Deliverable 1.2

WORKING PAPER FOR MEASURING THE INTANGIBLES USING REGISTER DATA

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1. SUMMARY

This paper (deliverable 1.2) introduces framework for measuring intangibles (IA) at firm level for the purpose of indicator development and productivity analysis. The paper outlines the theoretical foundations and empirical methodology to tested and utilized in the GLOBALINTO project. The approach builds on work by the FP7 Innodrive project. The framework developed in this deliverable will be operationalised and tested in WP3 based on register-based firm-level data from national statistics institutes (NSIs) in four countries: Denmark, Finland, Norway and Slovenia. This work will also be informed by the results of the large scale pilot survey of intangibles in WP4. The constructed and validated data will then be used in a series of econometric analyses in WP5 that explore the relation between intangible assets and productivity, and factors that may influence this relationship.

Intangibles are derived from innovation type work using linked employer-employee data that includes occupational and education data on employees. In the analysis of productivity, the main interest is labor-augmenting technological change, and hence new innovation that potentially can have important spillovers.

Three types of intangible assets are defined and measured: research and development (R&D), organizational capital (OC) such as management and marketing, and information and communication capital (ICT). Organizational capital can be an important motor of labor-augmenting technical change besides R&D and ICT. On the other hand, R&D leads to commercialized innovations and hence may contribute more to the accumulation of IAs and hence to innovations that are not freely available or shared. The level of IA and knowledge spillovers may also very depending on firm characteristics such as the size of the firms.

2. Introduction

The System of National Accounts applies similar methods to analyse physical and intangible capital. Both requires the knowledge of the amounts of investment and how they depreciate over time. Intangible investment is not usually standard part of accounting practises in firm or they may not be fully reported. A main reason is conservative accounting rules requiring that essentially all (internal) innovation labor expenses be immediately expensed when reported as normal labor compensations. One important difference between intangible and physical capital is that intangibles are also used as inputs in innovations which may directly affect the knowledge that is potentially available to other firms. Intangibles investments may thus generate knowledge spillovers, which may be unintentional by the company itself.

This paper models the role of intangibles in both capital deepening and knowledge that improves labor-augmenting technological change. The purpose of this paper is to model the theoretical foundations behind our approach to measure intangible assets at the firm level. The measurement framework developed here will form the basis for empirical work to construct and assess intangibles measures in WP3 of the GLOBALINTO project, and econometric analysis in WP5. Micro-level work in WP3 and WP5 will be based on register-based data of firms from NSIs in four countries: Denmark, Finland, Norway and Slovenia. As an example, firm level data for Finland will be employed to illustrate the framework developed in this paper.

Micro-level measurement of intangible assets (IAs) is important as firms are the foundation for aggregation to industry and national account levels, in both statistics and economic analysis. Furthermore, recruitment of skilled people is an important part of knowledge spillovers. Through learning by doing introduced by Arrow (1962) employees bring knowledge from their former job relationships to the new company. The value of IA also depends on to whom the profits accrue, which is determined by the market power of the supplier of knowledge, an aspect that may also vary by the size of firms.

The method applied here evaluates intangibles at the firm level from innovation-type occupations, which is an important step to broaden the concept of IA. Innovation-type occupations are managerial and technical positions that are assumed to generate new knowledge that can create additional value for the firm. We measure own-account IA, which is assumed to be produced with similar share of factor inputs as used in the production of purchased IAs. Much of the latter may also consist of intermediates used in the production of "own-account" IA and currently categorized as intermediate inputs from business and ICT services. Modelling follows the EU 7th framework project Innodrive, see (Piekkola et al., 2011), see also Piekkola (2016), and the Organization for Economic Cooperation and Development (OECD) study by Squicciarini and Le Mouel (2012). Three types of IAs are constructed: organizational capital (OC) relates to marketing and management, and research and development (R&D) to R&D work and engineering in general, and information and communication technologies (ICT). Each individual innovation-type occupation is assumed to contribute to a single type of IA so that measures of each type of IA are mutually exclusive.

Organizational capital (OC) is evaluated from management and marketing work, which is important part of economic competence in Corrado, Haskel, Jona-Lasinio, and Iommi (2012). Economic competence accounts for 38 % of all intangible capital in the EU countries. Marketing related design and branding are separate segments of economic competence but marketing is included in organizational capital here. Business and management consultancy activities (mainly NACE 702) are indeed an essential part of purchased OC by other industries, which are here included here in ad hoc manner as intermediates for OC. The methodology is to assume a multiplier for use of the intermediates and tangible investment for each unit of IA labor cost. The OC labor combined with other factor with multipliers may also give a good approximation of total OC. This result derives from production function estimations, where the output elasticity of OC is compared to the value added share of OC investment using the FP 7th framework project Innodrive methodology, see Piekkola (2016).

Information and communication technology (ICT) capital is evaluated from ICT services occupations. These register-based data are particularly important for analyzing low-market-share small firms, which are not entirely covered in R&D survey data. ICTs are also important to include in the analysis as Bronwyn H. Hall, Lotti, and Mairesse (2013) find underinvestment in ICT in Europe.

One important novelty in Globalinto project is to evaluate the effects of IA on labor-augmenting productivity as an extension to Hellerstein, Neumark, and Troske (1999) and Ilmakunnas and Piekkola (2014). In these papers IA labor shares proxy IA's relative productivity, which is here also referred to as labor-augmenting technical change. The improvement here is that the labor quality improvement is initially measured by the compensations paid to IA work relatively to other work done by skilled workers. Corrado, Haskel, Jona-Lasinio, and Iommi (2016) suggest that innovations are combination of increased IA accumulation related to new knowledge products that can be commercialized and new technology that shows up as an increase in total factor productivity (TFP). However, using residuals of the production function as a proxy for TFP can be problematic as it includes all the errors and mismeasurements of variables. Labor-augmenting technological change is a good approximation of technological improvement. Human capital is acomponent important input in innovation development, where about 80% of R&D costs are compensations to employees. Another addition here is to include in the same framework IA deepening; see e.g. Haskel and Westlake (2017) and Roth and Thum (2013) for studies related to the latter.

In explaining TFP, Añón Higón, Gómez, and Vargas (2017) find R&D, human capital, and design all to contribute to TFP but estimation with interactions make results more puzzling, showing no evidence of complementarity between R&D and human capital. However, the analysis suggests human capital to be considerably more important in explaining TFP than R&D. Human capital has also an important role to play as majority of tertiary educated staff are engaged in IA activity. The analysis also differs from the innovation literature where innovations are considered separately and R&D inputs are part of the "innovation production function" , see Hall, Mairesse, and Mohnen (2010). If accumulated R&D is a rough measurement of commercialized knowledge innovations, such a method using R&D as input may not include the knowledge that spreads freely.

Micro-level analysis in the Globalinto project will be conducted in four countries where linked employer-employee data is available: Finland (University of Vaasa), Denmark (Aarhus university), Norway (Statistics Norway) and Slovenia (University of Ljubljana). The framework in this paper will be illustrated using a Finnish dataset covering firms in 1995-2014, as is done in Piekkola (2019b). Analysis using register-based data on compensations, occupations and education has many advantages. Estimation of production functions can be done separately within each NACE 3-digit industry and for three types of firms: micro firms, small-market-share and large-market-share firms. Analysis thus gives large flexibility to production functions across firms and acknowledge that market power is likely to change with firm size. An Aghion and Howitt (2008) type approach on innovations assumes that suppliers of knowledge in the firm have full monopoly power. In such case, a substantial share of revenue productivity of large firms may be explained by higher than competitive prices on goods and services sold rather than by technology improvement. On the other hand, large firms can also be closer to steady state and have to innovate more themselves and firms' contribution to labor-augmenting technical change should be greater. SMEs may engage in more imitative growth, but they may also learn from each other and not just follow the leader in the industry. The analysis of IAs cover also micro firms with less than 10 employees.

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

In a simple framework, downstream industries produce final goods using IA from upstream industries. IAs are like intermediate inputs provided from upstream industry to downstream industry with one important difference: Schumpeterian or Romerian growth models as introduced in Aghion and Howitt (2008) consider these intermediate inputs as sources of new innovations and technological growth. However, IAs are enduring and accumulate over time. Because of this, analysis should include the capitalized value of intangibles labelled as R. The measurement of R depends on whether measuring from intermediates; see industry-level studies on (purchased) IA, such as those by Corrado, Haskel, Jona-Lasinio, and Iommi (2014) and Piekkola (2018), or from innovation-type work in downstream industries. Goodridge, Haskel, and Wallis (2014) describes income flows in intangible asset producing upstream industries and intangible asset consuming downstream industries (here we abstract from subindex for period t):

$$P^N N \equiv P^L L^N + P^K K^N + P_N^R R^N + P^M M^N \tag{1}$$

$$P^Y Q \equiv P^L L^Y + P^K K^Y + P_Y^R R^Y + P^M M^Y , \tag{2}$$

where N is intangible capital output in upstream industry, Q is output in downstream industry, L is labor, K is tangible capital, R is intangible capital, M is intermediates and P shows respective prices, all separately for upstream N and downstream Y industries. $P_Y^R R^Y$ is rental payment or implicit costs when the asset is purchased from upstream N industry and $P^M M^Y$ are intermediate inputs from other industries. An example of this is ICT intermediate inputs that are often combined with skilled labor in ICT activity in the firms. Output in the upstream industry adds R stock in the downstream industry and the price of renting this unit is

$$P_Y^R \equiv (\rho + \delta_R) P_N^N \ . \tag{3}$$

where δ_R is a suitably chosen (private) depreciation rate and ρ is net returns. The most usual convention in choosing 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 (2009), Copeland, Medeiros, and Robbins (2007, pp. 31-32). The parameter P_t^N here used in all sectors denotes the input cost based producer price (GDP) deflator for business services (NACE M69-74, excluding NACE M71 and NACE M72). R&D services were also dominated by large enterprises in Europe as a whole with main operations in other industries so that large manufacturing firms may have R&D units categorized as belonging to this industry. In 2012, large enterprises (employing 250 or more persons) employed about half of total workers in EU28 in the NACE M72 sector (1.2 million workers). Hence, the use of the M72 producer price deflator would not be very representative of IA activity in general, although it is preferred by statistical institutes.

In the method used, all IAs are own-account, which may be supplemented by information on purchased IAs if available, such as for external R&D expenditures in R&D surveys. The downstream industry may have its own knowledge production function so that in (2) $P_Y^R R^Y$ is the accumulated value of total IA from

$$P^Y N^Y \equiv P^L L_{oa}^Y + P_{oa}^K K_{oa}^Y + P_Y^R R_{purchased}^Y + P^M M_{oa}^Y . \qquad (2')$$

Upstream industry IA $P_Y^R R_{purchased}^Y$ would be part of the knowledge production function. The knowledge production function may not be subject to competitive forces or can be considered as additive when total IA is simply a sum of own-account IA and purchased $P_Y^R R_{purchased}^Y$. $P_Y^R R_{purchased}^Y$ may not be known while $P^M M_{oa}^Y$ (can be estimated at industry level from input-output tables but is not available at firm-level) can stand for the output from the knowledge-producing upstream industry. This should be combined with innovation-type labor and related tangible capital to produce the IA output, for industry-level analysis see Piekkola (2018)

Innovation work covers R&D, ICT and organizational assets (OC), which in the Innodrive approach are combined with the assumed use of tangible capital and intermediate following (2'). The information for this is obtained by observing how in upstream industry value added is divided into factor inputs in income flows. Another important feature in the Innodrive approach is that labor is divided into that used in final goods and knowledge production. Such division is not made for tangible capital as this typically represents a small proportion of factor inputs. In many instances, the knowledge production function uses only buildings that can be considered as fixed costs in the short term. The knowledge production function (2') is embedded in final goods production (2), where labor used in innovation activity is excluded from labor used in final goods production. Following the analysis of productivity in Hellerstein et al. (1999), innovation work L_m, $m = RD,$

ICT, OC is considered qualitatively different from other work so that labor-augmenting technological change A is given by:

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

where $a_m, m = RD, ICT, OC$ is labor-augmenting technological change (quality adjustment), L_{RD} is R&D work, L_{ICT} is ICT work , and L_{OC} is OC work, and the rest $L - (L_{RD} + L_{ICT} + L_{OC})$ is non-innovation type work. a_m is the direct effect of IA on technological change. Modelling technological change as part of innovation decision leads to endogenous Schumpeterian and Romerian growth models, see Aghion and Howitt (2008). In these models, innovations are dichotomous so that productivity improvement such as a_m takes place with some probability. Typically, IAs and related patents are owned by the firm, so the expectation is that employees receive compensation only after related intellectual property rights are taken into account. But if workers have all the knowledge, which e.g. may happen from recruitment of top innovation workers, quality adjustment a_m should reflect the wage differential between IA and other workers. The novelty here is that the initial a_m can be approximated by the wage differential between IA worker of type m and other skilled workers in the firm. An important implication of this Hellerstein et al. (1999) type analysis is also that shifts in the share of m workers L_m / L is driven by new IA employees that may bring with them knowledge from previous work relationships. Thus technological change links to knowledge spillovers between firms, some of which may be unintentional as also considered here, see also Piekkola (2019c).

Besides this technological link, IAs are typically considered as capital that depreciate over time and hence behave much like other fixed capital. IAs even depreciate usually at higher rate; for example

OC by 20-25% annually, while the deprecation rate of buildings is typically 3% and 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, Hulten, and Sichel (2005) is retained for services. Depreciation rates of 15% are used for R&D.[1] The implied ICT life length of 4 years is an average of the 3.2-year life length of software in Awano et al. (2010) and the 5-year life length of hardware in Wallis (2009). The perpetual inventory method is applied here for stock calculation:

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

where N_{mt} denotes real investment, R_{mt} denotes real IA stock at time t and δ_m is the depreciation rate for IA of type $m = RD, ICT, OC$. If the stock of intangible capital is rented for shorter period T, the annual value of investment follows in each period:

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

where N_{mt} denotes real IA investment of type m at time t. Here IAs are assumed to grow over a sufficiently long period at a constant (firm-specific) rate g_m so that (dropping time subscripts), see Bronwyn H Hall (2007):

$$\begin{gathered} R_{mt} = \frac{N_t}{g_m + \delta_m} \quad or \\ ln R_{mt} = ln N_{mt} - ln(g_m + \delta_m) \end{gathered} \quad . \tag{7}$$

This equation holds in 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%, aimed to reflect the sample average

[1] Recent estimates of depreciation are from a survey by Awano, Franklin, Haskel, and Kastrinaki (2010)

real output growth rate of business services over the 2008-2013 period (NACE M69-M70, M73, M74-M75).

The intuition is that all assets are accumulated to a level where their rate of return equals their depreciation. 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 production function estimation, since the firm-level differences in depreciation and growth rates will be incorporated into the firm effect. The elasticity of output with respect to R and N is the same, ε. This is also the main reasonwhy output elasticity also shows the optimal IA investment/value added share, see (13) in later analysis. The choice of the gross $\partial Y / \partial R$ and net rates of return ρ_R are still different:

$$\begin{aligned} &\frac{\partial Y}{\partial R} = \varepsilon \frac{Y}{R} \text{ and} \\ &\rho_m = \varepsilon \frac{Y}{R^*} - \delta_m \end{aligned} \tag{8}$$

Knowledge of δ_m is needed to convert gross returns $\varepsilon Y / R^*$ to net returns ρ_m. Fixing net returns ρ_m is required to derive the optimal share of IA investment/value added in (13) as IA investment is derived from user cost of IA and this varies depending on ρ_m. We consider technological improvement though RD, ICT and OC while K denotes tangible capital. The production function of value added $Y_t = Q_t - M_t$ with double deflation and abstracting from the time dimension is given by the Cobb-Douglas production function yielding constant returns with $\alpha_L + \sum_m \alpha_m + \alpha_K = 1$ or $\alpha_L = 1 - \sum_m \alpha_m - \alpha_K$, m= RD, ICT and OC. The production function for each firm i is given by

$$Y_{it} = \left(AL_{it}\right)^{1-\sum_m \alpha_{mi} - \alpha_{ki}} \prod_m \left(R_{mit}\right)^{\alpha_{mi}} K_{it}^{\alpha_{Ki}}, \qquad (9)$$

We can approximate this in log form (dropping subscripts) using $\ln AL = \ln L + \ln\left[1+(a_R-1)L_R/L+(a_O-1)L_O/L\right] \approx \ln L + (a_R-1)L_R/L+(a_O-1)L_O/L$ 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) can be estimated in the log form for each industry j:

$$\begin{aligned}\ln Y_{it} = \alpha_{Yj} \ln Y_{it-1} + \alpha_{Lj} \ln L_{it} + \sum\nolimits_{m,i\in j} \alpha_{Amj}(a_{mj}-1)L_{mit}/L_{it} + \sum\nolimits_{m,i\in j} \alpha_{mj} \ln R_{mit} \\ + \alpha_{Kj} \ln K_{it} + \alpha_{Zj} \ln Z_{it} + e_{it}\end{aligned}, \qquad (10)$$

where a_{Amj} is labor-augmenting technological change for m=R&D, ICT, OC in industry j given by $a_{mj} = \alpha_{Amj}/\alpha_{Lj} + 1 > 1$ where parameters vary from one industry j into another, Z_t is the vector of year dummy variables and e_{it} is log of disturbance term $\exp(e_{it})$. It is noteworthy that R&D, ICT and OC assets have high correlation to each of around 0.6, while L_{mit}/L_{it} for m=R&D, ICT, OC has correlation below 0.3 to these IAs. The variance inflation factor (VIF) does not imply that the multicollinarity is too high.

Our preferred estimation goes beyond Hellerstein et al. (1999) and uses as an initial proxy for labor-augmenting technical change relative compensations $\hat{a}_{wmi} = \overline{w}_{mit}/\overline{w}_{Lit} - 1$, where $\overline{w}_m$ is the median compensation on innovation work of type m in firm i and $\overline{w}_{Lit}$ is the median compensation 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 human capital possessed. Median compensations of skilled workers in firms (total annual earnings divided number of employees) $\overline{w}_{Lit}$ are set to be within the 5 percentile and 95 percentile distribution of overall average compensations across all firms. $\overline{w}_{mit}$ is measured from median annual compensations for m type innovation work divided by the number of m type workers. Compensation ratio $\overline{w}_{mit} / \overline{w}_{Lit}$ of each firm is finally set within the 1 and 99 percentiles of the overall distribution.

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 compensations in producing them. The production function can be estimated in the form:

$$\begin{aligned}\ln Y_{it} &= \alpha_{Yj} \ln Y_{it-1} + \alpha_{Lj} \ln L_{it} + \alpha_{wmj} \sum\nolimits_{m,i\in j} (\hat{a}_{mit} - 1) \frac{L_{mit}}{L_{it}} + \sum\nolimits_{m,i\in j} \alpha_{mi} \ln R_{mit} \\ &\quad + \alpha_{Kj} \ln K_{it} + \alpha_{Zj} \ln Z_{it} + e_{it}\end{aligned} \quad , (11)$$

where $\alpha_{wmj}(\hat{a}_{mit} - 1) = \alpha_{Lj}(\hat{\hat{a}}_{mit} - 1)$ so that $\hat{\hat{a}}_{mit} = \alpha_{wmj}(\hat{a}_{mit} - 1)/\alpha_{Lj} + 1$. The labor-augmenting technological change $\hat{\hat{a}}_{mit}$ is firm- and time-varying depending on changes in relative median compensations $\hat{a}_{mit} = \overline{w}_{mit} / \overline{w}_{Lit}$.

It is likely that the technological information also spreads to some extent to all firms in the industry. In endogenous growth models, this follows learning by doing first introduced by Arrow (1962). Workers shift jobs and hence spread knowledge on innovations, creating productive externalities to all firms. It is likely that such endogenous but unintentional growth for any single firm is even more important for IAs than for existing operational knowledge. Spillovers are created by the improved quality of all IA workers in the industry and this may affect technological improvement across the industry. The estimations can be done separately for the three firm types k: micro, small-market share, and large-market-share firms, but cover knowledge spillovers from all types of firms in the same industry (first term in brackets in (12)). Estimation can also include, and in (11), a wage ratio proxy for labor-augmenting technological change (second term in brackets):

$$\ln Y_{it} = \alpha_{Yj} \ln Y_{it-1} + \alpha_L \ln L_{it} + \sum_m \left(\sum_k \alpha_{spill,mk} \sum_{i \in k,j} \frac{L_{imt}}{L_{jkmt}} (\hat{\hat{a}}_{mit} - 1) + \alpha_{wjm} (\hat{a}_{mit} - 1) \frac{L_{imt}}{L_{it}} \right) \quad (12)$$
$$+ \sum_m \alpha_m R_{mit} + \alpha_K \ln K_{it} + \alpha_Z \ln Z_{it} + e_{it} \,,$$

In IA knowledge spillovers (first term in brackets), labor-augmented productivity change $\hat{\hat{a}}_{mit}$ from estimation of (11) is aggregated to industry level j and separately in all firm types k. Aggregation uses as weights each firm's labor shares in each k category. The contribution to knowledge spillovers of each firm of type k in industry j thus depends on the relative size of the firm. In (12), with $\hat{a}_{mit}$ again a wage ratio $\overline{w}_{mit} / \overline{w}_{Lit}$, an estimated α_{wjm} higher than α_L indicates that labor-augmented technical change exceeds the wage ratio. Our main interest here is knowledge spillovers of intangibles of type m depending on firm-size.

Output elasticities of IAs are likely to vary depending on how labor-augmented technical change and knowledge spillovers enter the production function. It is also of considerable interest to assess whether expenditures of IAs, in the first place, measure well their performance. Appendix B shows the derivation of performance-based values of IAs following again the Innodrive methodology. The performance-based approach is first applied using production function (9) in log forms with quality adjustment yielding log form (11). The aim is to estimate how the expenditures on IAs also reflect the actual performance of IAs. This uses information about the output elasticities of intangible capital R_m^* for m= R&D, ICT, OC using the production function. The net return ρ is fixed and thus externally set e.g. due to competition (the price change component in user costs is also ignored). The analysis isdone close to steady state so that the growth of IAs are fixed following the productivity improvement.

Note that the elasticity can be biased if not adjusting for knowledge spillovers with endogenous growth and if the price of knowledge faced by the downstream sector is not the competitive price due to imperfect competition. The factor shares in that sector will be biased measures of output elasticities since they include mark up.

4. Linked employer-employee data and the measurement of IA

An illustrative example is provided here based on linked employer-employee data for Finland covering1994-2014. Compensations used to evaluate IA are annual payments including rent-sharing, while IA compensations relative to skilled workers use hourly wages. Firm-level data is full data of firms with around 1.6 million firm-year observations, where about 1.3 million are firms with average less than 10 employees. To have reasonable estimates it was required that both R&D and OC type work has been done at least in one year and in general in all years firm has IA of some type. All this reduces sample size of micro firms considerably and about the third of total sample remains in other firms. The sample size for firm-year observation was 37.9 thousand for micro firms, 26.3 thousand for small-market share firms and 55.6 thousand for large firms out of the original 1.6 million firm-year observations.

IAs are measured by investments in intangibles from the wage incomes of employees within selected occupations that are related to innovation-type work. Measured this way, various kinds of IAs do not overlap with each other and hence there is no double counting. Organizational assets accumulate through investments in management and marketing activities building up organizational knowhow. R&D assets are accumulated through the technical activities of the firm, and thus are broader than measures based on the formal definition of R&D expenditures given in the Frascati Manual (OECD, 2015). ICT assets are accumulated through the performance of ICT-related services.

The EU Innodrive 2008-2011 seventh framework project (FP7) developed the measurement of internal IA based on identifying IA labor input from related occupations. We need to identify two things. The first is which share of worktime is spent on innovative work that affect the future and which time share is just running existing operations and should be thus excluded. The second open question is how the IA work is combined with the use of other factor inputs: intermediate inputs and tangibles.

Occupations related to intangible work areclassified according to their function (top management, corporate management, research, development, implementation, computer, marketing, personnel management, etc.). ISCO 2010 coding (ISCO-08, previous version from 2001) has been formed in a comparable matter across European countries and is applied here. A good approximation for the task quality is that IA workers are assumed to have attained upper tertiary education level.

Appendix A provides a detailed description of the innovative work coding in IA work. Workers are additionally switched to being ICT workers in other IA occupations if their educational field (isced2011) 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. The occupational classification is similar to 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. Following early research in Innodrive the share of the work in IA related work dedicated to producing IA is assumed to be 25% for OC workers, 50% for R&D workers and 35% for ICT workers when using broad definitions of occupations with ISCO two-digit level, see Table A.1 in the Appendix. 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: tangibles and intermediates.

Intermediate and capital costs are also incurred in the production of IC goods in each industry. These goods are evaluated based on how labor costs, intermediate inputs, and tangible capital combine as the value added in R&D services (NACE M72). In other industries, not only IC work but also a part of the intermediate inputs and tangible capital are used to produce internal IC, which can be separated from the production of final goods. The EU Innodrive 2008-2011 seventh framework project (FP7) provided the methodology described in Piekkola (2016) and Görzig, Piekkola, and Riley (2010) used to combine IC labor inputs with other factor inputs to produce IC investment. The use of intermediate inputs and tangible capital in intangible investments as the factor multiplier is evaluated based on the benchmark of business services (NACE M) and not only R&D services. Real expenditure-based investments of type IC = R&D, ICT, OCare as follows:

$$P_{jt}^{N} N_{it}^{IC} \equiv A^{IC} W_{it}^{IC}, \qquad (5)$$

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 A.1). Following Innodrive, the factor multiplier is the intermediate and capital costs of one unit of innovative work set to represent the entire EU27 area and is the weighted average of the factor multipliers in Germany (40% weight), the UK (30% weight), Finland (15% weight), and the Czech

Republic and Slovenia (both countries have weights of 7.5%). The combined multiplier A^z is 1.8 in OC wage expenses, 1.6 in R&D wage expenses, and 1.45 in ICT wage expenses;see Table A.1 in appendix. Tangible capital investment is drawn from gross fixed capital formation: equipment, property, and construction reflecting its use in IA services that produce the same kind of IA for sale as the firms can produce internally.

The share of IA work for all employees is in Finland 4.7% for OC, 1.6% for ICT and 5.6% for formal R&D from surveys (totaling 11.9%) or 8.2% for broad R&D (totaling 14.5%).[2] The share of OC, ICT and R&D workers then approximately follows the Innodrive FP7 described by Görzig, Piekkola, and Riley (2010) and Piekkola (2016). A fairly large share of organizational work is also suggested by Squicciarini and Le Mouel (2012); they also analyze ICT and OC work together. IA work is here excluded from employment figures to avoid double accounting. Schankerman (1981) and Bronwyn H 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.

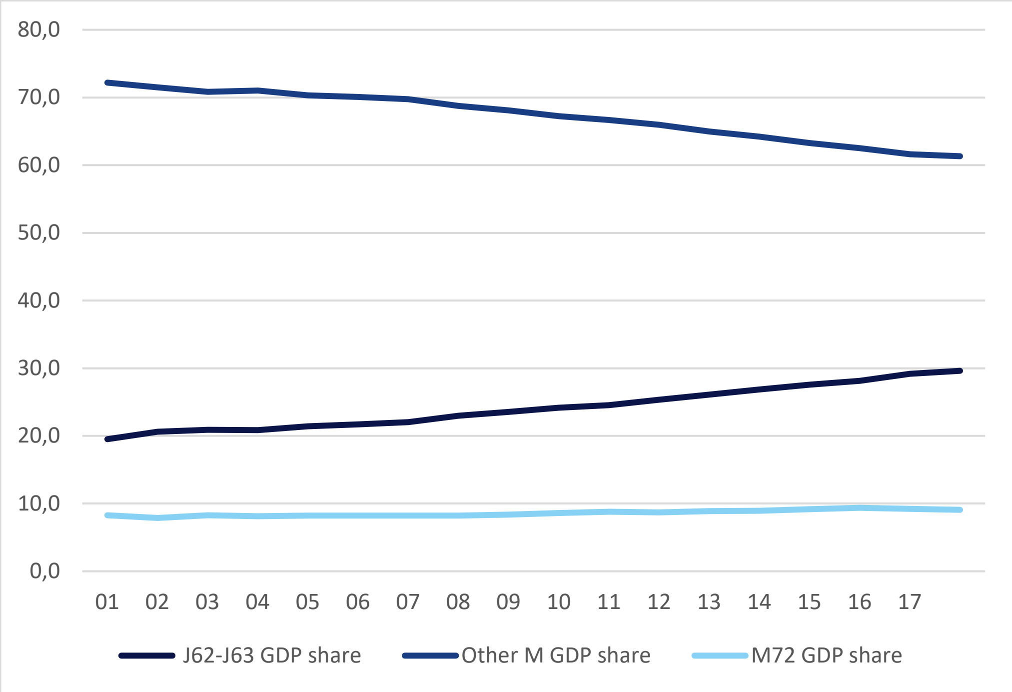
One way to check whether IAs values are of the right magnitude is to see whether performance-based estimates are close to expenditure-based values. Here we use output elasticities of IAs in NACE Digit 3-industry level estimated from (11) thus controlling for labor-augmenting technological change. Piekkola (2019) suggests that the expenditure-based estimates are rather good approximates and reflect the true value of total IAs. Since the distribution of firm size is highly skewed, it is useful to report the mean and median values of IAs. In Finland, the number of employees has a mean value of 110 and a median value of 71.

[2] 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 and are likely to be important in the production of R&D .

Business (NACE M) and ICT services (NACE J62-J63) are most intensive in IAs and can be considered as upstream industries providing purchased IA to other industries. In the EU area in 2012 the total number of persons employed of the total workforce for professional, scientific and technical activities and ICT services was around 10% in 2000 in the upstream industries, which had decreased to 9% by 2015. The employment share is also close to the employment share of IA work in all business, ICT and manufacturing that produce own-account IA, which was here 11.9%. Hence IAs evaluated from innovation-type work or from innovation-type intermediate input from upstream industries such as business services end up with around the same figure. This is also true for the value added share of IAs. The median value is 11.3% in innovation-type data used here, while IAs evaluated from innovation type industry-level intermediates from upstream industries (business and ICT services) gives 10.8% (from updated data for 2008-2016 from that used in Piekkola (2018)). Own-account and purchased IA measure the same thing so that intermediates from upstream industry are the intermediates that are used in own-account production of IAs.

To evaluate IAs in the European context, Figure 1 shows development of value added shares within business and ICT services in EU28. ICT services such as computer programming, consultancy, and related information service activities have increased in importance by 10%-point at the cost of traditional business services, whose share has decreased from over 70% to 60%. R&D activity (NACE M72, part of NACE M) has retained the same 10% value added share of business and ICT services (the shares are based on European business - facts and figures data from 2012).

Figure 1. Value added shares in Business services and ICT services in EU28



The basic insight here is that OC produced in business services is potentially important part of IA, although we do not have estimate of own-account. Also, the multiplier to combine OC type work with intermediate inputs of 1.8 (such as from business services) was higher than for R&D type work 1.45. Average personnel costs within the EU-28's R&D services were 72 thousand euros per employee in 2000 (2010 prices), increasing to 78 thousand euros per employee by 2014 (2010 prices) showing high and increasing qualifications held by persons. It is still below the average 88 thousand euros (2010 pricese) per employee in the rest of business services. The compensation difference gives a first support that labor-augmenting technological change is furthermost achieved through OC.

Figure 2 shows that the value added per labor costs (average labor costs per worker multiplied by personnel wL) was in 2014 for the EU-28's 200% for business services (other than R&D services) and 172% for R&D services.

Figure 2. Value added per labor cost, % in EU28.

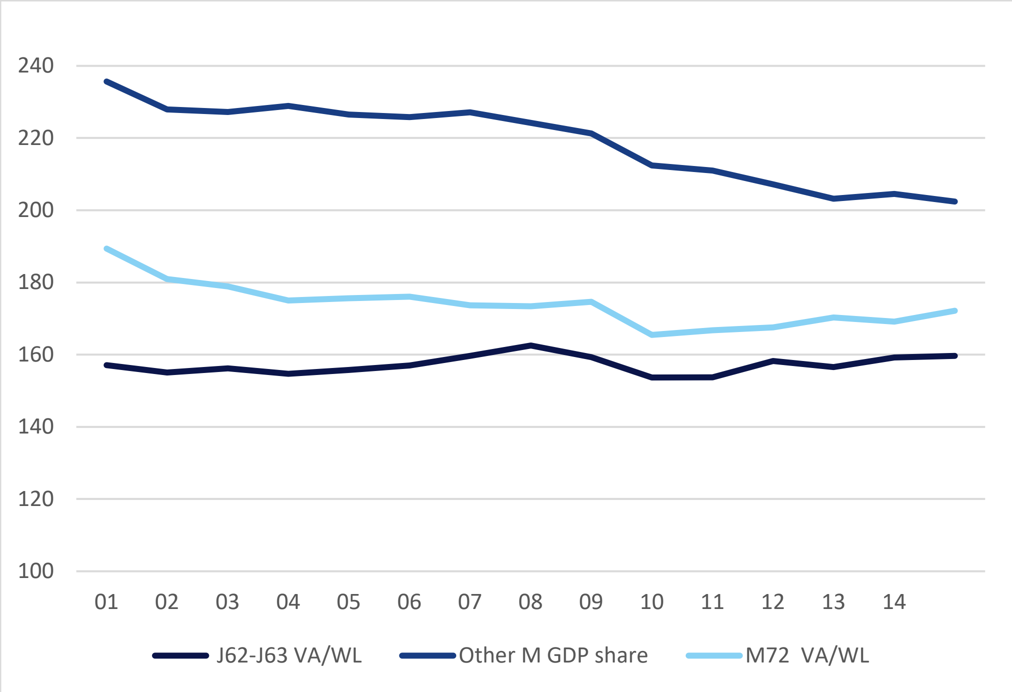


Figure 2 shows that in business services, value added per labor cost decreased over the time in other than R&D and ICT services in particular since 2004. The share is still higher than in R&D services, which suggests that organizational capital produced is valuable. Business services suffered from financial and debt crises of Europe since 2008. This is in line with finding by Piekkola (2018) that relied on measurement of purchased IA from these upstream industries. Most of the decrease in labor productivity after financial crises was explained by a decrease in such (purchased) IC in the Euro area. Since much of this IA is unaccounted and not part of capital deepening, this shows up as a decrease in total factor productivity. ICT services performed better as the value added per labor costs has stayed around 160% throughout the period in Figure 2.

5. Conclusion and expected results

Our framework models IAs as part of separate production function of knowledge in companies. This includes "purchased" IAs from upstream industries that are in current accounting practices considered as intermediates. The way how OC work is combined with intermediate investment (value added from upstream industry such as NACE 702) and tangibles can measure well the overall amount of OC, since intermediates used approximate well purchased OC. For R&D external R&D is also included mostly from large firms where this information is available. This broad R&D reflect the overall R&D quite well. Considering own-account IA and purchased IA as separate in the knowledge production function may easily lead to double counting for OC.

Organizational capital should not be ignored as expected to having higher effects on productivity than R&D. Ilmakunnas and Piekkola (2014) applied precise functional occupational classification and was unable to find R&D to have a significant effect on total factor productivity. Labor-augmenting technological change can be assumed to spread to a high extent through inter-firm labor mobility. However, technology also spreads unintentionally as found here in NACE 3-digit industry level. In these knowledge spillovers, besides R&D, organizational capital may play the pivotal role.

The R&D capital stock is expected to be higher than the OC capital stock, because the depreciation rate is much lower. For example, in Finland the median value of R&D per employee is 19 thousand euros, whereas that of OC is 6 thousand €2010 using 1994-2014 data. R&D produced hence more commercialized knowledge that is marketable and accumulates over time.

Piekkola (2019a) found productivity growth of SMEs to be described by this "imitative" behaviour but also by negative selection: firms with low initial productivity are more likely to make innovations since they have less to lose if they fail (opportunity costs of not innovating are lower). SMEs with low market share absorb more the general knowledge produced in the industry, but innovations can also be more risky. Not all high growth in productivity turns out into higher profitability, also because of negative selection.

All this show should show important policy implication of innovation policy. We expect important differences between countries as the relative abundancy of various forms of IAs vary.

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Appendix A. Measurement of intangible capital (IC) and tables

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

- Managing directors and chief executives 112 (112)
- Administrative and commercial managers 12 (123 all)
- Services and administration managers 121, Sales, marketing and development managers 122
- Managing, mining, construction and distribution managers 13, 131 (122)
- Manufacturing, mining, construction and distribution managers 132 (122)
- Professional services managers 134 (122)
- Teaching professionals 23 (23)
- Business and administration professionals 24 (241 all)
- Finance professionals 241, Administration professionals 242, Sales, marketing and public relations professionals 243
- Legal, social, cultural and related associate professionals 34 (all) (242)
- Legal, social and religious associate professionals 341 (343), Sport and fitness workers 342 (347), Artistic, cultural and culinary artist professionals, 343 (347)
- Business and administration associate professionals 33 (excluding 335):
- Financial and mathematical associate professionals 331 (343), Sales and purchasing agents and brokers 332 (342), Services agents 333 (342)
- 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

- Technical and mathematical work professional R&D managers 1223 (1237)
- Science and engineering professionals 21 (excluding telecommunication engineering 2153)
- Physical and earth science professionals 211 (211), Engineering professionals 212 (212) Mathematicians, statisticians, life science professionals 213 (212), 214 (212), Electrical, electronics engineering 2151, 2152 (212), Architects, planners 216 (212)
- Health professionals 22
- Medical doctors 221 (222), Nursing and midwifery professionals 222 (223), Other health professionals 226 (223), 22 (isco3 not available)
- Science and engineering associate professionals 31
- 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 (Isced2011) computing and Isco3 in 2, 21, 22, 3, 31, and 32.

ICT work

- ICT managers 133 (1236)
- Telecommunication engineering 2153 (213)
- Information and communications technology professionals 25
- Information and communications technicians 35 (312)
- Nursing and midwifery associate professionals 226 (322)

Business services NACE M are the main providers of IA to other industries and R&D plants of large firms are also classified into these industries. Marketing and management utilizes services provided by head offices, and management consultancy services (NACE M69-M70); advertising, and market research services (NACE M73); and other professional, scientific and technical services and veterinary services (NACE M74-M75). Scientific research and development industry M72 is the source to derive the deflator for all kind of R&D activities, but naturally do not create a good picture of R&D activity in the economy as a whole.

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), and the Czech Republic, and Slovenia (both countries have weights of 7.5%) from upstream industry N=OC, R&D, ICT. 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 A.1 summarizes the combined multiplier A^{IC} (the product of the share of effort devoted to IA production and the factor multiplier).

Table A.1 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 $a^N l^Y$ (rounded)	45%	80%	50%

Appendix B. Performance-based estimates of intangibles

Applying Cobb-Douglas technology (constant returns), the output elasticity of IA ε (dropping m for the type of IA) is equal to it's income share of the value added

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

where the rental rate equals depreciation δ and the external rate of return ρ (assumed 4% here), and $P^Y Y$ is the nominal value of value added. (B.1) yields using perpetual inventory method from (3) $N^* = (g_R + \delta) R^*$ that

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

The nominal value of an intangible capital investment of type IA in the production function-based approach is given by

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

where N is the expenditure-based intangible investment used as a proxy for performance-based value N^* and κ is the performance multiplier, i.e. a production-function-based productivity adjustment. Equation (B.2), taken as holding with equality, and (B.3) yield the value of the performance multiplier for the expenditure-based estimation of IA investment.

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

where the net return requirement on R ρ is set fixed at 4% although it could be firm-specific and depend on the output/IA ratio Y / R^{*} $\rho = \varepsilon \frac{Y}{R^{*}} - \delta$. Here the share Y_t / N_t should be assessed at the same aggregate level as the output elasticity. IA figures that are extreme (such as close to zero) and factor multipliers $P^{Y} Y / P^{N} N$ are limited to between the 90th and 10th deciles of overall figures. Higher (future) growth g_R and a lower (future) rental cost ρ implies that the value of intangibles must be revised upwards. If they remain the same in the future, IAs are imprecisely measured or their valuation reflect monopolistic competition in downstream market.

Increasing N by some constant multiplier greater than one (see factor multipliers applied Innodrive methodology) increases proportionally N and R that would affect the constant in production function estimation but would not alter (significantly) the output elasticities ε. However, N^{*} would be lower as the higher N enters the denominator of (B.4). Hence, an upward-biased initial expenditure-based estimate would lead to undervaluation of the performance-based estimate and vice versa for downward-biased initial expenditure estimates. The performance-based analysis thus brings forth a knife-edge solution. Hence, the expenditures are more likely correctly measured the closer the initial value N is to the true value N^{*}.