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Abstract

This paper revisits the Heckscher-Ohlin-Vanek (HOV) theorem and investigates its fit for digital tasks and ICT capital, which both represent endowment factors that are expected to shape the digital transformation. We use a theory-consistent methodology for calculating the measured net factor content of trade (Trefler and Zhu, 2010) and apply it to a unique dataset on digital and non-digital tasks performed in detailed occupations, as well as recent data on ICT capital stocks. Equipped with these data we provide new evidence on the factor-based trade patterns for 25 EU countries and use it to test the HOV theorem. Overall, the performance of the sign test and the rank test is good if not impressive. In 83% of the cases countries are net exporters of those factors with which they are abundantly endowed, with a higher score achieved for digital tasks than for ICT capital. We conclude that the fit of the HOV theorem for highly relevant endowments of the digital era is as good as that of traditional endowment factors.

Keywords: Heckscher-Ohlin-Vanek theorem, factor content of trade, comparative advantages, digital tasks, ICT capital

JEL classification: F11; F14; D57

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1. Introduction

The digital transformation ranks highly on the political agenda of the European Union. In March 2021 the European Commission presented a 'Digital Compass' designed to guide Europe through its digital transformation until 2030 (European Commission, 2021). The compass for the digital era centres on digital skills, the digital transformation of companies, secure and sustainable digital infrastructure, and digital public services. Budgetary support for the digital transformation comes from the EUR 800bn Recovery and Resilience Facility, the centrepiece of the NextGenerationEU plan,[1] in which at least 20% of the funds are dedicated to the digital transition. This interest in the digital transformation reflects the belief that digitalisation is the foundation for technological leadership and international competitiveness.

This paper relates directly to the digital transition and approaches the topic from a theoretical perspective. More precisely, it makes use of one of the main concepts of trade theory, namely endowments based on comparative advantages. According to the Heckscher-Ohlin model, factor endowments determine countries' comparative advantages, and with it global trade patterns. In particular, a country that is relatively abundant in a certain factor or production, say capital, tends to export capital-intensive goods. It is then said to hold comparative advantages in capital. Modern formulations of the Heckscher-Ohlin model also take account of differences in technology across countries.

The construction of international input-output data gave a boost to empirical work on the Heckscher-Ohlin theory, in particular in its so-called 'factor content' version. The factor content version of the Heckscher-Ohlin model, developed by Vanek (1968), stipulates that countries which are relatively abundant in a certain factor of production will also be a net exporter of that factor. In other words, its production vector is more capital-intensive than its consumption vector. The availability of international input-output data revived the empirical work on the Heckscher-Ohlin-Vanek (HOV) theorem, because it allows for differences in technologies across countries[2] and for the existence of trade in intermediates. These two features make it possible to calculate the factor contents of trade in a theory-consistent manner (Trefler and Zhu, 2010). Taking into account differences in technology either via country- and industry-specific primary input requirements (Hakura, 2001; Stehrer, 2014; Trefler and Zhu, 2010) or via country- and industry-specific factor productivities (Trefler, 1995) considerably improves the fit of the HOV theorem.[3]

In this paper we make use of the recent advances in the empirical HOV literature to investigate whether the HOV theorem serves as guidance for international trade patterns with respect to digital and ICT-related endowments. More precisely, we subdivide each of the traditional factor endowments – labour and capital – into two components. Labour is split into digital labour services ('digital tasks') and non-

1 The NextGenerationEU plan is the EU's temporary recovery instrument to mitigate the economic and social impact of the coronavirus pandemic. For details, see https://ec.europa.eu/commission/presscorner/detail/el/ip_21_3330.

2 The technology differences take the form of country-industry-specific primary input requirement coefficients.

3 The remaining deviations from the prediction of the HOV-theorem can be associated with the assumption of homothetic preferences on which the HOV tests rely. The effects of relaxing the assumption of homothetic preferences are explored in Stehrer (2014).

digital labour services ('non-digital tasks'). The information is granular enough to identify 'digital tasks' within the task bundle performed by workers in narrowly defined occupations, so that total labour services can be divided between digital and non-digital tasks. In a similar manner we distinguish between ICT capital and non-ICT capital with the help of data on gross fixed capital formation from Eurostat and the EU KLEMS database.

The paper's contribution to the literature is twofold. First, it provides new empirical evidence on the endowments of EU member states with digital tasks and ICT capital as well as the actual factor-based trade patterns, better known as the measured factor content of trade (FCT). Second, it tests the fit of the HOV theorem for the digital and ICT endowments using the tools developed in the literature for a complete test of the HOV theorem, including a sign test and a rank. Owing to data limitations, all analyses are performed for a sample of 25 EU countries, so what is captured are intra-EU trade patterns.

The rest of the paper is structured as follows. Section 2 presents the methodology employed to calculate the measured FCT and to test the predictions of the HOV theorem, followed by an overview of the various data sources in Section 3. Section 4 presents and discusses the results, and section 5 concludes and indicates potential routes for future research.

2. Methodology

This paper builds on the large body of literature on the factor content version of the Heckscher-Ohlin theory developed by Vanek (1968), known as the Heckscher-Ohlin-Vanek (HOV) theorem. The methodology employed serves two purposes. First, we are interested in the amounts of digital labour services (or digital tasks) and ICT capital that are needed to produce the observed trade flows between EU countries. More precisely, we calculate the *actual* (Trefler and Zhu, 2010) or *measured* (Stehrer, 2014) FCT.[4] To this end we use the Vanek-relevant definition of the FCT in the presence of cross-country technology differences and trade in intermediate goods suggested in Trefler and Zhu (2010). Second, we are interested whether the measured FCTs reflect countries' factor abundances as predicted by the HOV theorem. In other words, we test the prediction of the HOV theorem for digital and non-digital tasks as well as ICT and non-ICT capital stocks with the help of sign and rank tests for the measured and predicted factor abundances.

2.1. MEASURED FACTOR CONTENT OF TRADE

The calculation of the measured factor endowments requires an international input-output table that account for differences in production technologies across countries (Trefler and Zhu, 2010). Combining the global input-output table with information on countries' factor inputs allows calculating the total primary factor requirements in production.

The starting point for the calculations are the country-industry-specific factor endowment vectors. As we consider four primary factors (*f=4*), there are also four endowment vectors: digital tasks ($\mathcal{L}_{dt}$) and non-digital tasks in labour services provided ($\mathcal{L}_{nt}$), which together equal labour endowments on the one hand; and ICT capital (K_{ict}) and non-ICT capital (K_n), which sum up to total capital stocks on the other hand. Each of these endowments vectors are of dimension *N J x 1*, where *N=25* is the number of countries and *J=56* is the number of industries considered. These endowment vectors are elementwise divided by gross outputs ***X***. The resulting vectors are transposed and stacked into a matrix which contains the direct factor requirements for each country and industry. This direct factor requirement matrix, denoted by $\boldsymbol{D}$, contains for each country and industry the amount of the respective factor used to produce one unit of output. Denoting individual industries by *i* and countries by *c*, $\boldsymbol{D}$ takes the following form:

$$\boldsymbol{D} = \begin{pmatrix} \ell_{dt}^{c,i} & \cdots & \ell_{dt}^{c,J} & \cdots & \ell_{dt}^{N,i} & \cdots & \ell_{dt}^{N,J} \\ \ell_{nt}^{c,i} & \cdots & \ell_{nt}^{c,J} & \cdots & \ell_{nt}^{N,i} & \cdots & \ell_{nt}^{N,J} \\ k_{ict}^{c,i} & \cdots & k_{ict}^{c,J} & \cdots & k_{ict}^{N,i} & \cdots & k_{ict}^{N,J} \\ k_{n}^{c,i} & \cdots & k_{n}^{c,J} & \cdots & \ell_{n}^{N,i} & \cdots & \ell_{n}^{N,J} \end{pmatrix}$$

$\boldsymbol{D}$ is therefore a *f* x *N·J* matrix which contains in individual rows the *N J* the direct factor requirements of country-industries for each of the *f=4* primary factors.

[4] In the following we will use the term *measured* factor content of trade to refer to the factor endowments embodied in international trade flows.

In a next step, the total primary factor requirements[5] per one unit of output in each industry are needed. These are summarised in the matrix $\boldsymbol{A}$. The $\boldsymbol{A}$ matrix is obtained by post-multiplication with the Leontief Inverse $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{\Lambda})^{-1}$, which contains the direct and indirect intermediate input requirements per one unit of output[6]. Intuitively, the Leontief Inverse, $\boldsymbol{L}$, summarise all domestic and international inter-industry sales of intermediate inputs, expressed as input requirements per EUR 1 worth of output. The typical element $l^{cn,ij}$ indicates the amount of goods and services from country *c*'s (selling) industry *i* that is used in the production of EUR 1 worth of industry *j* output in country *n*. $\boldsymbol{L}$ is a square matrix of dimension *N·J* x *N·J*. All *J x J* submatrices along the main diagonal of $\boldsymbol{L}$ denote domestic inter-industry sales, while all off-diagonal elements involve trade in intermediates.

$$\boldsymbol{L} = \begin{pmatrix}
l^{cc,ii} & l^{cc,ij} & \dots & l^{cc,iJ} & \dots & l^{cn,ii} & l^{cn,ij} & \dots & l^{cn,iJ} & \dots & l^{cN,ii} & l^{cN,ij} & \dots & l^{cN,iJ} \\
l^{cc,ji} & l^{cc,jj} & \dots & l^{cc,jJ} & \dots & l^{cn,ji} & l^{cn,jj} & \dots & l^{cn,jJ} & \dots & l^{cN,ji} & l^{cN,jj} & \dots & l^{cN,jJ} \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
l^{cc,Ji} & l^{cc,Jj} & \dots & l^{cc,JJ} & \dots & l^{cn,Ji} & l^{cn,Jj} & \dots & l^{cn,JJ} & \dots & l^{cN,Ji} & l^{cN,Jj} & \dots & l^{cN,JJ} \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
l^{nc,ii} & l^{nc,ij} & \dots & l^{nc,iJ} & \dots & l^{nn,ii} & l^{nc,ij} & \dots & l^{nn,iJ} & \dots & l^{nN,ii} & l^{nN,ij} & \dots & l^{nN,iJ} \\
l^{nc,ji} & l^{nc,jj} & \dots & l^{nc,jJ} & \dots & l^{nn,ji} & l^{nc,jj} & \dots & l^{nn,jJ} & \dots & l^{nN,ji} & l^{nN,jj} & \dots & l^{nN,jJ} \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
l^{nc,Ji} & l^{nc,Jj} & \dots & l^{nc,JJ} & \dots & l^{nn,Ji} & l^{nn,Jj} & \dots & l^{nn,JJ} & \dots & l^{nc,Ji} & l^{nc,Jj} & \dots & l^{nN,JJ} \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
l^{Nc,ii} & l^{Nc,ij} & \dots & l^{Nc,iJ} & \dots & l^{Nn,ii} & l^{Nn,ij} & \dots & l^{Nn,iJ} & \dots & l^{NN,ii} & l^{NN,ij} & \dots & l^{NN,iJ} \\
l^{Nc,ji} & l^{Nc,jj} & \dots & l^{Nc,jJ} & \dots & l^{Nn,ji} & l^{Nn,jj} & \dots & l^{Nn,jJ} & \dots & l^{NN,ji} & l^{NN,jj} & \dots & l^{NN,jJ} \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
l^{Nc,Ji} & l^{Nc,Jj} & \dots & l^{Nc,JJ} & \dots & l^{Nn,Ji} & l^{Nn,Jj} & \dots & l^{Nn,JJ} & \dots & l^{NN,Ji} & l^{NN,Jj} & \dots & l^{NN,JJ}
\end{pmatrix}$$

The total primary factor requirements matrix $\boldsymbol{A}$ is defined as $\boldsymbol{A} \equiv \boldsymbol{D} \cdot \boldsymbol{L}$. It has the same dimension as $\boldsymbol{D}$ (*f* x *N·J*)

Country *c*'s measured factor content of trade, F^c, as defined by Trefler and Zhu (2010), is obtained by post-multiplying $\boldsymbol{A}$ with its net trade vector. This trade vector, $\boldsymbol{T^c}$, is asymmetric in the sense that it contains country *c*'s (industry-specific) exports to all other trading partners, x_i^{c*}, along with (industry-specific) bilateral imports from any trading partner *n*, m_i^{nc} individually. All bilateral imports enter the net trade vector with a negative sign. $\boldsymbol{T^c}$ is of dimension *N·J* x 1 and takes the following form:

5 Total primary factor requirements refer to the direct and indirect factor requirements that take into account trade in intermediates.

6 *I* is an identity matrix, and matrix Λ contains the intermediate input coefficients. We deviate from the common practice in the input-output literature to label this matrix *A*, because the empirical factor content of trade literature uses the capital letter *A* to denote the direct and indirect primary factor requirements.

$$T^c = \begin{pmatrix} x^{c*,i} \\ x^{c*,j} \\ \dots \\ x^{c*,J} \\ \dots \\ -m^{nc,i} \\ -m^{nc,j} \\ \dots \\ -m^{nc,J} \\ \dots \\ -m^{Nc,i} \\ -m^{Nc,j} \\ \dots \\ -m^{Nc,J} \end{pmatrix}$$

The measured factor content of trade of country *c*, $\boldsymbol{F^c}$, is therefore calculated as follows:

(1) $$F^c = \begin{pmatrix} f^c_{\mathcal{L}\,dt} \\ f^c_{\mathcal{L}\,nt} \\ f^c_{K\,ict} \\ f^c_{K\,n} \end{pmatrix} \equiv \boldsymbol{A} \cdot T^c$$

This way of calculating $\boldsymbol{F^c}$ yields a *f* x 1 vector containing each of the measured FCT of each of the four primary factors at the country level ($f^c_{\mathcal{L}\,dt}$, $f^c_{\mathcal{L}\,nt}$, $f^c_{K\,ict}$ and $f^c_{K\,n}$). Appendix 2 illustrates the methodology for calculating the industry-specific FCT.

2.2. PREDICTED FACTOR CONTENT OF TRADE AND TESTS OF THE HOV THEOREM

The predicted FCT is the difference between each country's endowment with the factor of interest (e.g. digital tasks in labour services) and its share in global consumption (s^c) of the worldwide endowment of this factor. Given the data constraints for both ICT capital stocks and digital tasks, the 'world' will be defined as the sum of EU member states (plus the United Kingdom). The starting point of the analysis is the EU-wide[7] endowment with the production factors of interest (V^W) and country *c*'s endowment with these factors (V^c). The restriction of the analysis to EU member states (plus the United Kingdom) is certainly a severe one, but given the importance of intra-EU trade in member states' total trade, the analysis is still insightful.

The HOV formulation (Vanek, 1968) of the Heckscher-Ohlin model predicts that a country is a net exporter of those factors of production with which it is relatively abundantly endowed. More specifically, a country's net factor content of trade – according to the Heckscher-Ohlin framework – is predicted to be

[7] Ideally, we would want to work with worldwide factor endowments, but data limitations impede such an approach. Therefore, the analysis will be restricted to the EU. Treating the EU as 'the world' for the purposes of the calculation of the factor content of trade seems justifiable, given the importance of intra-EU trade in the exports and imports of member states. However, if the appropriate information can be gathered, we intend to expand the analysis to include the US and Japan in order to compare member states with major international competitors.

a linear function of the country's endowment vector and its share in world consumption of that factor.[8] Country *c*'s *predicted* factor content of trade $\tilde{F}^c$ is then defined as:

(2) $$\tilde{F}^c \equiv V^c - s^c \cdot (V^W),$$

where V^c and V^W denote the vector of endowments of country *c* and the world, respectively (see e.g. Leamer, 1980). Though $\tilde{F}^c$ is a theoretical construct (in contrast to the measured factor content of trade), it is an interesting result in itself, as it reveals whether country *c* is a country that is abundant in digital tasks and ICT capital. This is the case if $\tilde{F}^c$ is positive for the factor in question.

Importantly, s^c captures the actual shares of country *c* in global absorption. The latter is obtained by adjusting the GDP share of country *c*, *GDP^c*, by the trade balance position, TB^c, and analogously for the 'global'[9] counterpart, *GDP^W*, so that $s^c = \frac{GDP^c - TB^c}{GDP^W - TB^W}$. Note that in this calculation the trade balances are the balances against all countries in the world, as opposed to all countries in the sample (i.e. the intra-EU trade balance).

Mirroring the procedure for the measured FCT, labour and capital are split into two factors each, which are digital tasks ($\mathcal{L}_{dt}$) and non-digital tasks ($\mathcal{L}_{nt}$) in the case of labour endowments; and ICT capital (K_{ict}) and non-ICT capital (K_n) in the case of capital stocks. Therefore, at the country level,[10] the endowment vector is of dimension *4x1* and has the following form:

$$V^c = \begin{pmatrix} \mathcal{L}_{dt} \\ \mathcal{L}_{nt} \\ K_{ict} \\ K_n \end{pmatrix}$$

If the fit of the HOV theorem were perfect, the measured FCT, F^c, would be equal to the predicted FCT, $\tilde{F}^c$. We therefore have:

(3) $$\underbrace{\boldsymbol{A} \cdot T^c \equiv F^c}_{\text{Measured factor content of trade}} = \underbrace{\tilde{F}^c \equiv V^c - s^c \cdot (V^W)}_{\text{Predicted factor content of trade}}$$

Following Trefler (1995), we also calculate the deviations of the measured factor content of trade, F^c, from the predicted factor content of trade, $\tilde{F}^c$, for any country *c* and factor *f* denoted by ε_f^c:

(4) $$\varepsilon_f^c = \boldsymbol{A} \cdot T^c - V^c - s^c \cdot (V^W)$$

The deviations ε_f^c will be analysed in the results section. In addition, the standard error of ε_f^c, defined as $\sigma_f^2 = \sum_c \left(\varepsilon_f^c - \bar{\varepsilon}_f\right)^2 / (N-1)$, is used to weight all the data related to factor f (Trefler, 1995). In this, $\bar{\varepsilon}_f$ is the factor-specific average of ε_f^c across all *N* countries, i.e. $\bar{\varepsilon}_f = \sum_c \left(\varepsilon_f^c\right)/N$. This weighting is necessary

8 Stehrer (2014) explores this framework using WIOD data, focusing on the home bias of trade.

9 We refer to 'global' variables to denote the sum of all the countries in the sample.

10 The actual calculations will be done at the country-industry level and only aggregated after the results have been derived.

to transform the factor endowments in comparable units, which is necessary if the HOV theorem is to be satisfied. The data are further rescaled by $(s^c)^{1/2}$ in order to control for country size (Trefler, 1995).

These adjusted data for the measured as well as the predicted FCT will be used to perform several tests of the HOV theorem. The first test is a simple sign test, which was pioneered by Bowen et al. (1987). This test is employed because equation (3) is unlikely to hold with equality. Requiring equation (3) to hold with equality would mean raising the bar of the test too high, given that we are dealing with empirical data. However, the correlation between the two should be high, and in particular they should have the same sign. What the sign test then does is to count the number of cases where $\boldsymbol{A} \cdot T^c$ and $V^c - s^c \cdot (V^W)$ have the same sign, and to calculate the share of observations with a matched sign in the total number of observations.

Furthermore, a rank test is performed, which counts the number of cases in which pairwise comparisons of f^c and $\tilde{f}^c$ for any two factors have the same ordering. For example, if $f^c_{\mathcal{L}\ dt} > f^c_{K\ ict}$, it should also be the case that $\tilde{f}^c_{\mathcal{L}\ dt} > \tilde{f}^c_{K\ ict}$ in order to fulfil the criterion of the rank test.

In addition to these sign tests and rank tests, we also investigate the correlation between the two types of FCTs with a simple regression of F^c on $\tilde{F}^c$. Both the slope coefficient and the coefficient of determination, R^2, can serve as measures of the goodness of fit of the regression and with that of the HOV theorem (see Trefler and Zhu, 2010).

3. Data

The paper relies on several sources of data for the calculation of countries' factor endowments with digital and non-digital tasks on the one hand, and ICT and non-ICT capital on the other hand. These are the European Labour Force Survey (LFS); the Survey on Italian Occupations (ICP) for digital tasks; the EU KLEMS database; and the Eurostat database for capital stocks. For the calculation of the measured factor content of trade we relied on the World Input-Output Database (WIOD) Release 2016. In the following section we briefly introduce our data sources.

3.1. EUROPEAN LABOUR FORCE SURVEY

The Labour Force Survey (LFS) of the European Union is a collection of national LFSs conducted by the national statistical offices of the member states.[11] The LFS is the largest European household survey and is conducted on a quarterly basis. Included in the survey are people aged 15 or more. National LFSs are harmonised at the EU level since national statistical offices rely on: (i) the same concepts and definitions (in line with ILO guidelines); (ii) the same classifications, e.g. for industries (NACE) and occupations (ISCO); (iii) the same set of variables (country-specific ad-hoc modules are allowed); and (iv) the same quality standards concerning field and post-field survey activities.

For the analysis of comparative advantages, the number of employed persons is the main variable of interest. Equally important are the economic activities (NACE Rev.2 industries at the 1-digit level) to which these employed persons are assigned as well as their occupations (reported at the ISCO 3-digit level). In contrast, no use is made of additional characteristics such as nationality, age, sex, marital status, part-time or full-time employment, educational attainment level, or whether a person is participating in education and training. For the factor content of trade calculations we use the employment data by occupation and industry for the year 2012. All data are benchmarked against the employment totals at the country-industry level as found in the Socio-Economic Accounts (SEA) of the WIOD Release 2016.

3.2. SURVEY ON ITALIAN OCCUPATIONS (ICP)

The Survey on Italian Occupations (*Indagine Campionaria sulle Professioni,* ICP) is a unique dataset compiled by the National Institute for Public Policy Analysis of Italy (INAPP). Following closely the American O*Net approach,[12] the ICP focuses on occupations that provide an extensive amount of information on skills, tasks, work content, technology and organisational characteristics of the workplace. As a result, a growing number of studies rely on the ICP to analyse, among other things, the impact of digitalisation on employment (Cirillo et al., 2021); the relationship between task specialisation and labour market transitions (Cassandro et al., 2021); the role of organisational factors in shaping the Italian occupational structure (Cetrulo et al. 2020); and the diffusion of telework and its implications in terms of

[11] See: https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey.

[12] For a detailed description of the O*Net repertoire, see: https://www.onetonline.org/.

inequalities (Cetrulo et al., 2022). The information is collected at the 5-digit occupational level (i.e. 811 occupational codes), ensuring representativeness with respect to sector, occupation, firm size and geographical domain (macro-regions). Occupation-level variables are built relying on both survey-based worker-level information – 16,000 Italian workers are included in the sample – as well as on post-survey validation by focus groups of experts. The survey has been carried out in two waves, 2007 and 2012. Since granular information on digital tasks is not available for the year 2007, we rely on 2012 data to carry out this analysis. The occupations follow the Classificazione delle Professioni (CP) provided by the Italian National Statistical Institute (ISTAT) as of 2011.[13] The structure of the CP is based on the logic of the International Standard Classification of Occupations (ISCO). For this reason, a crosswalk between the two classifications is easily possible.

To measure digital comparative advantages, we rely on the ICP-based digital tasks (DTI) and digital use (DUI) indicators, which are defined at the 4-digit level of occupations according to the CP, as described at length in Cirillo et al. (2021). The scores of the digital indicators of each CP occupation are transposed to the ISCO-08 classification and then aggregated to the 3-digit ISCO level.

Indeed, according to the role played by IT technologies in each occupation, digitalisation may assume very different shapes (e.g. developers vs users of digital technologies). As a result, aggregate indicators and proxy variables may risk missing the target, providing an inaccurate measurement of digitalisation and/or overlooking important heterogeneities. The ICP-based indicators proposed by Cirillo et al. (2021), in turn, allow measuring the digitalisation of occupations in a highly detailed way. Relying on such indicators, it is possible to distinguish between occupations for which digital tools are marginal or irrelevant and, at the other extreme, those directly involved in the development of such technologies. The DUI – the 'broader' digitalisation indicator of the two proposed by Cirillo et al. (2021) – measures how often and how well workers in any professional group interact with digital technology. This indicator builds on two rather generic ICP items: 'Working with computers' and 'Using e-mail as part of one's occupation'. Stemming from the ICP 'General workplace activities' section, the first item captures the proficiency of respondents in using computers.[14] The second item, stemming from the 'Working conditions' section, lists how often respondents use e-mail as part of their work. Despite being generic, the DUI represents a useful signal of digitalisation of the workplace, beyond the activities of the individual employee.

The narrower and more fine-grained measure of digitalisation proposed by Cirillo et al. (2021) is the DTI. The latter is built exploiting a free-form section included in the 2012 wave of the ICP, wherein individual workers – using their own words in a lightly coordinated manner – describe up to 15 work activities (or tasks) characterising their occupation. For each task, the respondents report a score indicating its importance. Operationally, the DTI is built following three steps. First, 5,700 individual words used to describe tasks are analysed, ending up with 51 items identified as expressly denoting digital technology, e.g. informatics (IT), network, database, computer, or describing it in a specific context, such as programming, information, recording, network. Second, task descriptors using such words are analysed 'in context' to rule out false positives. This process leads to the identification of 131 activities that explicitly involve digital technologies and thus define 'highly digital' occupations. Third, the DTI is derived by computing, for each occupation, the weighted average, i.e. the 'importance score' of the digital tasks

[13] See the Italian Institute of Statistics: https://www.istat.it/it/archivio/18132.

[14] The benchmarks, ranging from 'using software applications' to 'developing ICTs', are meant to be contextualised by the interviewer based on the relevant profession and industry of the interviewee (Cirillo et al. 2021).

compared with all the tasks used to describe the occupation. As Cirillo et al. (2021) underline, the DTI allows to measure the digitalisation of tasks at both the extensive margin, i.e. whether digital tasks are carried out at all, and the intensive margin, i.e. how important they are relative to the other tasks in that occupation.

A simple example focusing on the digital task intensity of two Italian occupations can help to explain the logic underlying the measurement of digital factor endowments. As archetypical examples we selected the following occupations: *Database and network professionals (ISCO 252)* and *Machinery mechanics and repairers (ISCO 723)*, see Table 1. As can be seen, there are 30,860 database and network professionals who spend more than half of their time performing digital tasks (52.5%). This implies that the labour services supplied by this occupation perform a total of 16,190 digital tasks. The same logic applies to machinery mechanics and repairers, who are much more numerous (329,617 persons) but have a negligible digital task content (0.04). As a result, the digital tasks performed by this occupation amounts to only 25. The remaining labour services constitute non-digital tasks. Summing digital tasks over all occupations yields a factor endowment of 714,205 for Italy and an average digital task content of 2.88% (see also Cirillo et al., 2021).

Table 1 / Digital tasks intensity at the occupation level and factor endowment with digital tasks

Occupation	Employment	Digital tasks content	Factor endowment for digital tasks
Database and network professionals (ISCO 252)	30,860	52.46	16,190
…	..	..	..
…	..	..	..
Machinery mechanics and repairers (ISCO 723)	329,617	0.04	125
Total employment	24,764,800	2.88	714,205

Note: Codes refers to the ISCO 08.
Sources: European LFS; Survey on Italian Occupations; WIOD Release 2016.

We rely on the Italian DTI and DUI to assess the digital task intensity of occupations for all EU countries. The implicit assumption here is that the Italian occupational structure is rather comparable with that of other European economies, particularly when it comes to tasks and job contents. Since we define occupations at a very detailed level, the mapping of the Italian task structure of occupations to other EU member states appears to be permissible.[15] Given its more fine-grained nature, we rely on the DTI to perform our baseline analysis. A robustness check using the DUI is reported in the Appendix.

[15] Indeed, most of the studies relying on task-based indicators to analyse the impact of ICTs on European industries and occupations (see, among others, Goos et al. 2009) have used variables stemming from the American O*Net repertoire. In that case, the implicit assumption is that the US employment structure overlaps with that of the EU economies. We believe that by relying on Italian data to measure the digitisation of European occupations we make a less strong assumption.

3.3. EU KLEMS

The EU KLEMS Growth and Productivity Accounts provide useful sectoral-level (NACE Rev. 2) information on different categories of inputs, including capital (K), labour (L), energy (E), material (M) and service inputs (S) (Timmer et al., 2007). The EU KLEMS are denoted as Growth and Productivity Accounts because the detailed information on inputs allows the calculation of (real) productivity and growth measures.

This paper uses the 2019 Release of the database.[16] It provides measures of economic growth, productivity, employment, capital formation and technology for all EU member states (as well as some additional countries such as Japan and the United States). All productivity measures have been developed using growth accounting techniques, and for the first time the 2019 Release includes supplementary indicators on intangible assets (Adarov and Stehrer, 2019).

For the EU countries, the EU KLEMS are based on data stemming from the European System of National Accounts (ESA).[17] While the EU KLEMS database now includes in principle all EU countries, the coverage of individual indicators still varies across member states, and it turns out that for some countries Eurostat provides additional data. This is also true for the data on capital stock (and various asset types) needed in this analysis. Therefore, the EU KLEMS Release 2019 data are supplemented with ESA data available from Eurostat. The EU KLEMS data are used because for some countries (Germany, Spain and Romania) data were published at the time the EU KLEMS Release 2019 was set up but were no longer provided on Eurostat. These combined data will be simply referred to as EU KLEMS.

As mentioned, our key variable of interest stemming from EU KLEMS is the capital stock. More precisely, what is needed are capital stocks related to information and communications technology (ICT), or ICT capital for short. Among the detailed asset types within gross fixed capital formation (for details, see Adarov and Stehrer, 2019), we define the relevant measure – ICT capital, net of depreciation – to include the following three items: (i) computer hardware (N11321); (ii) telecoms equipment (N11322); and (iii) computer software and databases (N1173). Hence, the definition of ICT capital employed includes tangible assets – computer hardware and telecoms equipment – and intangible assets – computer software and databases.

All other asset types are labelled non-ICT capital and are defined as gross fixed capital formation (GFCF) less ICT capital for each country and industry.

3.4. WORLD INPUT-OUTPUT DATABASE (WIOD) RELEASE 2016

The calculation of the measured FCT benefits from the World Input-Output Table (WIOD) Release 2016[18] (Timmer et al., 2015), which is required for the calculation of the theory-consistent measured factor content of trade in the presence of trade in intermediate goods and cross-country differences in technology. The WIOD summarises the entire domestic and international intra-industry and inter-industry relationships of 43 countries and the rest of the world for a total of 56 industries. As the availability of

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16 See: https://euklems.eu/

17 See: https://ec.europa.eu/eurostat/web/national-accounts/data/database.

18 More precisely, we use the WIOD 2016 Release available at: http://www.wiod.org/release16.

data on both employment at the required level of detail and on capital stock is limited to EU countries, we focus on a sample of 25 EU countries (all EU member states in 2012 except Malta and Cyprus). Moreover, it would be implausible to apply the Italian ICP-based digital task indicators to important countries in the WIOD, such as China, India or Brazil. Therefore, we trim the global world input-output table down to 25 EU countries, yielding a matrix of dimension 1400 (25 countries x 56 industries).

In addition to the inter-industry table, which is the basis for the calculation of the Leontief Inverse described in Section 2, we also use country-industry level information on employment and capital stocks from the Socio-Economic Accounts (SEA) of the WIOD Release 2016.

4. Results

Before presenting the results on the measured factor contents of trade and the tests of the HOV theorem, some descriptive results are presented.

4.1. DESCRIPTIVE RESULTS ON DIGITAL TASKS AND ICT ENDOWMENTS

We start the discussion with an overview of the occupations which are most digital task-intensive (Table 2). While the digital task contents of individual occupations do not enter into the calculation of the measured factor content of trade directly, they are decisive as they determine the digital task endowments at both the industry and the aggregate level. This is because the digital task contents of the occupations are summed up to the industry level before the factor contents in trade are calculated. Put differently, industries which feature many employees in digital task-intensive occupations will have a relatively high digital task endowment.

Moreover, the descriptive results at the level of occupations may also serve as a plausibility check. For example, looking at Table 2, one finds that *Information and communications technology operations and user support technicians* (ISCO 351), *Database and network professionals* (ISCO 252) and *Mathematicians, actuaries and statisticians* (ISCO 212) are among the most digital task-intensive occupations. This seems reasonable, as these are all professions which are associated with the manipulation or application of digital technologies, with fixing problems related to such technologies or with supporting others in applying these technologies.

Table 2 / Occupations with the highest digital task content, all countries, 2012

Rank	Occupations	Code*	Digital task content
1	Information and communications technology operations and user support technicians	(351)	65.61
2	Database and network professionals	(252)	52.46
3	Mathematicians, actuaries and statisticians	(212)	52.46
4	Physical and earth science professionals	(211)	52.46
5	Software and applications developers and analysts	(251)	52.46
6	Telecommunications and broadcasting technicians	(352)	32.85
7	Process control technicians	(313)	20.21
8	Keyboard operators	(413)	18.38
9	Electrotechnology engineers	(215)	10.24
10	Engineering professionals (excluding electrotechnology)	(214)	10.24
11	Electronics and telecommunications installers and repairers	(742)	8.22
12	Fishery workers, hunters and trappers	(622)	8.05
13	Other clerical support workers	(441)	7.70
14	Librarians, archivists and curators	(262)	6.78
15	Authors, journalists and linguists	(264)	6.76
16	Secretaries (general)	(412)	6.66
17	General office clerks	(411)	6.26
18	Physical and engineering science technicians	(311)	5.87
19	Regulatory government associate professionals	(335)	5.24
20	Numerical clerks	(431)	5.13

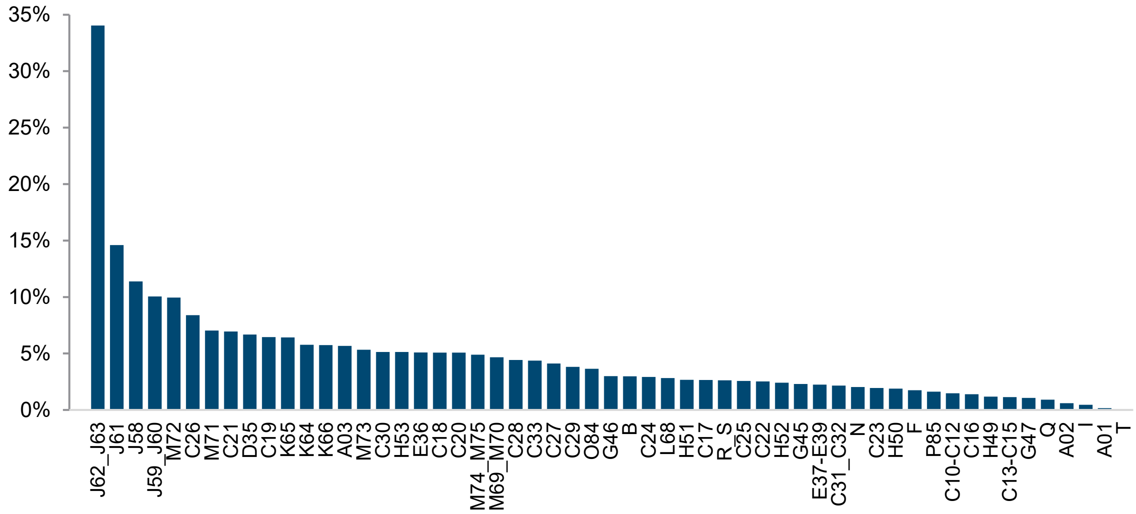
Source: Survey on Italian Occupations. Authors' own work.

There are certainly some occupations whose appearance in this list is slightly surprising, such as *Secretaries* (ISCO 412) or *General office clerks* (411). In this case, however, the DTI is mirroring the continuous interaction with (basic) digital tools that characterises office-related occupations, as opposed to tasks related to the very development of digital technologies performed by top DTI occupations such as database and software developers. In other words, some relatively low-skilled occupations may rank highly because of the ubiquity of digital tools in their everyday work, despite their marginal contribution to the very development of IT technologies. Overall, the list of 'highly digital' occupations shown in Table 2 seems to be consistent with the expectations.

Moving from digital task content of occupations to that of industries, Figure 1 shows the 56 industries ordered by their digital task content.[19]

It turns out that *Computer programming and information service activities* (J62_J63) is by far the most digital task-intensive industry, with a digital task content of 34%, followed by *Telecommunications services* (J61). The most digital task-intensive manufacturing industry is the *Computer, electronic and optical products industry* (C26) with a digital task content of 8.4%. Again, the ranking of industries according to their digital task content is broadly in line with expectations.[20]

Figure 1 / Digital task content across industries, all EU countries, 2012



Note: NACE Rev.2 industry code as used in the WIOD Release 2016. For a list of the industry descriptions corresponding to the NACE Rev.2 industry codes, see Appendix 1.
Sources: Survey on Italian Occupations. Authors' own work.

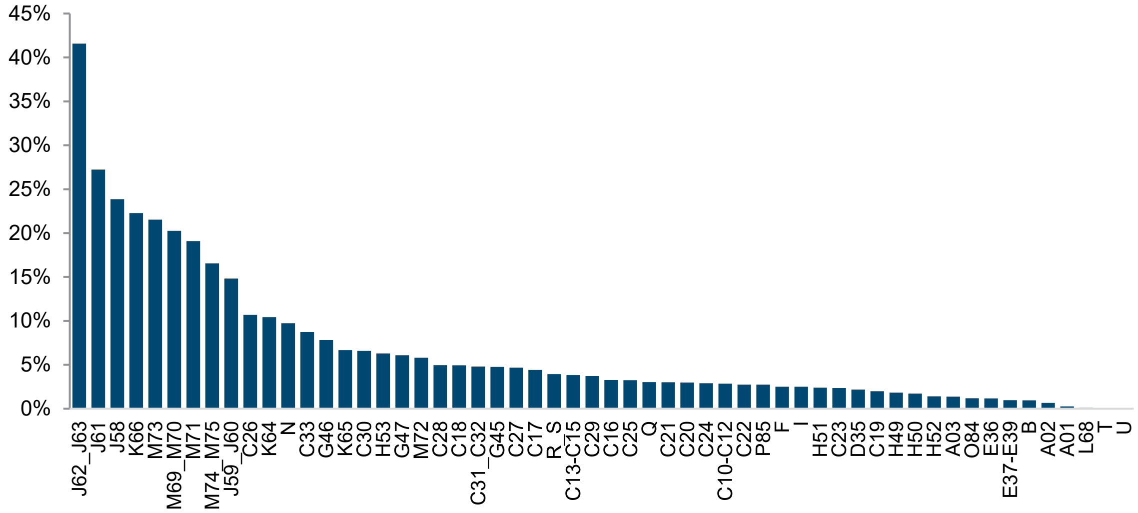
19 Note that the digital task intensity of industries has no industry-intrinsic determinants, meaning that the digital task-intensity of occupations does not vary across industries. In other words, a general secretary employed in the education sector has the same digital task-intensity (6.7) as a general secretary working in the paper industry. Rather than industry characteristics, it is the occupational composition of industries that determines their digital task-intensity. Hence, the higher the number of persons working in digital task-intensive occupations, the higher the resulting digital task content of an industry.

20 For example, Computer programming and information service activities (J62_J63), Telecommunications services (J61) and the Computer, electronic and optical products industry (C26) are also part of the ICT sector as defined by the OECD (Mas et al., 2017).

Analogous to the digital tasks, we also rank industries according to the relative importance of ICT capital in the total capital stock (Figure 2). Again, it is *Computer programming and information service activities* (J62_J63) which has the highest share of ICT capital at 42%, compared with an average share of just 2.4% across all countries in the sample. The *Computer, electronic and optical products industry* (C26) is the manufacturing industry with the highest ICT capital share (10.7%), but it is only found in 10th position. This is explained by the fact that manufacturing industries are typically more (physical) capital-intensive, which tends to lower the share of ICT capital in the total capital stock.

Taken together, the descriptive results for the digital task and ICT capital intensity of industries suggests a high complementarity at the industry level between these two types of factor endowments.

Figure 2 / Share of ICT capital in total capital stocks across industries, all EU countries, 2012

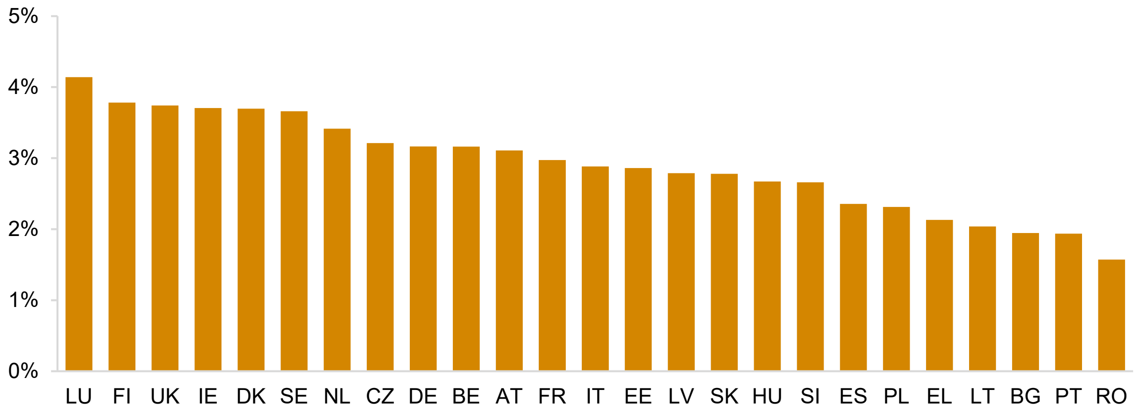


Note: NACE Rev.2 industry code as used in the WIOD Release 2016. For a list of the industry descriptions corresponding to the NACE Rev.2 industry codes, see Appendix.
Sources: EU KLEMS; Eurostat; WIOD Release 2016. Authors' own work.

Aggregating over industries and focusing on individual countries shows that there is also significant variation both for digital task intensity (Figure 3) and for ICT capital intensity (Figure 4). While there are no strong priors as to what the country ranking for these endowments may look like, one factor may be the degree of technological development. If these are relevant factors, we should expect to find EU countries with GDP per capita above the EU average at the top end of the ranking (e.g. Luxembourg and Finland), while the EU countries with a GDP per capita below the EU average would be found at the bottom of the distribution (e.g. Bulgaria or Romania).

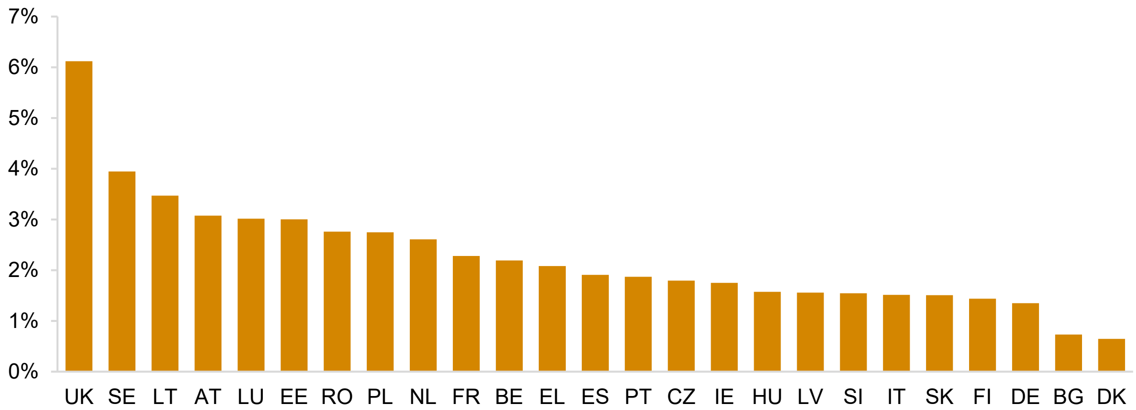
As far as ICT capital shares are concerned, a mixed picture emerges, which seems to reflect countries' economic structure rather than their development level (Figure 4). While the top rankings of the United Kingdom and Sweden were to be expected, the position of Finland, Germany and Denmark at the lower end of the spectrum is less obvious. It is not implausible, though, if one assumes that strong manufacturing industries also imply large physical, non-ICT capital stocks.

Figure 3 / Share of digital tasks in total labour services across EU countries, 2012



Note: Country names corresponding to the country codes are provided in the Appendix.
Sources: Survey on Italian Occupations. Authors' own work.

Figure 4 / Share of ICT capital in total capital stocks across EU countries, 2012



Note: Country names corresponding to the country codes are provided in the Appendix.
Sources: EU KLEMS; Eurostat; WIOD Release 2016. Authors' own work.

4.2. FACTOR CONTENTS OF TRADE

Equipped with these data on digital tasks (and, by implication, non-digital tasks) and ICT capital (and, by implication, non-ICT capital), we can now turn to the results for the measured (F^c) and predicted factor content of trade ($\tilde{F}^c$) and the test of the HOV theorem.

Table 3 summarises the combined results, where the countries are sorted by their innovation performance group as defined by the European Innovation Scoreboard (EIS).[21] These performance groups are: innovation leaders, strong innovators, moderate innovators and modest innovators. As argued, the corresponding results for the factor contents of trade measure relying on the DUI are provided in the Appendix.

[21] See: https://ec.europa.eu/commission/presscorner/detail/en/QANDA_20_1150.

Table 3 / Measured and predicted factor content of trade of EU countries, 2012

Group	Country	Measured factor content of trade				Predicted factor content of trade			
		Digital tasks	ICT capital	Non-digital tasks	Non-ICT capital	Digital tasks	ICT capital	Non-digital tasks	Non-ICT capital
Innovation leaders	DK	-10,517	-3,836	-365,356	-6,722	-14,375	-12,389	-1,161,644	92,743
	FI	-6,441	-1,472	-199,722	-18,920	-3,425	-5,934	-824,957	18,201
	LU	-12,790	-2,730	-254,851	-20,991	-1,266	296	-194,185	-12,127
	NL	12,921	2,428	91,464	111,784	11,424	8,433	-1,007,196	174,149
	SE	-15,955	4,217	-468,010	-1,833	-29,925	21,371	-2,091,753	28,361
Strong innovators	AT	-16,977	2,482	-500,571	11,359	-24,615	14,576	-1,031,520	246,473
	BE	-14,270	-1,174	-339,087	5,741	-45,596	-3,563	-1,821,048	-40,750
	DE	25,181	-11,124	-423,238	139,174	68,762	-70,988	-761,165	1,087,300
	EE	69	-86	22,549	-1,699	7,756	169	273,155	-5,940
	FR	-44,703	2,042	-1,353,694	-164,916	-270,608	-5,175	-9,073,471	161,547
	UK	8,540	19,635	-863,490	-193,487	51,607	135,635	-6,241,266	-1,987,927
	IE	-11,630	-3,797	-304,532	-18,462	-3,308	-3,499	-576,661	-26,428
	PT	-4,600	-928	68,514	-19,924	-985	-3,337	1,543,988	-11,811
Moderate innovators	CZ	23,016	1,160	713,410	53,405	84,726	575	2,338,556	200,395
	ES	-4,613	-1,099	277,888	42,970	-107,575	-17,986	168,691	-30,264
	EL	-8,981	-1,583	-282,997	-36,447	-17,576	-5,460	567,135	-152,643
	HU	13,128	6	595,728	33,590	61,939	-350	2,417,586	129,918
	IT	7,220	-2,164	-195,718	85,601	-95,331	-35,840	-2,551,968	693,251
	LT	-696	1	43,234	-3,785	9,281	739	699,382	-11,777
	LV	871	-258	41,313	1,673	12,714	-756	466,854	-7,487
	PL	37,885	-1,640	2,156,025	-45,678	164,220	-13,981	8,745,802	-646,135
	SK	7,400	584	202,153	48,187	25,516	-584	968,598	97,917
	SI	1,440	-242	69,694	4,630	7,232	-725	330,570	16,457
*)	BG	5,487	-575	464,413	-2,905	45,015	-2,398	2,663,425	2,807
	RO	9,015	154	804,878	-2,344	64,394	1,173	6,153,092	-16,230

Note: *) Bulgaria and Romania are ‘modest innovators’. Digital tasks and non-digital tasks add up to total labour endowment. ICT capital and non-ICT capital add up to total capital endowment. Country names corresponding to the country codes are provided in the Appendix.
Sources: Survey on Italian Occupations; EU KLEMS; Eurostat; WIOD Release 2016. Authors’ own work.

Focusing on the results for the measured factor content of trade, it is easy to see that the innovation leaders in the EU are not necessarily those with positive net exports of digital tasks and ICT capital. In fact, only the Netherlands turns out to be a net exporter of both. All other countries in the leader group are net importers of digital task-intensive goods and (with the exception of Sweden) also have a negative factor content of trade in ICT capital. The results are also mixed across the other innovation performance groups, with no clear patterns discernible. This is somewhat surprising but says nothing about the appropriateness of the HOV theorem. However, this evidence may lend some additional support to theoretical positions (see, among others, Dosi et al., 1990, 2015; Guarascio et al., 2017) underlining the importance of ‘out-of-equilibrium’ explanatory factors going beyond production functions – such as country- and industry-specific capabilities or institutional heterogeneities that are likely to explain real-world specialisation and trade patterns more than an oversimplified representation than the HOV is capable of doing – and emphasising the poor ability of neoclassical models such as the HO model to explain effectively what happens in terms of specialisation and competitiveness. On the other hand, this evidence may also reflect the differentiated pattern that was already visible in the descriptive part of the results section. Germany and Italy, for example, which have a relatively low share of ICT capital in their overall capital stock, are net importers of ICT capital but net exporters of digital tasks. Exactly the opposite is true for France which, like Germany, belongs to the strong innovator group. In contrast, the Czech Republic and Romania emerge as net exporters of digital tasks. It cannot be ruled out that this reflects to some extent Trefler's (1995) 'endowment paradox'. This paradox refers to the phenomenon that 'rich countries' tend to be in short supply of most factors, while 'poor' countries are found to be abundant in most factors, so that the latter tend to have positive measured factor contents of trade.[22] Possibly, and despite the fact that the calculation of the measured factor content of trade took into account differences in technology both in direct factor input requirements and in the input-output structure, some traces of this 'endowment paradox' are still in the data. Moreover, as the data on digital tasks and ICT capital are defined at a very granular level, measurement error may also be an issue, especially in light of the fact that the employment and capital data had to be aligned with the corresponding values in the WIOD database.

There is, however, an alternative, economic explanation for the rather unsystematic distribution of digital comparative advantages across member states, namely the lack of clear digital leadership within the EU (see e.g. Adarov et al., 2021). This concern about digital leadership – or the lack thereof – is not entirely new and can be seen as the latest version of the EU's eternal concern about losing the technology race against the US (as the permanent economic rival) and other emerging economic superpowers of the time, currently China (Landesmann and Stöllinger, 2020). If one accepts, the common notion that EU member states struggle with keeping up with the 'digital frontier', then the mixed pattern of the comparative advantages in digital tasks and ICT capital can be attributed to this weakness. As this paper is confined to EU countries, this assertion remains a hypothesis for the time being.[23]

Turning to the predicted factor content of trade, Table 3 shows that these 'predictions' are even more closely related to the descriptive evidence on the digital task and ICT capital endowment. However, the fit between the measured and the predicted factor endowments is relatively good.

This statement is confirmed by the HOV tests which are summarised in Table 4.

Overall, the performance of the sign test and the rank test is moderately good. In 83% of the cases countries are net exporters of those factors with which they are abundantly endowed.[24] It is also interesting to note that there is only one case (France) where the sign test is successful in only half of the cases, i.e. equal to flipping a coin. The rank test leads to the same conclusion regarding the fit of the HOV model: it is good but not outstanding.

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22 Notice that if one calls into question the broader HO theoretical edifice, as do Dosi et al. (1990), then Trefler's (1995) paradox may be another way to argue that different factors (e.g. asymmetrically distributed technological capabilities, ownership of strategic intangible assets) beyond relative endowments are at the origin of trade patterns and countries' competitive performance.

23 In future work similar analyses of the factor contents of trade for the US and the EU will be undertaken, which could then provide empirical evidence in favour or against this hypothesis.

24 The corresponding results for digital use are similar and provided in Appendix 3.

Table 4 / Sign and rank tests of the HOV theorem, overall and individual countries 2012

Country	Sign test	Rank test
All countries	0.830	0.793
AT	1.000	0.833
BE	0.750	1.000
BG	0.750	1.000
CZ	1.000	1.000
DE	1.000	0.833
DK	0.750	0.667
ES	0.750	1.000
EE	0.750	0.833
FI	0.750	0.667
FR	0.500	0.833
UK	1.000	1.000
EL	0.750	0.500
HU	0.750	0.833
IE	1.000	0.333
IT	0.750	0.667
LT	0.750	0.667
LU	0.750	0.333
LV	0.750	0.833
NL	0.750	0.833
PL	1.000	1.000
PT	1.000	0.500
RO	1.000	1.000
SK	0.750	0.833
SI	1.000	1.000
SE	0.750	0.833

Note: Country names corresponding to the country codes are provided in the Appendix. Sign and rank tests follow the methodology by Trefler (1995) as provided at: http://www.robertcfeenstra.com/graduate-text.html. This includes the weighting of factor endowments.
Sources: Survey on Italian Occupations; EU KLEMS; Eurostat; WIOD Release 2016. Authors' own work.

The global sign score we find for our four factors is considerably lower than the 0.95 score reported in Trefler and Zhu (2010) for their data, which comprise 41 countries but only the factor labour. It is also lower than the score of the sign test for employment and similar to that for capital in Stehrer (2014). When running the tests separately for each of the four factors (Table 5), we find that our scores for both types of labour services get close to the result in Trefler and Zhu (2010), which include only labour. In comparison, the fit of the HOV theorem for ICT capital and non-ICT capital is inferior, mirroring the pattern in Stehrer (2014).

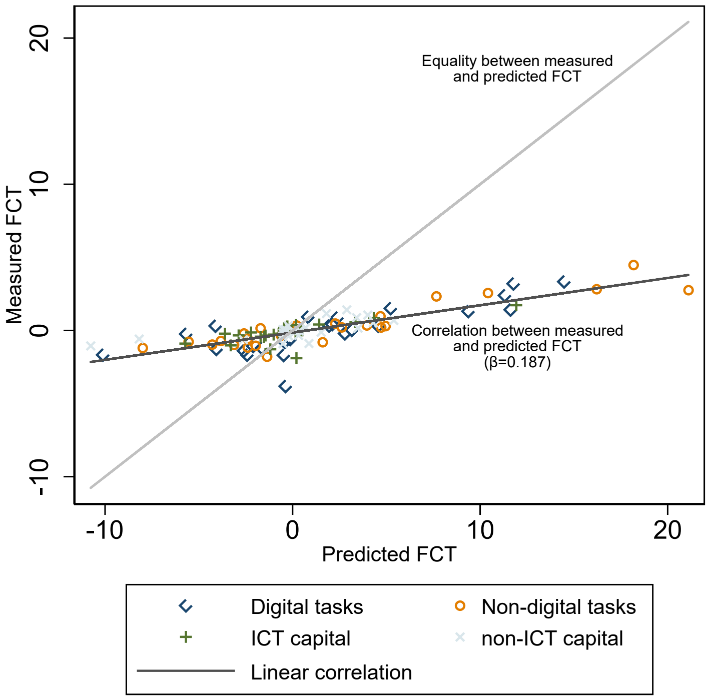
Table 5 / Sign tests of the HOV theorem for individual factors, 2012

	All factors	Digital tasks	Non-digital tasks	ICT capital	Non-ICT capital
Sign test	0.83	0.92	0.92	0.80	0.68
Slope coefficient	0.1867	0.2168	0.1920	0.1581	0.1273
t-statistics	(14.28)	(6.27)	(10.80)	(5.12)	(4.54)
R-square	0.6753	0.6310	0.8352	0.5328	0.4730
Obs.	100	25	25	25	25

Note: Sign and rank tests follow the methodology by Trefler (1995) as provided at: http://www.robertcfeenstra.com/graduate-text.html. This includes the weighting of factor endowments.
Sources: Survey on Italian Occupations; EU KLEMS; Eurostat; WIOD Release 2016. Authors' own work.

The results from the HOV regression described in Section 3 and reported in Table 5 are again visualised in Figure 5. The figure plots the measured factor content of trade (denoted measured FCT) and the predicted factor content of trade across all countries and factors. The graph illustrates the good fit of the regression but also the 'missing trade statistic', which refers to the phenomenon that the variance of the measured factor content of trade is much lower than that of the predicted factor content of trade. This implies that the regression coefficient is below 1 – in our case 0.19. This constellation signals an issue with the predictive power of the HOV theorem, and the literature has offered many explanations for this pattern, which centres on deviations from homothetic preferences and (industry-specific) home-market bias more specifically (see Stehrer, 2014). Trefler and Zhu (2010) also analyse the role of non-tradability of some industries as well as trade barriers that are assumed in individual industries, such as agriculture.

Figure 5 / Regression correlation between measured and predicted factor content of trade, 2012



Note: FCT = Factor content of trade.
Source: Regression reported in Table 5.

Despite the fact that the predictive power of the HOV theorem, even when properly specified, is far from impeccable, we conclude that the fit of the HOV theorem for those factors that are expected to shape the digital transformation is as good as that of the traditional endowment factors.

5. Conclusions

The digital transformation and its impact on countries' comparative advantages raises the question of whether factor endowments are still playing a role in the 'digital era'. Making use of a unique dataset on the task contents of very detailed occupations allows us to split labour services into digital tasks and non-digital tasks and identify the digital labour endowments of countries. We complement this information with data on ICT capital and non-ICT capital. Inspecting these data for a sample of 25 EU countries we find that the best performers in terms of innovation are not necessarily those that are abundant in digital tasks and ICT capital. Rather, what emerges is a mixed picture, with both innovation leaders but also modest innovators holding comparative advantages in digital tasks or ICT capital. We believe this to be a very important finding, and a working hypothesis could be that this mixed pattern is due to a lack of digital leadership in any of the EU member states (and hence the EU as a whole). A lack of digital leadership would obviously have drastic implications for the EU's future international competitiveness, as it will lose not only comparative but also absolute advantages in industries in which digital technologies are introduced at an accelerated pace. However, as we only consider EU countries, the risk of falling behind and losing out in the digital race remains a hypothesis at this stage.

Apart from providing new empirical evidence on the measured and predicted factor content of trade, we test the HOV theorem. We find that in 83% of the cases countries are net exporters of those factors with which they are also abundantly endowed. Similar scores are obtained for the rank test, which leads us to the conclusion that the fit of the HOV model of digital and non-digital and ICT and non-ICT endowments is good but not outstanding. In line with the literature, we find that the fit of the HOV theorem is better for the two types of labour services than for the two types of capital, a fact possibly owed to measured error in the latter. Looking at the factor-specific results of our HOV tests, we conclude that the HOV theorem performs neither better nor worse for the factors that are expected to shape the digital transformation than for the traditional endowment factors analysed in the literature.

There are several routes for further research. One limitation of this paper is that the analysis is restricted to EU countries and that the digital task content of occupations relies on Italian data for all countries in the sample. Interesting results could be obtained by comparing EU data with available data from other countries, with the US offering itself as one country where the required information is available. Such an extension would also provide an answer to the question of whether the EU does indeed lack comparative advantages in digital tasks and ICT capital compared with its major competitors. Furthermore, one could extend the research by going back in time and compare the factor contents of trade at different points in time, where current data limitations restrict such an analysis to the years 2007 and 2012 and a cruder industry structure.

6. Literature

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7. Appendix

APPENDIX 1. COUNTRIES, INDUSTRIES AND OCCUPATIONS

Table A.1.1 / List of countries

Country code	Country name	EU member (in 2012)	In sample
AU	Australia	no	no
AT	Austria	yes	yes
BE	Belgium	yes	yes
BG	Bulgaria	yes	yes
BR	Brazil	no	no
CA	Canada	no	no
CH	Switzerland	no	no
CN	China	no	no
CY	Cyprus	yes	no
CZ	Czechia	yes	yes
DE	Germany	yes	yes
DK	Denmark	yes	yes
ES	Spain	yes	yes
EE	Estonia	yes	yes
FI	Finland	yes	yes
FR	France	yes	yes
UK	United Kingdom	yes	yes
EL	Greece	yes	yes
HR	Croatia	no	no
HU	Hungary	yes	yes
ID	Indonesia	no	no
IN	India	no	no
IE	Ireland	yes	yes
IT	Italy	yes	yes
JP	Japan	no	no
KR	Korea	no	no
LT	Lithuania	yes	yes
LU	Luxembourg	yes	yes
LV	Latvia	yes	yes
MX	Mexico	no	no
MT	Malta	yes	no
NL	Netherlands	yes	yes
NO	Norway	no	no
PL	Poland	yes	yes
PT	Portugal	yes	yes
RO	Romania	yes	yes
RU	Russia	no	no
SK	Slovakia	yes	yes
SI	Slovenia	yes	yes
SE	Sweden	yes	yes
TR	Turkey	no	no
TW	Taiwan	no	no
US	USA	no	no
ROW	Rest of the World	no	no

Table A.1.2 / List of industries

WIOD code	Industry description
A01	Crop and animal production, hunting and related service activities
B	Mining and quarrying
C10-C12	Manufacture of food products, beverages and tobacco products
C13-C15	Manufacture of textiles, wearing apparel and leather products
C16	Manufacture of wood and of products of wood and cork, except furniture
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31_C32	Manufacture of furniture; other manufacturing
C33	Repair and installation of machinery and equipment
D35	Electricity, gas, steam and air conditioning supply
E36	Water collection, treatment and supply
E37-E39	Sewerage; waste collection, treatment and disposal activities; materials recovery
F	Construction
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles
G46	Wholesale trade, except of motor vehicles and motorcycles
G47	Retail trade, except of motor vehicles and motorcycles
H49	Land transport and transport via pipelines
H50	Water transport
H51	Air transport
H52	Warehousing and support activities for transportation
H53	Postal and courier activities
I	Accommodation and food service activities
J58	Publishing activities
J59_J60	Motion picture, video and television, sound recording, music publishing, broadcasting
J61	Telecommunications
J62_J63	Computer programming, consultancy and related activities; information service activities
K64	Financial service activities, except insurance and pension funding
K65	Insurance, reinsurance and pension funding, except compulsory social security
K66	Activities auxiliary to financial services and insurance activities
L68	Real estate activities
M69_M70	Legal and accounting activities; activities of head offices; management consultancy
M71	Architectural and engineering activities; technical testing and analysis
M72	Scientific research and development
M73	Advertising and market research
M74_M75	Other professional, scientific and technical activities; veterinary activities
N	Administrative and support service activities
O84	Public administration and defence; compulsory social security
P85	Education
Q	Human health and social work activities
R_S	Other service activities
T	Activities of households as employers
U	Activities of extraterritorial organizations and bodies

APPENDIX 2. CALCULATION OF THE MEASURED FACTOR CONTENT OF TRADE AT THE COUNTRY-INDUSTRY LEVEL

The calculation of the FCT of trade at the country-industry-level consist of the same building blocks as the corresponding calculations at the aggregate (country) level, which are the direct input requirements matrix, ***D***, the Leontief Inverse, ***L***, and the country-specific net trade vector, T^c.

In order to identify the measured FCT at the industry level, the ***D*** matrix is set up in a slightly different manner. In particular, four factor-specific diagonal matrices $\boldsymbol{D}^f$ are constructed, one for each of the factors considered. Each of these $\boldsymbol{D}^f$ matrices is of dimension *N J x N J* and contains positive values only along the main diagonal. For example, the direct input requirements matrix for digital tasks, which has the typical element $\ell_{dt}^{c,i}$ (referring to country *c* and industry *i* while dt indicates digital tasks), takes the form:

$$\boldsymbol{D}^f = \begin{pmatrix} \ell_{dt}^{c,i} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & .. & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \ell_{dt}^{c,J} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & .. & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \ell_{dt}^{N,i} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & .. & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \ell_{dt}^{N,J} \end{pmatrix}$$

where *N* denotes the last country in the sample and *J* is the last industry.

The Leontief Inverse as well as the net trade vector remain unchanged (see Section 2.1 in the main text).

Post-multiplying each of the $\boldsymbol{D}^f$ matrices with the Leontief Inverse yields corresponding factor-specific total factor input requirements matrices, $\boldsymbol{A}^f$, which have the same dimensions as $\boldsymbol{D}^f$.

$$\boldsymbol{A}^f = \boldsymbol{D}^f \cdot \boldsymbol{L} = \begin{pmatrix} \ell_{dt}^{c,i} l^{cc,ii} & .. & \ell_{dt}^{c,i} l^{cc,iJ} & .. & \ell_{dt}^{c,i} l^{cN,ii} & .. & \ell_{dt}^{c,i} l^{cN,iJ} \\ .. & & .. & & .. & & .. \\ \ell_{dt}^{c,J} l^{cc,Ji} & .. & \ell_{dt}^{c,J} l^{cc,JJ} & .. & \ell_{dt}^{c,J} l^{cc,Ji} & .. & \ell_{dt}^{c,J} l^{cc,JJ} \\ .. & & & .. & & & .. \\ \ell_{dt}^{N,i} l^{Nc,ii} & .. & \ell_{dt}^{N,i} l^{Nc,iJ} & .. & \ell_{dt}^{N,i} l^{Nc,ii} & .. & \ell_{dt}^{N,i} l^{Nc,iJ} \\ .. & & .. & & .. & & .. \\ \ell_{dt}^{N,J} l^{Nc,Ji} & .. & \ell_{dt}^{N,J} l^{Nc,JJ} & .. & \ell_{dt}^{N,J} l^{NN,Ji} & .. & \ell_{dt}^{N,J} l^{NN,JJ} \end{pmatrix}$$

The reminder of the calculation is the same as for the country-level calculations. The FCT of each country – and in this case function $\boldsymbol{F}^{c,f}$ – is obtained by post-multiplying the $\boldsymbol{A}^f$ matrix with the net trade vectors. This yields an *N J x 1* vector for each country and each of the four functions under considerations:

$$\boldsymbol{F}^{c,f} = \boldsymbol{A}^f \cdot T^c$$

An important note is to me made at this stage. The way $F^{c,f}$ is calculated assigns endowment factors embodied in trade to its 'sector of origin', not necessarily to the exporting sector (though the two can certainly coincide). This is an important differentiation, because manufacturing industries typically export a considerable amount of factor inputs used in the 'production' of services. The methodology described here assigns these endowment factors to the respective services industry and not the exporting (manufacturing) industry. Rather, the exporting industries are summed up in this procedure. More specifically, the *N J x 1* $F^{c,f}$ vector of country *c* and factor *f* is defined as follows:

$$\boldsymbol{F^{c,f}} \equiv \boldsymbol{A^{f}} \cdot T^{c} =$$

$$= \begin{pmatrix} \ell^{c,i}_{dt} l^{cc,ii} x^{c*,i} & +..+ & \ell^{c,i}_{dt} l^{cc,iJ} x^{c*,J} & + & \ell^{c,i}_{dt} l^{cn,ii} (-m^{nc,i}) & +..+ & \ell^{c,i}_{dt} l^{cn,iJ} (-m^{nc,i}) & +\cdots+ & \ell^{c,i}_{dt} l^{cN,ii} (-m^{Nc,i}) & +..+ & \ell^{c,i}_{dt} l^{cN,iJ} (-m^{Nc,J}) \\ .. & & .. & & .. & & .. & & .. & & .. \\ & .. & & & & & & & & .. & \\ .. & & .. & & .. & & .. & & .. & & .. \\ & .. & & & & & & & & .. & \\ .. & & .. & & & & & & .. & & .. \\ \ell^{N,J}_{dt} l^{Nc,Ji} x^{c*,i} & +..+ & \ell^{N,J}_{dt} l^{Nc,JJ} x^{c*,J} & + & \ell^{N,J}_{dt} l^{Nn,Ji} (-m^{nc,i}) & +..+ & \ell^{N,J}_{dt} l^{Nn,JJ} - m^{nc,i}) & +\cdots+ & \ell^{N,J}_{dt} l^{NN,Ji} (-m^{Nc,J}) & +..+ & \ell^{N,J}_{dt} l^{NN,JJ} (-m^{Nc,J}) \end{pmatrix}$$

The illustration of the $F^{c,f}$ vector makes clear that in the matrix operation process the exports of the respective endowment factor, say digital tasks, employed in country c's industry *i* (i.e. the first *J* elements in the first row) along with the imports of digital tasks, employed in country c's industry *i* (the remaining elements, which are again at a bilateral level) are summed up. This sum is built over all exporting and importing industries.

In a last step, the elements within each column are summed up over the country of origin to yield a *J x 1* vector with measured net FCT of trade at the industry level (from a 'sector of origin' perspective).

APPENDIX 3. ADDITIONAL RESULTS

Table A.3.1 / Measured and predicted factor content of trade of EU countries – digital use indicator 2012

		Measured factor content of trade				Predicted factor content of trade			
Group	Country	Digital use	ICT capital	Non-digital use	Non-ICT capital	Digital use	ICT capital	Non-digital use	Non-ICT capital
Innovation leaders	DK	-189,993	-3,836	-185,880	-6,722	-580,960	-12,389	-595,059	92,743
	FI	-111,884	-1,472	-94,279	-18,920	-393,872	-5,934	-434,509	18,201
	LU	-162,778	-2,730	-104,863	-20,991	-84,429	296	-111,023	-12,127
	NL	74,992	2,428	29,393	111,784	-309,837	8,433	-685,935	174,149
	SE	-257,775	4,217	-226,190	-1,833	-1,057,173	21,371	-1,064,505	28,361
Strong innovators	AT	-263,101	2,482	-254,447	11,359	-488,887	14,576	-567,248	246,473
	BE	-174,509	-1,174	-178,847	5,741	-855,641	-3,563	-1,011,002	-40,750
	DE	116,057	-11,124	-514,114	139,174	1,535,773	-70,988	-2,228,177	1,087,300
	EE	9,778	-86	12,841	-1,699	147,508	169	133,403	-5,940
	FR	-684,564	2,042	-713,833	-164,916	-4,642,955	-5,175	-4,701,123	161,547
	UK	-301,321	19,635	-553,628	-193,487	-2,303,304	135,635	-3,886,355	-1,987,927
	IE	-184,989	-3,797	-131,173	-18,462	-276,815	-3,499	-303,153	-26,428
	PT	-20,151	-928	84,065	-19,924	392,776	-3,337	1,150,227	-11,811
Moderate innovators	CZ	367,359	1,160	369,068	53,405	1,287,282	575	1,136,000	200,395
	ES	79,855	-1,099	193,420	42,970	-728,298	-17,986	789,414	-30,264
	EL	-145,103	-1,583	-146,874	-36,447	144,984	-5,460	404,575	-152,643
	HU	272,729	6	336,127	33,590	1,201,811	-350	1,277,714	129,918
	IT	-85,416	-2,164	-103,082	85,601	-2,188,888	-35,840	-458,412	693,251
	LT	18,166	1	24,371	-3,785	360,866	739	347,796	-11,777
	LV	16,309	-258	25,874	1,673	238,891	-756	240,678	-7,487
	PL	982,135	-1,640	1,211,775	-45,678	4,221,411	-13,981	4,688,612	-646,135
	SK	96,541	584	113,013	48,187	466,991	-584	527,122	97,917
	SI	40,379	-242	30,755	4,630	192,476	-725	145,326	16,457
*)	BG	181,982	-575	287,918	-2,905	1,181,989	-2,398	1,526,451	2,807
	RO	325,302	154	488,591	-2,344	2,538,302	1,173	3,679,183	-16,230

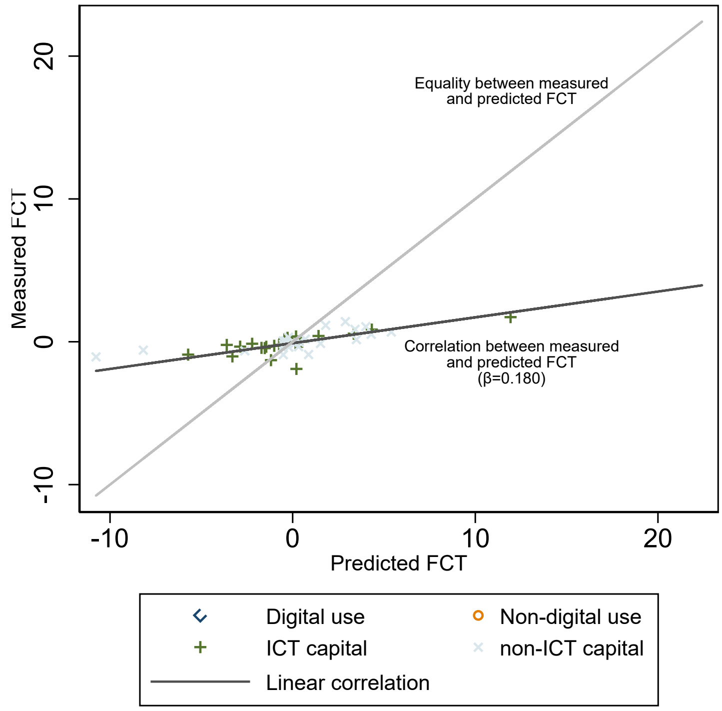
Note: *) Bulgaria and Romania are 'modest innovators'. Digital tasks and non-digital tasks add up to total labour endowment. ICT capital and non-ICT capital add up to total capital endowment. Country names corresponding to the country codes are provided in the Appendix.
Sources: Survey on Italian Occupations; EU KLEMS; Eurostat, WIOD Release 2016. Authors' own work.

Table A.3.2 / Sign tests of the HOV theorem for individual factors for digital use, 2012

	All factors	Digital use	Non-digital use	ICT capital	Non-ICT capital
Sign test	0.81	0.84	0.92	0.80	0.68
Slope coefficient	0.1806	0.1909	0.1913	0.1581	0.1273
t-statistics	(17.71)	(9.29)	(11.50)	(5.12)	(4.54)
R-square	0.7620	0.7894	0.8519	0.5328	0.4730
Obs.	100	25	25	25	25

Note: Sign and rank tests follow the methodology by Trefler (1995) as provided at: http://www.robertcfeenstra.com/graduate-text.html. This includes the weighting of factor endowments.
Sources: Survey on Italian Occupations; EU KLEMS; Eurostat; WIOD Release 2016. Authors' own work.

Figure A.3.1 / Regression correlation between measured and predicted factor content of trade for digital use, 2012



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