	0.034***	0.040***	0.025***	0.039***	0.056***	0.025***
	(0.001)	(0.009)	(0.006)	(0.004)	(0.003)	(0.011)	(0.001)
$\ln(K)$	0.072***	0.028*	0.075***	0.118***	0.053***	0.040***	0.076***
	(0.002)	(0.014)	(0.009)	(0.010)	(0.005)	(0.010)	(0.003)
$\ln(\overline{L})$	0.792***	0.892***	0.857***	0.790***	0.807***	0.965***	0.758***
	(0.002)	(0.017)	(0.010)	(0.010)	(0.005)	(0.011)	(0.003)
s_R	-0.037	0.061	0.205	-0.049	-0.056	0.246***	0.085
	(0.022)	(0.116)	(0.109)	(0.110)	(0.049)	(0.060)	(0.047)
s_{OC}	-0.082***	0.193	0.123	-0.053	0.015	0.095	-0.127***
	(0.020)	(0.153)	(0.090)	(0.084)	(0.040)	(0.095)	(0.028)
s_{ICT}	-0.064**	-0.142	0.624	-0.056	-0.031	0.103	-0.023
	(0.024)	(0.243)	(0.435)	(0.156)	(0.035)	(0.146)	(0.057)
$\ln(X_{ICT})\times s_R$	0.029***	-0.042	-0.034	0.084***	-0.003	-0.023	-0.006
	(0.005)	(0.026)	(0.030)	(0.022)	(0.012)	(0.014)	(0.013)
$\ln(X_{ICT})\times s_{OC}$	0.034***	0.061	0.017	0.110***	0.020	-0.011	0.020*
	(0.006)	(0.047)	(0.032)	(0.030)	(0.011)	(0.027)	(0.009)
$\ln(X_{ICT})\times s_{ICT}$	0.028***	-0.008	-0.230	0.017	0.008	0.034	0.045*
	(0.005)	(0.065)	(0.157)	(0.047)	(0.007)	(0.042)	(0.018)
$\ln(X_R)$	0.002*	-0.005	-0.008**	0.003	0.004**	-0.016***	0.001
	(0.001)	(0.004)	(0.003)	(0.003)	(0.002)	(0.005)	(0.001)
$\ln(X_{OC})$	0.002**	-0.017***	-0.005	-0.000	0.002	-0.012***	0.004***
	(0.001)	(0.005)	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)
Elast. wrt. *ICT*[9)]	0.119***	0.045	-0.207	0.236***	0.064	0.056	0.084***
	0.009	0.084	0.163	0.060	0.017	0.053	0.023
Elasticity of scale [10)]	0.987***	0.943***	0.712***	1.147***	0.930***	1.033***	0.923***
	(0.010)	(0.089)	(0.163)	(0.061)	(0.019)	(0.058)	(0.024)
No. of obs.	326,692	10,892	17,883	21,673	58,282	15,413	202,549
R^2 - within	0.419	0.318	0.417	0.366	0.500	0.499	0.386
R^2 - between	0.711	0.802	0.827	0.248	0.704	0.741	0.689
R^2 - overall	0.711	0.801	0.816	0.261	0.717	0.754	0.687
σ_e^2 [11)]	0.429	0.498	0.382	0.409	0.469	0.473	0.405
σ_u^2 [12)]	0.660	0.703	0.495	1.852	0.706	0.631	0.634

Notes: [1)] Variables in first column refer to the explanatory variables of Equation (2.10) (subscript *i* and *t* suppressed). Fixed time effects are included but not reported. Robust standard errors in parenthesis; *, ** and *** refer to significant estimate at 10, 5 and 1 percent level (p-value<0.1,0.05 and 0.01), respectively. When the coefficient depends of firm-years, e.g. the coefficient $\beta_{L,R}(w_{Rit}/w_{Yit}-1)$ of the variable s_{Rit}, the reported estimate represents an average over all firm-years: $\beta_{L,R}(\overline{w}_R/\overline{w}_Y-1)$.

[2)]All industries. [3)]High—High-middle technology manufacturing. [4)]Low-middle technology manufacturing. [5)] Low technology manufacturing. [6)]Knowledge intensive market industries in services and ICT services. [7)]R&D services. [8)] Other services [9)] Elasticity with respect to *ICT*: $\beta_{ICT}+\overline{s}_R\beta_{R\times ICT}+\overline{s}_{OC}\beta_{OC\times ICT}+\overline{s}_{IC}\beta_{ICT\times ICT}$, where $\overline{s}_j$ refers to sample average. [10)]Estimate of elasticity of scale: $\beta_L+\beta_K+\beta_{ICT}+\beta_{KBC}+\overline{s}_R\beta_{R\times ICT}+\overline{s}_{OC}\beta_{OC\times ICT}+\overline{s}_{IC}\beta_{ICT\times ICT}$, where $\overline{s}_j$ refers to sample average. [11)] Variance of idiosyncratic error term. [12)] Variance of fixed effect.

5. Conclusion

In this paper we have assessed the importance of information and communication technology (ICT), and intangible investments in research and development (R&D) and organizational and marketing capital (OC) for labour productivity. For this purpose, we have used a matched employer–employee panel data set of Norwegian firms covering all firms in selected industries in the period 2008–2019. Different types of intangible capital are treated as inputs in a neo-classical production function: ICT capital, R&D capital and OC. To operationalize the concepts of R&D capital and OC, we have applied novel GLOBALINTO measures of investments in R&D and OC that are based on firm-level wage costs related to specific tasks and occupations. We have further explored the interactions between ICT and heterogenous labour skills by modifying the concept of intangible-work biased technical change (IBTC) proposed by Piekkola (2020) in a way that is suitable for analysing labour productivity.

In an EEA or OECD context, Norway is a quite average country when it comes to intangible investments as a share of GDP. For example, public support to Business enterprise R&D (BERD) was 1.05 per cent in 2020, which is close to the median for the OECD.[14] However, our data on ICT investments are unique and makes our research interesting beyond just being an application of well-established methods to a small country. For example, as data source for intangible ICT investments, we use register data based on general financial statements in the tax return which are collected annually and, since 2002, comprise information about annual investments in hardware (purchased) and software (both purchased and on own-account). This is more comprehensive and detailed data on ICT than available in any EU country.

Our estimates indicate that the overall elasticity of output with respect to ICT capital lie in the range of 0.10-0.15 across a wide range of high-tech and low-tech manufacturing and service industries. These estimates are generally higher than the estimated elasticity of output with respect to tangible capital, which lie in the range of 0.07 to 0.12 across the same industries. Positive interaction effects between ICT capital and specific labour skills contribute considerably to the overall impact of ICT on output and productivity. If we do not account for such interactions effects, the estimated elasticity with respect to ICT lie in the range of 0.03 to 0.05 across the same industries. We estimate positive interaction effects of similar magnitude between (high) ICT capital and (high) shares of workers engaged in either R&D-, organizational- or ICT-related activities at the firm level.

[14] See https://www.oecd.org/sti/rd-tax-stats-norway.pdf.

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