Intangibles and innovation-labor-biased technical change

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Abstract

Purpose – This paper analyzes the productivity effects of structural capital such as research and development (R&D) and organizational capital (OC). Innovation work also produces innovation-labor-biased technical change (IBTC) and knowledge spillovers. Analyses use full register-based dataset of Finnish firms for the period 1994–2014 from Statistics Finland.

Design/methodology/approach – Intangibles are derived from the labor costs of innovation-type occupations using linked employer-employee data. The approach is consistent with National Accounting and offered as one method in OECD (2010) and applied in statistical offices, e.g. in measuring software. The EU 7th framework Innodrive project 2008–2011 extended this method to cover R&D and OC.

Findings – Methodology is implementable at firm-level and offers way to link personnel reporting to intangible assets. The OC-IBTC as well as total resources allocated to OC are relevant for productivity growth. The R&D stock is relatively higher but R&D-IBTC is smaller than OC-IBTC. Public policy should, besides technology policy, account for OC and OC-IBTC and related knowledge spillovers in the industries that are most important among the SMEs (low market-share-firms).

Research limitations/implications – The data are based on remote access to Statistics Finland; the data cannot be disseminated.

Originality/value – Intangible assets are measured from innovation work that encompasses not only R&D work. IBTC is proxied in production function estimation by relative compensations on IA work. The non-competing nature of IAs is captured by IA knowledge spillovers. The sample sizes are much higher than in earlier studies on horizontal knowledge spillovers (such as for SMEs,) thus bringing additional generality to the results.

Keywords Intangible capital, R&D, Skill-biased technical change, Innovative work

Paper type Research paper

1. Introduction

This paper introduces an analysis of all Finnish industries from 1995 to 2013 using a production function that covers innovation-labor-biased technical change (IBTC), accumulating the intangible assets (IAs) of the firms within the industries and knowledge spillovers. The production function for different firm types is evaluated in the NACE 3-digit level industries. IBTC accounts for the direct effect of innovative work on technology (Hellerstein *et al.*, 1999; Ilmakunnas and Piekkola, 2014). The contribution in this paper is a different method that accounts for relative IA compensations rather than the IA labor share

JEL Classification — O33, O32, O30, J30, J42, M12

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as proxy for the quality of labor creating IBTC. IBTC also creates horizontal knowledge spillovers. Another novelty is the inclusion of IA capital accumulation in the same model (Corrado, Haskel, and Jona-Lasinio, 2017). Two types of IAs are constructed, i.e., the organizational capital (OC) related to marketing and management, and research and development (R&D). The novelty here is that they are measured in a comparable way to observe the large differences in the ways they improve productivity. Each individual contributes to a certain type of IA so that the alternative IAs are not overlapping. The IA measurement follows the EU 7th framework project Innodrive, see Piekkola *et al.* (2011) and the guidelines in OECD (2010).

We measure the own-account IA, which is assumed to be produced with a similar share of factor inputs as are used in the production of purchased IAs from IA producing industries (business services). Much of the purchased IAs may also consist of intermediates used in the production of own-account IAs and may currently be categorized as intermediate inputs from business and ICT services. This is our way of measuring the "overhead" of the innovation-type labor costs mentioned in the OECD (2010) approach. IAs are similar to tangible capital and require additional intermediates and physical capital to transform it into accumulating capital.

Organizational capital is evaluated in the management and marketing work, and is an important part of economic competence in Corrado *et al.* (2012). Economic competence accounts for 38% of all intangible capital in the EU countries, see also Roth and Thum (2013); Haskel and Westlake (2017). The measure IBTC is a good approximation of technological improvement together with related knowledge spillovers. The analysis obtains support from Añón Higón, Gómez, and Vargas (2017), who find that R&D, human capital, and design all to contribute to total factor productivity (TFP), but human capital influences it to higher degree than R&D. We find OC type IBTC to be important especially among large firms but it is negatively related to the amount of OC. R&D plays an important role in accumulating IAs and R&D type IBTC complements it. Knowledge spillovers are large and this non-rival part of IA can be a considerable share of what is usually considered as marketable IA. Especially SMEs are important sources of knowledge spillovers to all kinds of firms. The IA analysis also covers micro firms with less than ten employees, which have somewhat different roles compared with large SMEs.

Section 2 presents the literature review on IAs. Section 3 models the intangibles in upstream industries or the self-production of IAs. Section 4 describes the data and the IA measurement. Section 5 conducts empirical research on how IAs affect technical change and accumulate. Section 6 concludes.

2. Literature

IAs, or intellectual capital with a wider context, has gained considerable interest since the 1990s (Cheng *et al.*, 2010; Phusavat *et al.*, 2011). Thum-Thysen *et al.* (2017) defines IAs as all types of strategic investments in the long-run growth of individual companies and the economy as a whole. Corrado, Hulten, and Sichel (2005, 2009) advanced the research on intangible assets in the economics field by introducing a broad division of intangibles that covers computerized information (digitalization with software and database) and economic competences acquired through management, investments in branding and through purchases of management and consulting services. In accounting, different extensions have been used, such as including customer relations; for other definitions, see Hejazi *et al.* (2016). Andrews and De Serres (2012) analyze network externalities as a way to benefit from returns to scale; this view can be extended to several types of information and communication technologies (ICTs) that are not considered here.

Organization for Economic Co-operation and Development (OECD) (2005, annex B pp. 149–154) sets forth the guidelines for innovation surveys to cover a wider set of intangibles

[1]. Including intangibles from innovation-type occupations is an important step to broaden the concept of IA. The approach here closely follows the EU 7th framework project Innodrive. Following OECD (2010, p. 25) the method to evaluate IA from innovation-type occupations is an alternative to survey-based collection of IA data. The method also complies with the 2008 System of National Accounts.

OC relates to economic competencies. It consists of management and marketing capital evaluated from related occupations. Wyatt (2005) emphasizes the important role that management has in defining the firm's set of IAs. Intangibles that involve large discretion by management are more valued than the others, such as purchased goodwill or R&D. Wyatt (2005) also finds that the assets with a shorter technology cycle are better recorded in accounts. Nerdrum and Erikson (2001) find intellectual capital such as human capital and organizational capital as complementary and hence having wide use in various IAs. F-Jardón and Martos (2009) has a wider concept structural capital as "... what remains in the company when employees go home for the night" (Roos and Roos, 1997, p. 42). It does not only cover the organization but also the technology such as proprietary software systems and thus is closely the same as considering R&D and OC together. One difference is that they use survey on how the organizations use or institutionalize this knowledge in routines, culture and structures embodied in the structural capital of the organization. A first aspect of this is orientation to quality, innovation and environment care. Second, they analyze information (design and adjustment) and communication systems and team work (compensation systems). The other dimensions of intellectual capital: human capital and customer capital are tied to structural capital rather than directly affecting performance.

St-Pierre and Audet (2011) believe that SMEs rely on knowledge or the human capital of employees and customer relations rather than on managerial abilities relating to organizational capital. Businesses feel that their development is essentially due to the quality of their employees and their relationships with customers. In SMEs, human capital is managed informally and the entrepreneur plays the knowledge "storage" role. OC related IBTC may hence also have different knowledge spillovers depending on firm-size, as found in this study.

Productivity growth or the growth of output is likely to be a less significant factor for measuring the success of intangibles among SMEs. Piekkola and Rahko (2019) explain this by the large fixed costs in innovations and access to market, which causes negative selection among the fast growing SMEs. In a "negative selection mechanism," firms with low initial productivity and profitability invest only in innovations with the highest productivity growth. Wolff and Pett (2006) explain this by the sales growth objective to produce cash flow to cover the expenses and fixed costs rather than obtaining (long-term) profitability.

Corrado *et al.* (2009) consider computerized information and innovative property (including R&D) to be partly excludable and forming the major part of accumulating IA. Andrews and De Serres (2012) emphasize that firms have only partial control of the workers' skills, and the returns appropriated may improve the firm's technology in a way that benefits all firms in the industry. The latter is known as the learning by doing effect first introduced by Arrow (1962), stating that employees may utilize the knowledge attained at former jobs. Artz *et al.* (2010) integrates the intangibles that firms acquire in both capital deepening and IBTC. Corrado *et al.* (2016) also suggest that innovations not only require increased IA accumulation related to new knowledge products, but also new technology and knowledge that shows up as an increase in total factor productivity (TFP).

Since a large part of IBTC cannot be codified and stored, it is tacit knowledge. This is "embrained" in individuals, and therefore consists of "knowledge that depends on conceptual skills and cognitive abilities" (Blackler, 1995, 1,023). Engelbrecht (1997) indeed links tacit knowledge to human capital that play a key role in explaining the impact of knowledge on productivity. The novelty in this paper is the evaluation of IBTC in conjunction with the output elasticities of the respective intangibles. Earlier papers have analyzed either IA driven productivity change as in Ilmakunnas and Piekkola (2014), or IAs as an input in production function or TFP, but not both. IBTC is a way to measure the quality of innovation work: how innovation work is better exploited than in other firms. Therefore, it can be a source of competitive advantage. This tacit knowledge cannot be all measured or recognized in terms of higher wages and therefore production function estimation is needed. It also part of the way to lower entrepreneurial activity costs in order to allow greater flexibility and the improvement of goods (Arvanitis and Loukis (2009)).

Corrado, Haskel, and Jona-Lasinio (2017) find that labor "quality," IBTC, does not change the coefficients of (marketable) intangible capital much. This supports the view that tacit knowledge related to IBTC is an independent source of technical change, as is also found here. However, using this Hellerstein *et al.* (1999) framework, proxying IBTC by the share of IA workers can be biased as the IBTC is the same for all firms for which the production function has been estimated, such as here for three types of firms within each three-digit industry. Here, the IBTC is firm-specific and not industry-specific.

Tacit knowledge related to human capital is also interlinked and therefore can create knowledge spillovers, possibly more so within industries than across all firms (Almeida and Kogut, 1999; Møen, 2005; Kerr, 2008; Maliranta and Nurmi, 2019). The process of new knowledge commercialization through knowledge spillover, such as through new startups, also affects growth in industries and regions (Acs *et al.*, 2009; Audretsch and Keilbach, 2008). Del Giudice *et al.* (2019) are among the few that examine horizontal technology spillovers between SMEs. Here, IBTC and related tacit knowledge spreads depending on the size of the firms, which is positively related to the magnitude of worker mobility and hence to "learning by doing." We analyze knowledge spillovers from both R&D and OC type IBTC. To the best of my knowledge, in the extant firm-level analyses, there is very little earlier evidence for intra-industry intangible knowledge spillovers other than those created by R&D (Maliranta *et al.*, 2009) or patents.

One effort is Piekkola (2019b) where knowledge spillovers are positive when the value of the knowledge spillover stock in each new job relationship is higher than that if the new IC worker would just create the average value of IC per employee in the previous firm. Such valuation requires separate evaluation of new IA from job switchers and the old IA of incumbent workers.

3. Intangible capital as a factor input and contributing to technical change

The OECD (2010, p. 25) *Handbook of Deriving Capital Measures of Intellectual Products* consider in the supply-side macro approach the need to identify the number of people in those occupations that produce the target Intellectual Property Products (IPPs) and also the proportion of their time spent undertaking this production to derive the quantum of labor input. According to the OECD (2010) manual, this can then be multiplied by wage rates and other labor costs, and the cost of all the overheads in undertaking IA investment. Innovation-type occupations include managerial and technical positions that create new knowledge, which can cover a wide part of time use other than that is allocated to maintaining current operations. Employees bring knowledge from their former job relationships to the new company. Measuring the increasing share of IA labor costs relative to other labor costs can partly measure this.

Consider first the IAs that are enduring and accumulate over time. The capitalized value of IAs depends on whether the measurement is from intermediates, see industry-level studies on (purchased) IA, such as those by Corrado *et al.* (2014) and Piekkola (2018), or from innovation-type work in downstream industries. Goodridge, Haskel, and Wallis (2014) describe income flows in intangible assets produced in upstream industries and intangible asset consumed in downstream industries (here we abstract from the subindex for period t) as follows:

$$P^N N \equiv P^L L^N + P^K K^N + P^M M^N + P^R_N R^N \quad (1)$$

$$P^Y Q \equiv P^L L^Y + P^K K^Y + P^R_Y R^Y + P^M M^Y, \quad (2)$$

where N is the intangible capital output from the upstream industry, Q is the output from the downstream industry, L is labor, K is tangible capital, R is intangible capital, M is the intermediate input from other than IA producing industries and P shows the respective prices, all separately for the upstream N and downstream Q industries. $P^R_Y R^Y$ is the rental payment or implicit costs when the asset is purchased from upstream N industry, and $P^M M^Y$ are the intermediate inputs from other industries. The output from the upstream industry adds R stock to the downstream industry, and the price of renting this unit is as follows:

$$P^R_Y \equiv (\rho + \delta_R) P^N_N, \quad (3)$$

where δ_R is a suitably chosen (private) depreciation rate and ρ is net returns. The typical convention for choosing the deflator P^N for R&D in national statistical institutes is the use of the R&D services industry (US NAICS 5417, EU NACE 72) output deflator as the proxy for all internal private business R&D and other IAs. The Bureau of Economic Analysis (BEA) in the United States also applies an aggregate upstream (input) price index to deflate R&D in downstream industries, see also Copeland and Fixler (2012), Copeland *et al.* (2007, 31–32). In this analysis, the parameter P^N_t used for OC denotes the input cost based producer price (GDP) deflator for NACE M69–70, 73–74 business services. The R&D services (NACE M72) is used for R&D dominated by large enterprises. In 2012, large enterprises (employing 250 or more persons) employed approximately half of total workers, i.e., 1.2 million workers in EU28 in the NACE M72 sector. These large manufacturing firms may have R&D units categorized as belonging to this industry and apply intermediate pricing that may not measure the true costs.

The own knowledge production function from which to obtain $P^R_Y R_Y$ in the downstream industry in (2) is the accumulated value of total IA investment from the following:

$$P^Y N^Y \equiv P^L L^Y_{IA} + P^K K^Y_{IA} + P^M M^Y_{IA} + P^N_N N^Y_{purchased},$$

where subscript IA refers to the use of factor inputs in IAs. Innovation-type labor covers R&D and OC, which are combined with the assumed use of tangible capital and intermediate following (1'). Following OECD (2010, 19) $P^Y N^Y$ should include only own-account use and not IA produced for sale. A basic rule is that $P^N_N N^Y_{purchased}$ should be treated as intermediate consumption to avoid double accounting OECD (2010, recommendation 20).

Consider next the innovation-labor-biased technical change (IBTC). Following the analysis of the productivity in the innovation work of Hellerstein *et al.* (1999) (HNT), L_m, m = RD, OC is considered qualitatively different from other work so that labor augmented technical change A is given by the following:

$$\begin{aligned} AL^Y &= a_{RD} L_{RD} + a_{OC} L_{OC} + [L - (L_{RD} + L_{OC})] \\ &= L[1 + (a_{RD} - 1) L_{RD}/L + (a_{OC} - 1) L_{OC}/L], \end{aligned} \quad (4)$$

where $a_m, m = RD, OC$ is the labor augmented technical change (quality adjustment), L_{RD} is the R&D work and L_{OC} is the OC work and the rest $L - (L_{RD} + L_{OC})$ is noninnovation-type work. a_m is the direct effect of IA on technical change. Modeling technical change as part of the innovation decision leads to endogenous Schumpeterian and Romer growth models, see Aghion and Howitt (2008). In these models, innovations are dichotomous so that productivity improvements, such as a_m, take place with some probability. An important implication of the HNT analysis is that shifts in the share of m workers L_m/L are driven by new IA employees that may bring with them knowledge from previous work relationships. Thus, the technical change is linked to knowledge spillovers between firms, some of which may be unintentional, as also considered here, see also Piekkola (2019b). The novelty here is that the initial a_m is preferably approximated by the labor cost differential $w_m L_m / w_{skilled} L_{skilled}$ between an IA worker of type m $w_m L_m$ and other skilled workers $w_{skilled} L_{skilled}$ in the firm. The wages of tertiary educated workers are taken as the reference to show the opportunity cost of no innovation work, e.g., when working in firms with no innovations.

In addition to this technological link, IAs are typically considered to be capital that depreciates over time. IAs usually depreciate at higher rates; for example, OC depreciates by 20–25% annually, while the deprecation rate of buildings is typically 3% and the depreciation for machinery and equipment is 7%. The depreciation rate for OC is set at 20% because of the longer life cycle of production, but the higher rate of 25% used by Corrado *et al.* (2005) is retained for services. A depreciation rate of 15% is used for R&D [2]. The perpetual inventory method is applied here for the stock calculation at time t, as follows:

$$R_{mt} \equiv R_{mt-1}(1-\delta_m) + N_{mt,} \tag{5}$$

where N_m denotes the real IA investment, R_m denotes the real IA stock at time t and δ_m is the depreciation rate for IA of type $m = R\&D, OC$. If the stock of intangible capital is rented for a shorter period T, the annual value of the investment follows in each period, as follows:

$$R_{mt=0} = \sum_{t=0}^{T} \frac{N_{mt}}{(1+\rho_m)^t}, \tag{6}$$

Here, the IAs are assumed to grow over a sufficiently long period at a constant (firm-specific) rate g_m so that (dropping time subscripts) we have the following, see Hall *et al.* (2010):

$$R_{mt} = \frac{N_t}{g_m + \delta_m} \quad \text{or} \qquad \ln R_{mt} = \ln N_{mt} - \ln(g_m + \delta_m), \tag{7}$$

This equation holds in a steady state, where all growth in GDP per labor comes from technological productivity growth. The growth rate g_m of all IAs is set at 2%, which aims to reflect the sample's average real output growth rate of business services over the 2008–2013 period (NACE M69-M70, M73, M74-M75). The intuition is that all assets accumulate to a level where their rate of return equals their depreciation. The GDP then grows at the rate of productivity growth plus employment growth (or population growth at the national level). As long as the growth rate and depreciation do not change very much within firms over time, the estimated elasticity of output with respect to either N or R will be the same in the production function estimation, since in an estimation, the firm effects capture the differences in the depreciation and growth rates. The elasticities of output with respect to R and N are, hence, the same ε. This is also the reason why output elasticity also shows the optimal IA investment/value added share. The choice of the gross $\partial Y/\partial R$ and net rates of return ρ_R are still different, as follows:

$$\frac{\partial Y}{\partial R} = \varepsilon \frac{Y}{R} \quad \text{and} \qquad \rho_m = \varepsilon \frac{Y}{R^*} - \delta_m \tag{8}$$

Knowledge of δ_m is needed to convert the gross returns $\varepsilon Y/R^*$ to net returns ρ_m (here the price change component in user costs is ignored). Fixing the net returns ρ_m is required to derive the optimal share of IA investment/value added, as the IA investment is derived from the user cost of IA and this varies depending on ρ_m in (8). We consider technological improvement though R&D and OC. The production function uses the value added $Y_t = Q_t - M_t$ and the tangible capital K_t with double deflation, since the intermediate input M_t is an imprecise measure given that some unknown part of it is used to produce IAs. We abstract from the time dimension and use the Cobb–Douglas production function yielding constant returns with $\alpha_L + \sum_m \alpha_m + \alpha_K = 1, m =$ R&D and OC. The production function for each firm i is given by the following:

$$Y_{it} = Y_{it-1}(AL_{it})^{\alpha_L}\prod\nolimits_m (R_{mit})^{\alpha_{mi}} K_{it}^{1-\alpha_L-\sum_m \alpha_m}, \tag{9}$$

in log form (dropping subscripts) $\ln AL = \ln L + \ln[1 + (a_{R\&D} - 1)L_{R\&D}/L + (a_{OC} - 1)L_{OC}/L] \approx \ln L + (a_{R\&D} - 1)L_{R\&D}/L + (a_{OC} - 1)L_{OC}/L$ from (4). The approximation follows from the number of innovation-type workers being small (the second and third terms in square brackets do not significantly deviate from zero). The production function includes the lagged value of value added and (9) is given in the log form, as follows:

$$\begin{aligned}\ln Y_{it} = {} & \alpha_{Yj}\ln Y_{it-1} + \overbrace{\alpha_{Lj}\ln L_{it} + \sum_{m,i\in j}\alpha_{Amj}(a_{mj} - 1)\frac{L_{mit}}{L_{it}}}^{\approx \alpha_{Lj}\text{Log}\,A} + \sum_{m,i\in j}\alpha_{mi}\ln R_{mit} \\ & + \alpha_{Kj}\ln K_{it} + \alpha_{Zj}\ln Z_{it} + e_{it}\end{aligned} \tag{10}$$

where a_{mj} is IBTC for m = R&D, OC in industry j and an estimate of it is given by $\widehat{a}_{mj} = \alpha_{wmj}/\alpha_{Lj} + 1 > 1$, where the parameters vary form one industry j into another; Z_t is the vector of the year dummy variables and e_{it} is log of the disturbance term $\exp(e_{it})$. The estimation is done separately for the three firm types k, i.e., microfirms, small-market share firms and large-market-share firms. It is worth noting that R&D and OC assets have high correlations of approximately 0.6 to each of these class sizes, while IA labor shares L_{mit}/L_{it} for m = R&D, OC has a correlation below 0.3 to R&D and OC assets. The variance inflation factor (VIF) does not imply that the multicollinearity is too high.

Our preferred estimation goes beyond HNT and uses as an initial proxy for the IBTC relative compensations $a_{mit} = \bar{w}_{mit}/\bar{w}_{Lit} - 1$, where $\bar{w}_{mit}$ is the mean compensation for innovation work of type m in firm i and $\bar{w}_{Lit}$ is the mean compensations for skilled workers with tertiary education from non-IA work in the firm. The wage ratio would then reflect the relative productivity of the type of work that the employee is performing relative to the human capital possessed. The mean compensations of skilled workers in firms (total annual earnings divided number of employees) $\bar{w}_{Lit}$ are set to be within the 5-percentile and 95-percentile distribution of the overall average compensations across all firms. $\bar{w}_{mit}$ is measured from the sum of annual compensations for m-type innovation work divided by the number of m type workers. The compensation ratio $\bar{w}_{mit}/\bar{w}_{Lit}$ of each firm is finally set within the 1 and 99 percentiles of the overall distribution in the data.

The human capital of innovation workers is a good proxy when the upstream industries producing IAs do not have monopoly power while in downstream industries, technological improvement leads to an increase in the compensations in producing them. The production function can be estimated again separately for each firm types k in the following form:

$$\begin{aligned}\ln Y_{it} = {} & \alpha_{Yj}\ln Y_{it-1} + \alpha_{Lj}\ln L_{it} + \sum_{m,i\in j}\alpha_{Amj}(a_{mit} - 1)\frac{L_{mit}}{L_{it}} + \sum_{m,i\in j}\alpha_{mi}\ln R_{mit} \\ & + \alpha_{Kj}\ln K_{it} + \alpha_{Zj}\ln Z_{it} + e_{it},\end{aligned} \tag{11}$$

where $\alpha_{Amj}(a_{mit}-1)=\alpha_{Lj}(\widehat{\widehat{a}}_{mit}-1)$ so that $\widehat{\widehat{a}}_{mit}=\alpha_{Amj}(a_{mit}-1)/\alpha_{Lj}+1$. Here, $\partial\widehat{\widehat{a}}_{mit}/\partial\alpha_{Amj}=(a_{mi}-1)/\alpha_{Lj}$, whereas $\partial\widehat{\widehat{a}}_{mit}/\partial\alpha_{wmj}=1/\alpha_{Lj}$ in (10). Thus, the quality of the innovation labor increases with relative compensations in the firm rather than by a fixed amount for all firms in (10). This depends on the relative median compensations $a_{mit}=\bar{w}_{mit}/\bar{w}_{Lit}$., while the output elasticity of labor α_{Lj} is more stable across industries. IBTC is, thus, firm- and time-varying.

The estimations are done separately for the three firm types, but cover knowledge spillovers from all types of firms in the industry (first term in brackets in (12)). The final estimation with knowledge spillovers also includes, as in (11), the wage ratio proxy a_{mit} for IBTC (second term in brackets), as follows:

$$\begin{aligned}\ln Y_{it}=&\alpha_{Yj}\ln Y_{it-1}+\alpha_L\ln L_{it}+\sum_m\sum_k\alpha_{spill,mk}\sum_{i\in k,j}\frac{L_{imt}}{L_{jkmt}}(\widehat{\widehat{a}}_{mit}-1)++\alpha_{wjm}(a_{mit}-1)\frac{L_{imt}}{L_{it}}\\&+\sum_m\alpha_m R_{mit}+\alpha_K\ln K_{it}+\alpha_Z\ln Z_{it}+e_{it},\end{aligned}\tag{12}$$

IA knowledge spillover (first term in brackets) is aggregated intra-industry IBTC in an industry j and firm types k, where $\widehat{a}_{mit}$ is from estimation of (11). The aggregation uses as weights each firm's labor shares in each k category. These weights are thought to correspond to the knowledge flows to other firms; the larger the firm, the more potential there is for job switches and learning by doing. Our main interest here is the knowledge spillovers of intangibles of type m depending on firm size.

4. Data and the measurement of IA

The linked employer–employee data in Finland from Statistics Finland cover all firms and their around 700,000 employees in years 1994–2014, where the employer is member of the Confederation of Finnish Industries. Dataset covers 60% of all private sector employees not working in trusts or foundations. The firms are divided into microfirms with less than ten employees (the share of microfirms is nearly 90%), firms with small market shares in the NACE-3 industries and firms with large market shares in the NACE-3 industries. The dividing line between small-market-share and large-market-share firms is the median of market shares calculated as sales per total sales in NACE-3 industries. The median is 0.34% in manufacturing and 0.15% in services. The minimum number of firm-year observations in each industry-firm-size category is set to 100. The firms analyzed have both R&D and OC type work in the observation years. The sample size for the firm-year observations reduces to 34.1 thousand for microfirms, 22.5 thousand for small-market share firms and 38.9 thousand for large firms out of the original 1.36 million firm-year observations (also dropping the first recorded year of the firm as in the estimation sample). For small- and large-market-share firms, the coverage is 14.5% of all firms (59% for firms with R&D). The respective figure is 3.3% for micro firms (38% for firms with R&D).

IAs are measured from the labor costs of employees within selected occupations that are related to innovation-type work. Organizational assets accumulate through investments in management and marketing activities that build up organizational knowhow. R&D assets are accumulated through the technical activities of the firm and, thus, are broader than the measures based on the formal definition of R&D expenditures given in the Frascati Manual (OECD, 2015). The ISCO 2010 coding (ISCO-08, previous version from 2001) is comparable across European countries and is applied here, but it may fall short in evaluating the skill levels.

Appendix A provides a detailed description of the innovative work coding in IA work. Workers are additionally switched to being ICT workers (excluded here) in other IA occupations if their educational field (isced 2011) is computing, to being OC workers if their education field is social sciences and business and to being R&D workers if their educational field is technical. These shifts have minor effect on the relative share of R&D or ICT workers. The occupational classification is similar to the OECD study by Squicciarini and Le Mouel (2012), who use the US Occupational Information Network (O*NET) data. Skilled workers do not spend all their working time on innovative purposes. The share of the work in IA related work dedicated to producing IA is assumed to be 25% for OC workers and 50% for R&D workers when using the broad definitions of occupation at the ISCO two-digit level, see Table A1 in Appendix A. The relatively low share of OC occupations of 25% is also supported by Squicciarini and Le Mouel (2012), who argue that day-to-day and administrative activities that require general skills rather than IA work are common among management tasks. Second, we need information about the use of other factor inputs in the production of internal IA, i.e., tangibles and intermediates.

Finally, R&D includes not only R&D investment evaluated based on the innovative work but also purchased R&D, as reported in the annual R&D surveys on over 2000 thousand firms. In the survey, half of firms have 250 employees or more with full coverage and rest is a sample of SMEs. Piekkola and Rahko (2019) shows that R&D defined in this way has in their sample high coverage of over 80% of firms, while survey R&D is reported only in 24% service firms and 44% manufacturing firms.

The EU Innodrive 2008–2011 seventh framework project (FP7), which is in line with OECD (2010), provides the measurement method for internal IA. The first task as described above is to identify the IA labor input from the related occupations. The second task is to evaluate the work-time share spent on innovative work that affects the future. The third task is the measurement of overheads. Intermediate and capital costs are also incurred in the production of IC goods in each industry. The intermediate input and tangible capital expenditures per unit of the innovation-type labor cost in business services (NACE M69–70, 73–74) forms the factor multiplier for OC; R&D apply the respective shares from R&D service industry (NACE M72), and ICT those from information and communication industry (NACE J62-J63) for ICT not used here (see Table A1 in the Appendix A. Business services are most intensive in IAs. The share of persons employed for professional, scientific and technical activities and ICT services of the total workforce in the EU area in 2012 was approximately 9–10% in 2000–2015. This is approximately 60% of the IA work share here, which is 14.5% when including ICT work. Business services can be considered as upstream industries providing a major part of the purchased IA to other industries ($P_Y^R R_{purchased}^Y$ in (1')). Real expenditure-based investments of type IC = OC, R&D are as follows:

$$P_{jt}^N N_{it}^{IC} \equiv A^{IC} W_{it}^{IC}, \tag{13}$$

where W_{it}^{IC} represents the labor costs of IC workers in firm i multiplied by the combined multiplier A^{IC} (the product of the share of work effort devoted to IC production and the factor multiplier from Table A1 in Appendix A). The factor multiplier is the intermediate and capital costs of one unit of innovative work set to represent the entire EU27 area. The combined multiplier A^z is 1.8 in OC wage expenses and 1.6 in R&D wage expenses; see Table A1 in the Appendix A.

The share of IA work for all employees in Finland is 5.1% for OC and 9.0% for R&D [3]. The share of OC and R&D workers differs from Piekkola (2016) given that functional occupation categories used in the study are more precise for R&D work. The 3.5 times higher sample size of 119.5 thousand observations than in Piekkola (2016). This gives better account for the role of organizational capital and coverage of small-market-share firms. A fairly large share of organizational work is also suggested by Squicciarini and Le Mouel (2012); they also analyze ICT and OC work together. In what follows, the employment figures exclude IA work. Schankerman (1981) and Hall and Mairesse (1995), among others, have shown that the estimated output elasticity of R&D is downward biased if one does not correct for double counting.

The output elasticities of IAs are likely to vary depending on how the IBTC and knowledge spillovers enter the production function. It is also of considerable interest to assess whether expenditures of IAs measure their performance well. Our first Table 1 is a summary including performance-based values of IAs, where the method is described in Appendix B and the estimation follows (11). The idea is to compare the production function output elasticity of an intangible asset to the value added share of its user cost so that higher output elasticities increases the performance-based value.

The total 119.5 thousand observations cover 6,089 micro firms (with 6.2 observations per firm), 3,665 small-market-share firms (with average 7.2 observations per firm) and 6,079 large-market-share firms (with average 9.1 observation per year). The median value added is 69 (average 96) thousand 2010 € per employee, which includes the user cost of IA capital in all estimations (with the rental value of 4%. The number of employees has a mean value of 110 and a median value of 71. Tangible capital stock is drawn from gross fixed capital formation, i.e., equipment, property, and construction, reflecting its use in IA services that produce the same type of IA for sale as the firms can produce internally. The average value 173 thousand

Table 1.
Summary table

Variable	Mean	Q1	Median	Q3	SD	Obs. 0/Share %
Value added per employee	95.7	48.9	69.1	103.0	161.0	119531.0
Productivity growth	−0.0136	-0.167	−0.0145	0.141	0.459	100.0
R&D/L	35.4	8.39	18.8	40.3	74.1	100.0
R&D/L micro firms	46.1	14.1	28.4	57.2	82.6	28.5
R&D/L micro firms, performance	37.5	9.62	20.6	41.8	60.7	28.5
R&D/L small-market-share firms	35.3	8.36	17.2	39.1	51.0	18.8
R&D/L small-market-share f., performance	21.8	5.39	11.9	26.0	30.7	18.8
R&D/L large-market-share firms	33.4	6.63	16.6	36.6	87.5	32.6
R&D/L large-market-share f. performance	29.3	3.75	10.9	27.7	85.2	32.6
OC/L	10.6	3.0	6.0	12.8	13.0	100.0
OC/L micro firms	10.4	2.72	5.57	12.4	14.1	24.4
OC/L micro firms performance	17.8	3.64	7.96	16.8	44.7	24.4
OC/L small-market-share firms	9.67	2.46	5.15	12.0	11.5	19.5
OC/L small-market-share f., performance	6.67	0.903	3.17	7.65	16.0	19.5
OC/L large-market-share firms	11.1	3.09	6.27	13.5	13.3	34.7
OC/L large-market-share f.s, performance	10.7	1.76	4.5	10.6	25.3	34.7
Employment	110.0	14.0	30.0	71.0	483.0	100.0
Employment no IA workers	95.3	11.5	25.8	61.8	418.0	100.0
Tangible capital/L	173.0	14.0	32.4	85.3	1,267.0	90.2
Export/L	66.2	1.12	13.7	69.5	195.0	31.2
Import/L	103.0	1.58	18.8	87.4	362.0	38.9
Market share	0.0194	0.000872	0.00289	0.0108	0.0621	99.6

Note(s): In thousand $2010, f. = firms

2010 € per employee is four times to the sum of OC and R&D per employee, while the median value 34 thousand 2010 € is only 30% higher than median value of IA stock 25 thousand 2010 €. The average productivity growth (logarithmic difference of value added per employee) has been close to zero over the period.

The median R&D stock is 18.8 thousand (average 35.4 thousand) 2010 € per employee, but only 36% of the firm observations have formal R&D. The median OC stock is 6 thousand (average 10.6 thousand) 2010 € per employee due to lower depreciation. The organizational capital and ICT investments are the largest subcategories of intangible investment in many other studies (Van Ark *et al.*, 2009; Bloom and Van Reenen, 2010; Piekkola, 2016) but the depreciation of R&D (15%) is lower than that of OC (20–25%).

From Table 1, the performance-based values are generally 20% lower than the expenditure-based ones, but this can be explained by the estimations including the lagged value of the log value added so that the long-term effects are higher. The long-term multiplier is approximately 2, which would imply that performance-based values are higher in long run. The expenditure-based estimates are found to be rather good approximations. They reflect the true value of total IAs and are lower than the performance-based values in long term. Given the higher long-term effect expenditures do not appear to exceed the gains so that intangible are used in an efficient way.

5. Estimation results

We keep the estimations simple by using OLS. Productivity shocks are controlled for by including tangible capital and its lagged value in the production function. All estimations include year dummies to control for cyclical effects. The firm-level estimation includes four explanatory variables related to IAs, lagged value added, present and lagged tangible capital; the latter is to control for productivity shocks. Table 2 shows the median NACE-3 industry-specific IBTC both using the preferred (11) and HNT formulation (10). The 25 and 75% percentiles of the overall distribution shown in the table are calculated by letting α_{wmj} in (10) and α_{Amj} in (11) vary at the median employment coefficients α_{Lj}. The employment coefficient is in general rather stable. The median values are approximately 20% lower than the average values and are used in the calculations of $\widehat{a}_{mit}$ in (11) and $\widehat{a}_{mj}$ in (10).

Table 2 shows that the median compensations of R&D and OC work exceed the median compensations of skilled workers by approximately 24–27% in large-market-share firms and fairly little by approximately 10% in micro and small-market-share firms. Finally, we have reported the short-term effects, while the long-term effects are twice as high.

The median value of R&D-IBTC from the preferred method (11) in large-market-share firms is 1.86, which says that R&D workers increase productivity 86% more than other workers. The HNT formulation (10) yields an even higher median value of 178%. There is indeed large heterogeneity across firms, which is also due to the limited number of observations in some industries. The median productivity improvement generated by R&D is the lowest, i.e., 17%, in small-market-share firms in the preferred method. In microfirms, the median productivity advantage is 59% with the preferred method.

The median OC-IBTC values are much higher for the preferred method, as follows: 219% for large-market-share firms and approximately 150% for micro and small-market-share firms. The figures would be fairly similar using the HNT formulation (10). The largest productivity improvement, hence, rises from high-market-share firms for both R&D-IBTC and OC-IBTC. In the structural capital, management and marketing work has greater positive effect on IBTC than R&D work.

The results are qualitatively similar to Ilmakunnas and Piekkola (2014) who explained TFP and found organizational work to improve productivity by approximately 46%, while

	Microfirms <10 employees	Small-market-share firms	High-market-share firms
		R&D	
Compensation ratio $\bar{w}_{R\&Dit}/\bar{w}_{Lit}$	1.15	1.06	1.24
R&D-IBTC (eq. 11)	1.59	1.17	1.86
P25-P75 range	1.15–1.96	0.74–1.79	0.89–3.5
R&D-IBTC (eq. 10)	2.38	2.23	2.78
Long-term multiplier	2.06	1.90	2.14
		OC	
Compensation ratio $\bar{w}_{OCit}/\bar{w}_{Lit}$	1.09	1.11	1.27
OC-IBTC	2.53	2.43	3.19
P25-P75 range	1.03–3.22	0.61–3.94	1.02–5.39
OC-IBTC (eq.10)	2.09	2.2	3.63
Long-term multiplier (eq.11)	2.11	1.88	2.19

Note(s): The table shows the median technical change. The P25-P75 range shows technical range at the percentiles of 25 and 75% of the overall distribution, calculated at the median employment coefficients. The long-term multiplier for the reported short-term effects is 1/(1-aY) from (11), where αY is the coefficient of the lagged value added

Table 2.
Labor-augmenting technical change from production function estimates at the firm level

R&D had a significant negative effect of −0.15% (using OLS; in the comparison the total factor productivity effect must be divided by the labor share of value added). It can be seen that IA work causes significant technological improvement. Table 3 shows the more stable output elasticities of R&D and OC in the estimations of (11) and (10).

The output elasticities for R&D are around 5%, but HNT method (10) yields a lower output elasticity of 2% for small and large-market share firms. This suggests that output elasticity may be biased downwards with HNT. The output elasticities are approximately the same for OC, irrespective of the estimation method being approximately 5% for microfirms and approximately 3% for other firms and with higher output elasticity. Given that R&D is three-times higher than OC, it is more relevant in explaining productivity.

Table 4 shows with the preferred method (11) the OLS estimation results explaining the average IBTC by $\widehat{a}_{mjt}$ at the NACE-3 industry level j and year t and separately for small- and large-market-share firms. The IBTC through shifts in L_{mit}/L_{it} is left out because of its obvious correlation with IC, which is used as explaining variable, among others. The average $\widehat{a}_{mjt}$ is

	Microfirms <10 employees	Low-market share firms	High-market share firms
		R&D	
Output elasticity of R&D (eq. 11)	0.06	0.05	0.04
Standard deviation	0.10	0.07	0.13
Output elasticity of R&D (eq. 10)	0.06	0.02	0.02
Standard deviation	0.29	0.06	0.14
		OC	
Output elasticity of OC (eq. 11)	0.054	0.032	0.035
Standard deviation	0.11	0.083	0.112
Output elasticity of OC (eq. 10)	0.051	0.032	0.023
Standard deviation	0.22	0.103	0.146

Table 3.
Output elasticity estimates at the firm level

	R&D-IBTC		OC-IBTC	
	All firms	Large-market-share firms	All firms	Large-market-share firms
R&D asset per employee	13.630*	24.702**	−6.540*	−10.640**
	(5.653)	(7.731)	(3.004)	(3.947)
R&D asset per employee squared	−0.714*	−1.235**	0.328*	0.488*
	(0.282)	(0.391)	(0.150)	(0.200)
OC asset per employee	−0.616	−0.158	−0.624	−0.849*
	(0.545)	(0.866)	(0.329)	(0.353)
Export per employee	−0.473	−1.814***	0.679	0.938***
	(0.440)	(0.532)	(0.351)	(0.197)
Import per employee	0.818*	1.910***	−0.662	−0.897***
	(0.416)	(0.540)	(0.371)	(0.213)
Tangible capital per employee	0.263	−0.526	0.025	1.291**
	(0.688)	(1.267)	(0.303)	(0.417)
Small-market-share firm	3.439	-	1.308	-
	(1.789)		(0.862)	
Large-market-share firm	3.533	-	−2.404*	-
	(1.860)		(1.033)	
Observations	2,230	2,230	1,222	1,222
R squared	0.249	0.230	0.369	0.416

Note(s): All except the dummy variables are in logs. Dummies cover 33 NACE 2-digit industries, 18 NACE-3 regions and years. p-values: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table 4. IBTC related to the quality of innovation workers and IA at the industry level

referred to as IBTC related to the quality of innovation workers. All variables in the OLS estimations, except the dummies, are per non-IA employee and are in logs. Following (11), the technical change may also vary in each firm over time, as reflected by compensations on innovative work.

The first two columns explain R&D-IBTC and the next two columns explain OC-IBTC. The estimation results are shown separately for the full sample and for large-market-share firms. The estimations for the small-market share firms did not work equally well due to higher heterogeneity and are not reported. Both in large firms and all firms, the R&D-IBTCs are positively related to the R&D intensity. OC-IBTC is instead nonsignificantly or negatively related to the OC intensity. OC improves productivity in a way that is not related to the creation of new commercialized OC products and services that are marketable.

Internationalization and, hence, trade has been shown in the literature to increase the innovation input in the form of R&D, which may help to generate new product innovations, see Keller and Shiue (2008), Piekkola and Rahko (2019). It can be seen that export intensity promotes OC -IBTC, while import intensity relates positively to R&D-IBTC. One possible explanation is that R&D intensity and its square are correlated with export intensity, while import intensity brings additional information for the factor inputs used, e.g., in process innovations. The opposite holds for OC-IBTC; it is export intensity that increases the likelihood of OC-IBTC.

In Table 5, the NACE 3-digit level knowledge spillovers are from the estimation of (12). Spillovers are from the aggregation of the firm-level quality of R&D and OC workers $\sum_{m,i\in j}(\widehat{a}_{mit}-1)L_{mit}/L_{jt}$ in each industry j and the firm-type group m category. The firm weight is its average labor share of the total employment over time. The explanatory variables include the initial estimate of m type IBTC $\sum_{m,i\in j}(a_{mit}-1)(L_{mit}/L_{it})$ as done in (11), see (12). Table 5 shows the estimation results.

Small-market-share firms generate the largest spillovers that spread to all firm types. The second observation is that R&D knowledge spillovers are more important than those by OC

	Micro firms <10 employees	Small-market share firms	High-market share firms
VA/L lagged	0.6316***	0.5660***	0.6572***
	(0.0014)	(0.0051)	(0.0051)
Employee no IA	0.3289***	0.3467***	0.2858***
	(0.0014)	(0.0053)	(0.0049)
R&D knowledge spillover			
Micro firms	−0.5790***	−0.9183**	−1.1684***
	(0.0157)	(0.3216)	(0.1473)
Small-market-share firms	1.4078***	2.0431***	1.3127***
	(0.0379)	(0.1225)	(0.0795)
Large-market-share firms	0.0164***	−0.0054**	0.0051***
	(0.0014)	(0.0018)	(0.0012)
OC knowledge spillover			
Micro firms	−0.0862***	1.0931*	0.0157
	(0.0106)	(0.4732)	(0.0707)
Small-market-share firms	0.9664***	0.5989***	0.5369***
	(0.0439)	(0.0955)	(0.0884)
Large-market-share firms	0.0745***	−0.0709***	0.0483***
	(0.0054)	(0.0147)	(0.0105)
Initial R&D-IBTC	0.1063***	0.3464***	0.3077***
	(0.0047)	(0.0201)	(0.0286)
Initial OC-IBTC	0.2104***	0.7328***	0.6793***
	(0.0073)	(0.0368)	(0.0274)
R&D asset	0.0183***	0.0155***	0.0116***
	(0.0001)	(0.0002)	(0.0003)
OC asset	0.0151***	0.0088***	0.0137***
	(0.0001)	(0.0003)	(0.0004)
K/L	0.0173***	0.0165***	0.0208***
	(0.0002)	(0.0008)	(0.0010)
K/L lagged	−0.0082***	−0.0107***	−0.0137***
	(0.0002)	(0.0008)	(0.0010)
Long-term multiplier	2.71	2.3	2.92
Observations	1,146,978	106880	101581
R squared	0.825	0.779	0.909

Note(s): All except dummy variables are in logs. Dummies cover 33 NACE 2-digit industries, regions and years. p-values: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 5.
Labor productivity and knowledge spillovers

knowledge spillovers. Rosenbusch *et al.* (2011), in contrast, find that in SMEs, internal innovations are more important than external ones so that knowledge spillovers are unlikely to be explained by external IAs. On the other hand, Mansfield *et al.* (1981) find that the ratio of imitation costs to that of innovation costs can be, on average, as high as 0.65 and that the average ratio of the imitation time to the innovation time is 0.7. The likely important source of knowledge spillovers is then the learning by doing, i.e., by job switches to and networking with other SMEs. The output elasticities of OC and R&D are only approximately 1%, while they were earlier in Table 3 in the range of 3–6%. This suggests that part of the marketable IA assets are actually created by intra-industry knowledge spillovers.

The spillovers emanating from large-market-share firms are much lower or even create negative productivity effects for small-market-share firms. If the latter are more often followers, this may give evidence for Haskel and Westlake (2017) suggesting a widening gap of intangible investment between leader and laggard firms. Large-market firms exploit new IAs that are not directly useable for small-market-share firms.

6. Conclusion

This paper uses methodology that is implementable at firm-level and offers way to link personnel reporting to intangible assets. This paper also integrates the non-rival nature of IAs by incorporating in IA analysis technology improvement through IBTC (innovation labor-biased technical change). This is in conformity with the broad nature of IAs measured from IA type work and analysis fit with the large samples not relying on survey data. The significant value of IAs is supported by the performance-based estimation, which shows that the assumed expenditures in OC (management and marketing) and R&D investment evaluated from the related innovation work are likely less than that the gains in performance in the long term.

This paper shows that R&D capital stock is approximately three times higher than OC capital stock and enhances R&D-IBTC. OC-IBTC is in turn stronger than R&D-IBTC. Quality aspect of OC work are important as OC-IBTC is at least double to that generated by R&D labor. Especially large-market-share firms need qualified OC-type work, like in the adoption of new innovations. These results can explain why Añón Higón, Gómez, and Vargas (2017) find human capital to be considerably more important in explaining TFP than R&D. Analogous to F-Jardón and Martos (2009), human capital complements OC and related OC-IBTC, while may have more restricted role in explaining directly TFP.

What is surprising is that OC's role in improving productivity was the largest in large-market-share firms. St-Pierre and Audet (2011) instead argued that SMEs, in particular, pay attention to the quality of their employees and their relationships with customers. This finding supports a quality adjusted resources-based view to explain differences in performance by OC-IBTC. Tacit knowledge in OC-IBTC can be unique in building up, thus not easy to repeat or imitate, or the causal relation for success is accidental and hard to identify (Barney, 1991). The causal ambiguity can also relate to the productivity improvement being built on the experience of newly recruited managers in previous job engagements. These findings increase ambiguity in measuring the benefits of OC by mere resources devoted to it.

Findings also confirm national-level analysis of Hervas-Oliver and Dalmau-Porta (2007) that technological aspects and government business policies are the main factors in sustaining high levels of national IC and hence structural capital that relies on R&D and OC in particular. The results can thus aid policymakers to emphasize the importance of investment in renewal (technology) and process capital (business policy).

Technology also spreads unintentionally, as found here at the NACE 3-digit industry level, where R&D knowledge spillovers play the most important role. These findings are especially important for public policy point of view as markets themselves may not be able to internalize these benefits from technological change. The effects are strongest for knowledge spillovers generated by SMEs (i.e., for firms with low-market power but excluding micro firms). However, SMEs do not appear to be able to benefit from the knowledge flows from leaders, such as large-market-share firms. This gives a clear indication for public policy to support interlinkages of SMEs so that the knowledge spillovers are internalized. Second, these networks also increase the independent role of SMEs as large-market share firm do not share all their knowledge with SMEs.

Giant firms, such as Google, Apple and Microsoft, are global players that have competitive advantages in OC type IBTC needed in large firms and may better internalize knowledge spillovers, also through the large recruitment of innovation-oriented staff. This also opens a broader view on how a competition policy should be followed at the national level or at a more aggregate level, as in the EU. Digitalization appears not to boost all the innovation investments unless the giants are close competitors. On the other hand, large-market-share firms benefit from the presence of SMEs and have the largest spillovers from R&D type IBTC among SMEs. Supporting the formation of SME clusters is hence an indirect way to improve the competitive position of large-market-share firms.

We also studied the limited number of microfirms with less than ten employees, where the share of firms with R&D and OC-type labor of all microfirms is just 3%. For these firms, the amount of IA per employee is not less than that for larger firms. It is important to identify entrepreneurial start-ups characterized by a high rate of new knowledge formation in this heterogeneous group of firms. The clear difference to large firms is that micro firms create little knowledge spillovers among themselves or to other firms.

Earlier literature, like overview of Petty and Guthrie (2000), has relatively little to say about IA as part of sustainable growth. It has also stayed unclear whether firms are willing to invest in IC in order to better predict their future performance or do this in order to brand themselves as innovators. This paper is based on hard basic facts on employee's position in the firm, compensations and educational background rather than on branding intentions. Analysis fits well personnel reporting for intellectual capital evaluation.

Notes

1. Organizational innovation is defined as the implementation of a new organizational method in the firm's business practices, workplace organization or external relations. Marketing innovation is defined as the implementation of a new marketing method that involves significant changes in product design or packaging, product placement, product promotion or pricing.
2. The recent estimates of depreciation are from a survey by Awano *et al.* (2010).
3. One measure of R&D labor inputs would be to only include the number of scientists and engineers in NAICS 5417 instead of including all engineers with upper tertiary education. We also believe this measure of labor inputs to be overly narrow. Technical assistants and other occupations not deemed to be scientific are likely to be important in the production of R&D.

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Appendix A

Intangible capital (IC) occupations and multipliers

Following the EU 7th framework project Innodrive and Piekkola (2016), occupation data are used to evaluate the innovative labor input in IA activities. The following table shows the innovation occupations chosen using ISCO08 3-digit coding (the earlier ISCO2001 version is in parentheses). An important additional identifier of different types of IA work is the use of educational information to reallocate the type of IA work. Workers in the educational field isced2011 computing are reallocated to ICT work, and workers with the educational field code social sciences and business (at the 1-digit and 2-digit levels) are reallocated to OC work if the occupation suggests that they are IA workers.

Organizational work

(1) Managing directors and chief executives 112 (112)

(2) Administrative and commercial managers 12 (123 all)

(3) Services and administration managers 121, Sales, marketing and development managers 122

(4) Managing, mining, construction and distribution managers 13, 131 (122)

(5) Manufacturing, mining, construction and distribution managers 132 (122)

(6) Professional services managers 134 (122)

(7) Teaching professionals 23 (23)

(8) Business and administration professionals 24 (241 all)

(9) Finance professionals 241, Administration professionals 242, Sales, marketing and public relations professionals 243

(10) Legal, social, cultural and related associate professionals 34 (all) (242)

(11) Legal, social and religious associate professionals 341 (343), Sport and fitness workers 342 (347), Artistic, cultural and culinary artist professionals, 343 (347)

(12) Business and administration associate professionals 33 (excluding 335):

(13) Financial and mathematical associate professionals 331 (343), Sales and purchasing agents and brokers 332 (342), Services agents 333 (342)

(14) Administrative and specialized secretaries 334 (332)

OC work is reclassified as R&D work if the educational field code is not social sciences and business and isco3 in 1, 12, 13, 23, 24, and 34. OC work is reclassified as ICT work if the educational code is Isced2011 computing in 1, 12, 13, 23, 24, and 34.

R&D work

(1) Technical and mathematical work professional R&D managers 1,223 (1,237)

(2) Science and engineering professionals 21 (excluding telecommunication engineering 2,153)

(3) Physical and Earth science professionals 211 (211), Engineering professionals 212 (212) Mathematicians, statisticians, life science professionals 213 (212), 214 (212), Electrical, electronics engineering 2,151, 2,152 (212), Architects, planners 216 (212)

(4) Health professionals 22

(5) Medical doctors 221 (222), Nursing and midwifery professionals 222 (223), Other health professionals 226 (223), 22 (isco3 not available)

(6) Science and engineering associate professionals 31

(7) Physical and engineering science technicians 311 (311), Life science technicians and related associate professionals 314 (321)

R&D work is reclassified as OC work if the educational field code is social sciences and business and isco3 in 2, 21, 22, 3, 31, and 32. R&D work is reclassified as ICT work if the educational field code is International Standard Classification of Education (Isced 2011) computing and Isco3 in 2, 21, 22, 3, 31, and 32.

Skilled workers do not spend all their working time on innovative purposes. Table A1 shows that the share of this work dedicated to producing IC is assumed to be 25% among OC workers, 50% among R&D workers and 35% among ICT workers. The shares approximately follow the Innodrive FP7 described by Piekkola (2016, 2019a).

Intermediate and capital costs are also incurred in the production of IC goods in each industry. For R&D, these goods are evaluated based on the combined value added of labor costs, intermediate inputs, and tangible capital in R&D services (NACE M72). For ICT, the evaluation is done based on J62-J63. For OC, the use of intermediate inputs and tangible capital in intangible investments as the factor multiplier is evaluated based on the benchmark of all IC-producing services NACE J62-J63 and NACE M69–70, 73–74), excluding R&D services. The benchmark factor multipliers follow Innodrive to represent the entire EU27 area and are a weighted average of the factor multipliers for Germany (40% weight), the UK (30% weight), Finland (15% weight), the Czech Republic, and Slovenia (both countries have weights of 7.5%) from the upstream industry N=OC, R&D, ICT. The IA work shares l_Y are lower than from Innodrive, since IA type occupations are defined more broadly. The shares l_Y are considered the same in all countries and the combined multiplier $a^N l_Y^{IC}$ is 1.8 for OC wage expenses, 1.6 for R&D wage expenses, and 1.45 for ICT wage expenses. Table A1 summarizes the combined multiplier A^{IC} (the product of the share of effort devoted to IA production and the factor multiplier).

Table A1.
Combined multipliers for OC, R&D and ICT and their depreciation

	OC	R&D	ICT
Employment shares l^Y	25%	50%	35%
Factor multiplier a^N	1.8	1.6	1.45
Combined multiplier $A^{IC} = a^N l^Y$(rounded)	1.45	0.8	0.5

Appendix B
Performance-based estimates of intangibles

Applying the Cobb–Douglas technology (constant returns), the IA output elasticity ε (dropping m for the type of IA) is equal to its income share of the value added, as follows:

$$\varepsilon \approx \frac{P^N(\rho+\delta)R^*}{P^Y Y}, \tag{B.1}$$

where the rental rate $(\rho+\delta)R^*$ includes the depreciation δ and the external rate of return ρ (assumed 4% here), and $P^Y Y$ is the nominal value of value added. Perpetual inventory method from (5) in steady state $N^* = (g_R+\delta)R^*$ with constant growth of IA investment g_R and (B.1.) yields

$$\varepsilon \approx \frac{P^N N^*}{P^Y Y}\frac{\rho+\delta}{g_R+\delta}, \tag{B.2}$$

where N^* is the unknown performance-based value added. The nominal value of an intangible capital investment of type IA in the production function-based approach is given by the following:

$$N^* = \kappa N, \tag{B.3}$$

where N is the expenditure-based intangible investment used as the initial proxy for the performance-based value N^* and κ is the performance multiplier, i.e., a production-function-based productivity adjustment. Equation (19), taken as holding with equality, and (B.3) yield the value of the performance multiplier for the expenditure-based estimation of IA investment.

$$\kappa = \varepsilon\frac{P^Y Y}{P^N N}\frac{g_R+\delta}{\rho+\delta}, \tag{B.4}$$

where $\rho = 4\%$ and $g_R = 2\%$ follows average increase in wages. The net return requirement on R, ρ could also be firm-specific and depend on the output/IA ratio Y/R^* as given by (8) $\rho = \varepsilon\frac{Y}{R^*} - \delta$. In (B.4) the share Y_t/N_t is assessed at the industry level. $P^Y Y/P^N N$ in (B.4) is limited to between the 90th and 10th deciles of the overall figures. A higher steady-state growth g_R and a lower (future) rental cost ρ implies that the value of the intangibles must be revised upwards. If they remain the same in the future, the IAs are imprecisely measured or their valuation reflects monopolistic competition in the downstream market.

An upward-biased initial nominal expenditure-based estimate would affect the constant in the production function estimation but would not alter (significantly) the output elasticity ε. However, N^* would be lower as the higher N enters the denominator of (B.4). Hence, an upward-biased initial nominal expenditure-based estimate would lead to revision downwards of the performance-based estimate and vice versa for downward-biased initial expenditure estimates. If the supplier of intangible power has monopoly power (when purchased rather than being own-account) the price of P^N can also be too high, which should be adjusted accordingly to have the true lower real value of N.

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