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Assessing Digital Leadership:

Is the EU Losing out to the US?

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Abstract

Since Leontief's (1953) seminal work on the factor content of trade, the validity of the Heckscher-Ohlin-model has been judged not only on the basis of formal tests of the theory but also tested against prior expectation. In this vein, this paper uses the Heckscher-Ohlin-Vanek (HOV) approach to investigate whether supposed US leadership in the digital domain can be traced back to digital task endowments embodied in labour services. In a comparison between EU member states and the US, we find that the latter is more intensive in digital tasks than the EU and that this difference is explained by both an intensity-effect (US occupations being more digital-task intensive) and a structural component (relatively more digital-task intensive occupations). Viewed through the lens of the HOV theorem we find that the US is abundant in digital tasks relative to non-digital tasks, while the opposite is true for the EU. The standard tests for the predictive power of the HOV theorem are high and in line with the results for labour in previous literature.

Keywords: Comparative advantages, digitalisation, Heckscher-Ohlin-Vanek theorem, digital tasks

JEL classification: F11; F14; D57

CONTENTS

TABLES AND FIGURES

1. Introduction

Falling behind the technological frontier is one of Europe's greatest and most permanent economic concerns, leaving its mark on its industrial and innovation policies. The primary rival has been and continues to be the US. At different times newcomers have entered the arena, such as Japan in the 1980s, and China in this millennium.

With the growing importance of digital technologies permeating the entire economy, this eternal concern about defending a technological edge and external competitiveness has intensified for a number of reasons. First, the digital transformation may entail a new technological paradigm (Cimoli et al., 2020). Paradigm shifts of this kind increase the dynamics in the international technological pecking order of countries. Second, the EU's industrial structure is geared towards medium-tech industries, dominated by medium-sized companies, where (mainly incremental) technological progress often takes place on the factory floor rather than in the R&D lab[1]. Third, the EU's economic structure as a whole is comparatively static, meaning that the process of creative destruction is relatively slow, and start-up firms are rare[2]. To this one may add the fragmentation of the EU's digital market (Brattberg et al., 2020). All in all, this does not seem to be the ideal environment for embracing digitalisation and achieving leadership in the digital transformation. The almost complete lack of EU companies in the platform economy (EPSC, 2019) is just one indication of this.

In this paper we investigate the EU's readiness for the digital transformation and compare it to the US, by looking at the economies' endowment structures, notably the employment structure. More precisely, we identify the digital task content of occupations. This approach seems appropriate as capabilities are the basis for any economic transformation, including the digital transformation. By systematically analysing the digital tasks performed in an economy, we implicitly capture the capabilities of the workforce. This is because it is hard to imagine how, say, a software developer, can fulfil her job duties without having the necessary skills and experience. For this purpose, we rely on a recently developed digital task index (DTI) developed for the Italian economy (Cirillo et al., 2021) which we consider representative for EU countries. In addition, we use the task descriptions performed across US occupations contained in the O*NET database, which served as the basis for the widely used routine-task intensity index (Autor, Levy, and Murnane, 2003), the related automation index by Frey and Osborne (2017) and offshoring indicator (Firpo et al., 2011), to replicate the methodology of the Italian digital task index for the US economy. Thus EU occupations and US occupations do not necessarily have the same digital task contents. The DTI allows us to identify the digital task content in employment in EU member states and in the US economy. The fact that we are able to construct the DTI from separate databases describing US and EU (Italian) occupations respectively, takes into account the

1 These characteristics correspond to specialised supplier industries in the Pavitt taxonomy (Pavitt, 1984) and subsequent refinements (Castellacci, 2008; Bogliacino and Pianta, 2016). An important example is the machinery industry.

2 EU start-ups are, for example, highly underrepresented in the list of the world's top 100 unicorns, defined as enterprises with a market valuation of USD 1 billion or more. (EPSC, 2019).

likely variation between the EU and the US[3]. Hence, differences in digital task intensity between the EU and the US economy arise from (i) differences in the digital task content of occupations in the EU and the US (e.g. EU and US finance professionals may perform different tasks) and (ii) differences in the occupational employment structure in the two economies (e.g. the US may have more financial managers than the EU). In principle, we can also track changes in digital task intensity over time, though data limitations only allow us to partially capture these changes; this is why we do not put much emphasis on this dimension.

The theoretical angle from which we approach the digital task content of occupations is the Heckscher-Ohlin model. It stipulates that a country which is relatively abundant in a certain factor of production will specialise in the production of goods which make intensive use of this factor. The most suitable empirical approach to investigating this prediction is the factor content version of the Heckscher-Ohlin model developed by Vanek (1968). The Heckscher-Ohlin-Vanek (HOV) theorem predicts that countries which are relatively abundant in a certain factor – such as digital tasks performed in labour services – will also be a net exporter of that factor. While conceptually intriguing, the HOV theorem is difficult to test as soon as one goes beyond aggregate factors, such as labour and capital, because of the data limitations. The data requirements are also the reason why this analysis is limited to 25 member states and the US and timewise, restricted to two benchmark years, 2012 and 2018. To test the prediction of the HOV theorem, we perform formal tests of the HOV theorem on the one hand, while on the other hand we compare the results for the EU-US comparison against our prior expectation that the US, as the digital leader, is relatively abundant in digital tasks. This prior expectation is motivated by the omnipresence of tech giants such as Apple, Microsoft, Alphabet or Amazon, as well as existing indicators for hyperscale data centres and AI start-ups (UNCTAD, 2021), and the adoption of digital technologies (EIB, 2020) or digital patenting (Rikap and Lundvall, 2021; Fanti et al. 2022), including of SMEs (EPO and EIB, 2022).

Regarding the formal tests, we use the theory-consistent methodology for calculating the measured factor content of trade of Trefler and Zhu (2010) and perform some of the tests suggested in the literature (Bowen, et al., 1987, Leamer, 1980; Trefler, 1995), similar to those undertaken in Guarascio and Stöllinger (2022) in an analysis of digital task contents within the EU.

The paper contributes to the literature in three ways. First, we build a digital task index based on the descriptions of occupations in the O*NET database which parallels, to the extent possible, the Italian DTI developed by Cirillo et al. (2021). The implied within-occupation variation adds an additional layer to the analysis. This within-occupation dimension is shown to be relevant, for example, by Lewandowski et al. (2022) in the context of the routine-task intensity of occupations. Second, we integrate these detailed digital task endowments into a HOV-framework with trade in intermediates and cross-country differences in technology in order to test the hypothesis that the US is more digital task abundant than the EU. We focus on digital tasks because we believe that the US's digital leadership, to the extent that it is discernible in endowment-based comparative advantage, is primarily the result of superior digital skills, which translates into an abundance of digital tasks in labour services provided in the US economy. Third, we take a first glimpse at the changes in digital task contents over time. For the US, the analysis

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3 For a general explanation of why it is preferable to use data from Italy to describe the characteristics of European occupations rather than US data (in the context of the labour market implications of COVID-19) see Flisi and Santangelo (2022).

includes changes in the digital task contents of occupations over time. We also pay due attention to the limitations of such an analysis given the data constraints.

We find that digital task intensity in the US economy is higher than that in the EU, which is in line with our expectations. The result is driven by the higher digital task contents of US occupations on the one hand and by differences in the occupational structures of industries and the industry structure of the economy on the other hand. The US economy remains more digital task-intensive even when the same digital task index is applied to both EU member states and the US, though the gap narrows markedly. Moreover, in analysing the digital and non-digital task structures of the US and the EU, the US emerges as being digital task-intensive relative to non-digital tasks (Leamer, 1980; Trefler, 1995), while the opposite is true for the EU. Surprisingly, developments over time at the aggregate level point to a *decline* in the average digital task intensity of occupations between 2012 and 2018. The overall digital task content in the US economy and the EU economy declined as well. This raises some doubts about the encompassing digitalisation of economies, even advanced ones such as the US and the EU, and could signal another type of job polarisation and a 'digital divide'. This divide would mean that some already highly digital occupations have become even more digital, while other occupations involve fewer and fewer digital tasks. Finally, and in contrast to expectations, the calculation of the actual factor content of trade (FCT) for digital and non-digital tasks yields a negative FCT for the US and a positive FCT for the EU. We attribute this result to the significant US trade deficit, one of the key influential factors identified in Trefler (1995).

The remainder of the paper is structured as follows. Section 2 embeds the paper in the existing literature and puts forward the main hypotheses. Section 3 presents the methodologies for retrieving the digital task content of occupations and the HOV approach, along with the underlying data. Section 5 contains results for both digital task intensities and factor abundance retrieved within the HOV framework. Section 5 concludes.

2. Related literature and hypotheses

2.1. RELATED LITERATURE

The paper is related to the literature on technological leadership and more specifically on digital leadership (see, among others, Edler et al. 2021; Rikap and Lundvall, 2021; Caravella et al. 2021, Brattberg et al., 2020).

Looking back at the origins of the ICT industry, US leadership seems to be a well-established fact (O'Mara, 2020). Long-term 'mission-oriented' projects carried out by major US federal agencies (e.g., the Defense Advanced Research Projects Agency (DARPA)) contributed to the development of General-Purpose Technologies (GPTs) such as semiconductors (Dosi, 1984) or the Transmission Control Protocol/Internet Protocol (TCP/IP) (Greenstein, 2015), that have been crucial for the diffusion of personal computers and, later on, of the internet (Mazzucato, 2018). These actions gave a substantial advantage to the US economy in the nascent digital economy. Since the early days of IBM's domination of the mainframe industry, US-based multinational corporations have taken the lion's share of global ICT markets, with serious competition, starting only in the 1980s coming from a bunch of Asian high-tech companies (Japanese, above all others). In this context, the close relationships between corporations, federal agencies and top universities, paradigmatic examples being Stanford or CalTech (O'Mara, 2020), favoured technology transfer, incremental innovations and forged the US National Innovation System (NIS). Silicon Valley is the most paradigmatic example. With the 'commercialization of the Internet' (Greenstein, 2001), the US competitive advantage in the digital domain became even more pronounced and the role of the NIS even clearer. By the late 1990s companies that would later become Big Tech, jumped on the digital economy bandwagon, first thanks to massive technology transfer, and later by acquiring dominant positions in key internet market segments such as search engines (e.g., Google, now Alphabet) and social networks (e.g., Facebook, now Meta). Besides public investments and mission-oriented projects, competences also played a fundamental role. A strong domestic supply of digital skills as well as the capacity to attract the best competences from around the world strengthen the innovativeness and competitiveness of the US digital industry. Technological trajectories and related economic developments are never static processes, though. In fact, on the other side of the Pacific, China's industrial policy is working tirelessly to narrow the gap. And with remarkable results, as the former is challenging US leadership in key technological domains such as artificial intelligence (AI) (Rikap and Lundvall, 2021), while the ongoing US-China 'chip war' (Miller, 2022) testifies as to how intense the competition in this area has become. How is Europe positioned in such a 'digital race'? Historically, Europe's digital industry has always struggled to keep pace with that of the US. This was true at the time of mainframes, personal computers as well as in the early days of digitisation (O'Mara, 2020). At present, virtually all the relevant innovation indicators tend to confirm the EU's digital backwardness (UNCTAD, 2021). Indeed, as most of digital-related R&D and patents are concentrated in a few US and Chinese corporations, such a technological and competitive divide is a rather predictable outcome. So much so that digital technologies (and related business models) are characterised by increasing returns to scale, network effects and winner-take-the-most dynamics, which are deemed to widen the gap, transforming the digital race into a 'battle of two' (i.e., the US vs China). Unfortunately, data constraints prevents us from taking China into the analysis, but we will use the US as one of the participants in this 'battle of two' as a benchmark for assessing where the EU can be positioned in this digital race.

Methodologically, the paper belongs to the revived factor content of trade literature following the availability of international input-output data (Trefler and Zhu, 2010; Stehrer, 2014).

The endowment-based approach to comparative advantage looks back on several decades of empirical testing, starting with Leontief's (1953) analysis of US exports and imports. Relying on input-output data, Leontief found that US exports were labour-intensive rather than capital-intensive, which was a rather implausible finding.[4] One obvious issue in the analysis, which remained challenging for subsequent research, was that Leontief had to rely on US technology data for imports. This treatment of imports was certainly in line with the Heckscher-Ohlin model in a strict sense[5] but obviously at odds with the situation in the real world. Differences in technology were also Leontief's prime candidate among the numerous explanations[6] for why the prediction of the Heckscher-Ohlin theory did not hold.

Leontief's paradoxical result triggered a series of subsequent investigations of the US factor content of trade, for example Baldwin (1971), many of which confirmed Leontief's original finding, as well as analyses for other countries (for an overview see Baldwin, 2008). Relying on the Vanek (1968) formulation of the Heckscher-Ohlin model, Leamer (1980) resolved the paradox by showing that Leontief performed the wrong test for identifying endowment-based comparative advantage. Vanek had expressed the Heckscher-Ohlin model at the level of factor services rather than goods, which made it possible to deal with more than two factors because it is possible to establish a unique ordering of the factor intensities embodied in net exports (Vanek, 1968). Most importantly, the HOV model established a firm link between the factor content of trade and the corresponding endowments with that factor, predicting that a country which was relatively better endowed with a certain production factor will be a net exporter of that factor. This prediction is conditional on a set of assumptions, notably perfect factor mobility between sectors within countries; no international factor mobility; identical homothetic preferences; identical production functions; perfect competition in factor and goods markets; and international factor price equalisation. Leamer showed that for identifying factor abundance in trade, the comparison to be made is not between the capital-labour ratio of exports and imports – as Leontief had done – but rather between the capital-labour ratio of production and consumption. Based on Vanek's insights, Leamer (1980) therefore defined the relative factor abundance revealed in a country's trade on the basis of relative factor intensities in production and consumption. More precisely, a country is relatively abundant (as revealed in trade) in factor f, if its factor content relative to another factor f' in production exceeds the corresponding ratio in consumption.[7] Consumption is obtained by taking each country's income share in world endowments which hinges on the assumption of identical and homothetic preferences. See Section 3 for details.

While Leamer (1980) resolved Leontief's paradox, which was in contradiction to the obvious position of the US in the world economy, his findings on the relative factor contents of the US did not constitute a formal test of the HOV theorem. Bowen et al. (1987) proposed a sign and rank test which consists of

4 Leontief's test included labour and capital as production factors.

5 The Heckscher-Ohlin model assumes identical technologies across countries.

6 Alternative explanations put forward were, inter alia, the omission of other production factors, the neglect of the skill-level of labour and the fact that the US had not followed a free trade policy.

7 This comparison can also be made in terms of the predicted factor contents of trade.

comparing the actual (or measured) FCT – as revealed by US input-output and (country-specific) trade data – with the theoretically predicted FCT derived from the endowment structure. The sign test is passed if both measures have the same sign. This way, the sign test relates directly to Vanek's formulation of the Heckscher-Ohlin model since it consists of a comparison of production factors embodied in production and consumption.[8]

As the HOV prediction relies on several assumptions, in particular identical technologies and identical and homothetic preferences, the sign and rank tests were essentially a test of the validity of these underlying assumptions. With many countries and factors involved, it is possible to calculate the percentage share of cases in which this test is passed. When flipping a coin, the average number of successful tests would be 50%. Similarly, for the rank test, the FCT are compared pairwise at the country level. If the predicted FCT of a certain factor exceeds that of another factor, this should also be the case for the measured FCT. Again, the share of correct rankings among all country-factor combinations is calculated. Claiming some predictive power for the HOV-theorem would require that these tests perform considerably better than a coin flip. However, based on data for 27 countries and 12 factors, the sign and rank tests in Bowen et al. (1987) failed formidably. They found that the sign test was satisfied in 61% of all cases, while the rank test obtained a score of only 50%.

Among the (non-exclusive) candidate explanations for the poor performance of the HOV-theorem, differences in technology again received a lot of attention. Trefler (1993) showed that incorporating differences in technology across countries by adjusting endowments for their relative productivity – yielding 'effective factor endowments' – strongly improved the empirical fit of the HOV-theorem. In this approach, the technology parameters are estimated such that a perfect fit for the HOV prediction is obtained. The test for the empirical fit of the HOV-theorem consists of looking at the correlations of wages (or any other factor remuneration) and the estimated productivity parameters.

An alternative to using effective factor endowments for capturing cross-country technology is to use country-specific differences in the factor requirement matrices. Trefler (1995) adjusts the factor input coefficients in the input-output matrix for country-level productivity differences[9] and also finds that this leads to a considerably better fit of the data. In particular, it reduces a considerable part of the 'missing trade', Trefler's expression for the empirical regularity that the measured FCT tends to be much smaller than predicted by endowments. He further shows that the missing trade phenomenon is related to home market bias, non-tradable goods and trade costs. Davis and Weinstein (2001) were then the first to actually construct and estimate separate factor input requirement matrices for ten OECD countries. This was a major step forward, since until then, the sole basis of analysis was the US input-output structure, adjusted for technology differences.

Trefler and Zhu (2010) suggested a definition of the HOV-theorem that holds in the presence of both cross-country technology differences and trade in intermediates. With the availability of international input-output data, their approach actually became testable. Using labour as the sole production factor, they find that in their data, the sign tests were correct in 95% and the rank tests in 89% of the cases. Despite these enormous improvements in the fit of the HOV model, the issue of 'missing trade' remained

8 The concept of relative factor abundance can equally be applied to endowments alone. Trefler (1995), for example, ranks factor endowments relative to world endowments for each factor using a country's consumption share as the natural dividing line between abundant and scarce factors.

9 The assumption is that cross-country differences in productivity are uniform across factors and industries.

sizeable. The explanation for the missing trade phenomenon according to Trefler and Zhu (2010) is found in deviations from the consumption similarity assumption. They identify the agricultural sector and the construction sector as well as the food industry as the main 'deviators'. Using the approach of Trefler and Zhu (2010) and the newly available international input-output data, Stehrer (2014) tested the HOV theorem for three types of labour and capital. His results are similar to those of Trefler and Zhu (2010) but show that the HOV model performs better for labour services than for capital. More recently, Stöllinger and Guarascio (2022) used the approach by Trefler and Zhu (2010) to study the FCT of EU countries for digital tasks and ICT capital, confirming the relevance of the HOV theorem for the factors they study. However, this paper fails to find a match between innovation leaders among EU countries and comparative advantage in digital tasks and ICT capital. Both innovation leaders and modest innovators (as classified by the European Innovation Scoreboard[10]) hold a comparative advantage in digital tasks and ICT capital. The tentative explanation points to the relative digital backwardness of the EU which, in turn, may lead to unclear patterns as regards EU economies' (digital) competitiveness. This open question regarding the position of EU member states in the digital realm serves as the departure point for the present paper which brings the US into the analysis[11].

The use of digital tasks performed by workers in different occupations in Stöllinger and Guarascio (2022) also creates a link between the empirical HOV literature and the literature on routine biased technological change (Autor et al., 2003; Autor and Acemoglu, 2011) and job polarisation (Goos et al., 2007; Autor and Dorn, 2013). In all these contributions, detailed information on the work context of and the skills and abilities needed in an occupation are used to characterise them with regard to different labour market trends such as automation or offshoring. In Stöllinger and Guarascio (2022) as well as in this paper the main interest is their role in digitalisation, that is, their digital task content. To measure the digital tasks embodied in labour services, we draw on the work by Cirillo et al. (2021) and their digital-task index (DTI). The authors used the DTI to investigate the impact of digitalisation on employment. Focusing on the Italian economy and controlling for a number of structural factors - including demand dynamics, new processes and workforce characteristics – they found that relatively more digitised industries-occupations are those displaying more sustained growth patterns. In line with expectations, they find that digitalisation seems to reward more those industries and occupations at the top of the distribution – i.e. high-tech and high-skill – while the opposite occurs at the bottom. Guarascio and Stöllinger (2022) showed that this index is also suitable for identifying endowment-based digital comparative advantage.

2.2. MAIN HYPOTHESES

The literature discussion allows us to put forward a number of hypotheses which we are going to test empirically. Existing evidence on the US's digital leadership leads to the expectations that this lead position is also reflected in digital endowments, leading to our first hypothesis:

H1: *The US economy is more digital task intensive than the EU economy.*

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10 See: https://ec.europa.eu/commission/presscorner/detail/en/QANDA_20_1150.

11 Unfortunately, comparable data on China were not available so we have to restrict the analysis to the US and the EU. However, future analysis of the 'digital-innovation race' cannot avoid including Chinese industries in the picture.

With hypothesis 1, we provide an empirical account of something that, despite being common wisdom[12] – i.e. the EU's digital backwardness vis-à-vis the US (Rikap and Lundvall, 2021; Fanti et al. 2022; UNCTAD, 2021) –, is rather poorly documented in the empirical trade literature, in particular with respect to endowments.

A second, related hypothesis relates to the sources of any difference in the digital task endowments identified. Since we can differentiate between a within-occupation effect (or occupation-intensive margin effect) on the one hand and a structural effect on the other hand, we can investigate both dimensions and their relative importance. The prior expectation is that both dimensions contribute to the digital leadership of the US[13], if even we remain agnostic with respect to their relative contributions. This leads to hypothesis 2:

H2: *Both the occupation-intensive margin and the structural effect contribute to the superior digital task intensity of the US economy, while the relative importance of the two components is a priori unclear.*

Proceeding to the HOV-related aspects, we tackle two more questions with an associated hypothesis. In both cases, we continue to presume that the US occupies the position of digital leadership. The first of these HOV-related hypotheses is abundant in digital tasks, in the sense that it records a positive net FCT.[14] Hypothesis 3 therefore reads:

H3*: The US is abundant in digital tasks and scarce in non-digital tasks, while the opposite is true for the EU.*

Finally, in view of the intense academic debate on the Leontief paradox, an equally important issue is relative factor abundance (see Section 3.2 for details), which involves the comparison of factor intensity between any two factors (Leamer, 1980). The notion of relative factor abundance as revealed in trade correlates most directly to comparative advantages and our corresponding hypothesis is:

H4*: The US (EU) is abundant (scarce) in digital tasks relative to non-digital tasks.*

12 A recent report by McKinsey (2022, p. 15), evocatively entitled 'Securing Europe's competitiveness: Addressing its technology gap', boldly states that: *'Europe has many high-performing companies, but in aggregate, its firms are growing more slowly, creating lower returns, and investing less in R&D than their US counterpart. This largely reflects long-standing weakness in ICT and other forms of disruptive innovation'*.

13 Digital leaders are likely to employ numerous high-skilled occupations performing strategic functions for the development of frontier technologies. These high-skilled-occupations also include those directly related to the digital economy and therefore having a high digital task content. Digital leaders are therefore expected to have more occupations with high and very high digital task content. Similarly, in countries where leading digital corporations are domiciled, demand for digital skills and tasks will also be high such that 'digital industries' are accounting for a comparatively large share of the economy's employment. Both these factures contribute to the structural effect. In addition to this structural advantage, digital leaders will also outperform other countries along the occupation-intensive margin because workers, when employed in a technologically superior environment, are expected to develop more advanced and context-specific skills within the same occupation.

14 This hypothesis relates to the notion of absolute factor abundance as explained in more detail in Section 3.2.

3. Methodology and data

3.1. MEASURING DIGITAL TASKS

Investigating the digital task content of trade requires the proper measurement of digital tasks performed by workers in different occupations. While our objective is not to measure automation (Autor et al., 2003; Frey and Osborne, 2017; Arntz et al., 2017), offshoreability (Firpo et al., 2011) or viral transmission risk (Chernoff and Warman, 2022), we follow a similar approach, insofar as the digital task index is retrieved from tasks associated with occupations. Accordingly, following this task-based approach, we define endowments – or production factors – at the level of tasks, distinguishing between digital tasks and non-digital tasks. These two endowments add up to total labour services, measured in terms of employment[15].

We delve into the details of individual tasks performed in different occupations to capture the digital capabilities available to and employed in an economy. This is motivated by the belief that, maybe more than technologies, readiness for the digital transformation hinges on human capabilities (Cimoli et al., 2020). This is because even if digital technologies and innovations matter, these innovations are the result of human ingenuity, ultimately depending on capabilities[16]. The same is true for the adoption of foreign technologies. A second implicit assumption is that the task description of any occupation quite accurately reflects the actual skills of the persons working in that occupation. While there will be cases in which employees do not live up to their job demands, and even more instances in which workers are overqualified (e.g. immigrant workers), it is reasonable to assume that a person working as a mechanic (belonging to ISCO-08 occupation 723) has the required skills and qualifications to perform the usual tasks assigned to this occupation. The same is true for network professionals (ISCO-08 occupation 252) and all other occupations.

A simple example focusing on the digital task intensity of the two occupations just mentioned can help to explain the logic underlying the measurement of digital factor endowments. For these occupations total employment, their digital task content and the resulting endowment with the digital tasks associated with the respective occupations are shown for the EU and for the US (Table 1).

Focussing first on the EU, one finds approximately 547,000 database and network professionals (ISCO-08 252) for whom – according to the DTI – 52.5% of their total tasks constitute digital tasks. This implies that the labour services supplied by this occupation amount to a total of 287,000 digital tasks. The same logic applies to machinery mechanics and repairers (ISCO-08 723), who are much more numerous (3.5 million persons in the EU) but have a much lower digital task content (2.23).

[15] This parallels the distinction between skilled and unskilled labour.

[16] This holds true as long as no artificial superintelligence (ASI) (Turing, 1950) is developed.

Table 1 / Digital task content of occupations and associated factor endowments, 2012

Occupation (ISCO-08 code)	EU	US	EU	US	EU	US
	Employment		Digital task content		Digital tasks in occupation	
Database & network professionals (252)	547,211	834,331	52.46	63.46	287,089	529,467
…	..		..		..	
…	..		..		..	
Machinery mechanics & repairers (723)	3,522,213	2,030,063	2.23	1.07	78,632	21,726
	Total employment		**Digital task intensity**		**Endowment with digital tasks**	
Sum over all occupations	223,060,299	148,233,895	2.93	3.90	6,539,685	5,785,826

Note: Codes refers to the ISCO 08. The digital task content of occupations as reflected in the DTI. The implicit digital task intensity of the respective economy is defined as the ratio between digital tasks and total employment. Numbers refer to the year 2012.
Source: European LFS, OEWS; LFS CPS; Survey of Italian Occupations (ICP); O*NET database; OECD ICIO 2021.

As a result, the digital tasks performed by this occupation amount to less than 79,000. The remaining labour services constitute non-digital tasks. Summing digital tasks across all occupations yields the economy-wide endowment with digital tasks, which amounts to 6.5 million for the EU. The resulting average digital task intensity is 2.93%.

In this we have assumed that the DTI developed with occupational data from the Italian economy is applicable to all EU member states. 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.[17] Conversely, in order to allow for some within-occupation variation between the EU and the US, a separate digital task index is used for the US economy, which is derived from the US O*NET database. The comparison with the US shows, for example, that Database and network professionals (ISCO 252) are not only more numerous in the US compared to the EU but also have a higher digital task content. We refer to the first difference as part of the structural effect, while the latter difference is a within-occupation (or intensive margin) effect. In the case of the second exemplary occupation, Machinery mechanics and repairers (723), there are fewer employed persons in the US and their digital task content is below that of their European counterparts. This approach allows us to go beyond most of the existing task-based literature which relies on a single data source, typically the US American O*Net repertoire, to derive the indicators of interest.

3.2. EMBEDDING DIGITAL TASKS INTO THE HOV FRAMEWORK

We link digital tasks to the Heckscher-Ohlin-Vanek (HOV) theorem. In this we draw on the empirical literature on the factor content version of the Heckscher-Ohlin theory developed by Vanek (1968). The Heckscher-Ohlin-Vanek (HOV) theorem has the advantage that it lends itself to empirical testing of the predictions of the factor endowment model.

[17] Given this assumption, the digital task content of each occupation is the same across all EU member states. However, the resulting digital task intensity of the overall economy will vary from country to country because the occupational employment structures within industries differ, as does the industry structure. For example, the economy-wide digital task intensity is 2.88 in Italy for the year 2012 (Cirillo et al., 2021).

The methodology employed serves two purposes. First, we calculate the predicted factor content of trade (FCT) which can be used to identify countries' factor abundances as predicted by the HOV theorem. The HOV formulation (Vanek, 1968) of the Heckscher–Ohlin model predicts that each country should be a net exporter of those factors of production with which it is relatively abundantly endowed. Thus, for any country *c*, the predicted net FCT for factor f, $\tilde{F}_f^c$ is a linear function of the country's endowment vector, V_f^c, and its share in world consumption, s^c, of that factor $s^c \cdot V_f^W$ (Leamer, 1980):

(1) $$\tilde{F}_f^c \equiv V_f^c - s^c \cdot V_f^W$$

V^W is the 'world-wide' endowment, $V_f^W = \sum_c V_f^c$, and $s^c = (Y^c - TB^c)/(Y^W - TB^W)$, where Y^c is the GDP and trade balance of country *c* respectively and Y^W and TB^W are the 'worldwide' counterparts.[18] Here the fact that our sample is limited to 25 EU member states and the US leads to a complication. Since the economy-wide endowments, V_f^c, of a country cannot be restricted to the relevant amounts used for trade with countries in the sample, we also have to use the overall GDPs and also the 'global' trade balances (where the alternative would be to use the trade balances with other countries in the sample only). For this reason, and deviating from Trefler (1995) and Trefler and Zhu (2010), we also have to correct the global GDPs of all countries in the sample ($Y^W = \sum_c Y^c$) in the denominator for the sum over the global trade balances of all the countries in the sample, $TB^W = \sum_c TB^c$.

As long as identical and homothetic demand structures and full employment are assumed, equation (4) can be interpreted as follows: country *c*'s (predicted) FCT is positive in factor f if its production (equal to factor endowment V_f^c in case of full employment) uses more of this factor than its consumption ($s^c \cdot V_f^W$). Applied to our exercise, equation (1) can be written individually for the two factor endowments, V_{dt} and V_{nt}:

$$\tilde{F}_{dt}^c = V_{dt}^c - s^c \cdot (V_{dt}^W)$$

$$\tilde{F}_{nt}^c = V_{nt}^c - s^c \cdot (V_{nt}^W)$$

In line with our expectation above, we would expect a positive $\tilde{F}_{dt}^c$ for the US and a positive $\tilde{F}_{nt}^c$ for the EU. Since here we make calculations for each of the factors individually, this is a test of absolute factor abundance.

Equation (4) implies that a country *c* is abundant in factor f if its endowment of factor f relative to that of world endowment (V_f^c/V_f^W) exceeds country *c*'s share of world consumption, s^c (Feenstra, 2003). This type of analysis can be considered as a factor-specific or absolute concept of factor abundance which can be identified for a single factor and country. Having several factors (and countries) in his analysis, Trefler (1995) suggests ranking all factors f based on this ratio at the level of countries. Since we only have two factors, we can rank them as

(2) $$V_{f_S}^c/V_{f_S}^W < V_{f_A}^c/V_{f_A}^W$$

where $V_{f_S}^c$ is the scarce factor in country *c* and $V_{f_A}^c$ is the abundant factor in country *c*. The natural dividing line between scarce and abundant factors is the country's share in global consumption, s^c. This ranking of countries is fully aligned with Leamer's (1980) definition of relative factor abundance. Applied

[18] We make these calculations at the country-industry level but apply country-level consumption shares, s^c, in line with the HOV theorem.

to our factors, this definition implies that country *c* is abundant in digital tasks relative to non-digital tasks if $V_{dt}^c/V_{dt}^W > V_{nt}^c/V_{nt}^W$, where V_{dt} denotes endowments with digital tasks and V_{nt} denotes non-digital task endowments.

In view of concerns about the EU losing out in the digital race and the dominance of US tech companies, we expect the US to be relatively digital task abundant ($V_{nt}^{US}/V_{nt}^W < V_{dt}^{US}/V_{dt}^W$) and the EU to be relatively non-digital task abundant ($V_{dt}^{EU}/V_{dt}^W < V_{nt}^{EU}/V_{nt}^W$) where V_{dt} denotes endowments with digital tasks and V_{nt} denotes non-digital task endowments. Note that here we make use of the relative concept of factor abundance and apply it to the economy-wide endowments.[19]

Predicted FCTs, $V^c - s^c \cdot V^W$, are just one leg of the HOV theorem, and, per se, arguably not the most insightful (but relevant for the HOV tests). The *actual* FCT (Trefler and Zhu, 2010) or *measured* FCT (Davis and Weinstein, 2004) is needed to identify the actual amounts of each factor embodied in country *c*'s trade vector[20]. As in Guarascio and Stöllinger (2022), we employ the theory-consistent calculation of the FCT in the presence of cross-country technology differences and trade in intermediate goods following Trefler and Zhu (2010).

The calculation of the measured FCT requires three elements. First, a vector with the primary factor requirements for each factor of production, D_f; an international input-output table which allows us to calculate the global Leontief Inverse, $\boldsymbol{L}$, which summarises the global direct and indirect intra-industry relationships, and each country's net trade vector, T^c.[21] The primary factor requirements vector, together with the Leontief Inverse, accounts for differences in production technologies across countries and the latter obviously captures trade in intermediate goods – national and international – as well (Trefler and Zhu, 2010). The net FCT, F^c, of country *c* and factor f is then defined as:

(3) $$F_f^c \equiv diag(D_f) \cdot \boldsymbol{L} \cdot T^c$$

where F_f^c is a column vector of dimension *N·J x 1* containing the industry specific FCTs of country *c*, with *N* being the total number of countries (*N=26*) and *J* the number of industries (*J=41*). D_f is also of dimension *N·J x 1* and contains as its elements the country-industry specific amount of digital tasks, d_{dt}, per unit of gross output, *X*, and non-digital tasks, d_{nt}, per unit of gross output, *X*, respectively. $\boldsymbol{L}$, the Leontief a matrix, is of dimension *N·J x N·J*, with the typical element $l^{cn,ij}$ indicating 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*. T^c is a column vector of dimension *N·J x 1*. Post-multiplying the diagonalised vector D_f with the Leontief Inverse $\boldsymbol{L}$, yields the total factor requirement matrix for factor f, denoted by $\boldsymbol{A_f}$, which allows us to rewrite equation (3) as

(3') $$F_f^c \equiv \boldsymbol{A_f} \cdot T^c$$

The trade vector, T^c merits a short discussion because it is asymmetric with respect to how exports and imports are arranged. More precisely, T^c contains country *c*'s (industry-specific) exports to all other

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19 In this calculation, no actual trade flows are involved.

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

21 For a detailed exposition of the matrices for a 3-country-2- industry example, see Guarascio and Stöllinger (2022).

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.

Theoretically, the measured FCT should equal the predicted FCT such that for each factor f:

(4) $$\underbrace{\boldsymbol{A_f} \cdot T^c \equiv F_f^c}_{\text{Measured factor content of trade}} = \underbrace{\tilde{F}_f^c \equiv V_f^c - s^c \cdot V_f^W}_{\text{Predicted factor content of trade}}.$$

Empirically, equation (4), which is the statement of the Heckscher-Ohlin-Vanek theorem in its 'trade specification' (Davis and Weinstein, 2001), will not hold with equality.[22] It can be used, though, to derive several statements on the factor abundance of countries and it lends itself to empirical testing with the help of sign and rank tests (Bowen et al., 1987).

Country *c* is abundant in digital tasks *relative* to non-digital tasks if the ratio of digital tasks to non-digital tasks in production, (V_{dt}^c / V_{nt}^c), exceeds that in consumption, $(V_{dt}^c - F_{dt}^c)/(V_{nt}^c - F_{nt}^c)$ According to Leamer (1980), the relative factor abundance of production and consumption as revealed in trade is the actual test of the HOV-theorem and it can be applied even if trade is unbalanced. In this context it is important to note that F_{nt}^c reflects the factors embodied in trade $(\boldsymbol{A_f} \cdot T^c)$. With respect to the relative factor abundance as revealed in trade, we expect that for the US (V_{dt}^c / V_{nt}^c) exceeds $(V_{dt}^c - F_{dt}^c)/(V_{nt}^c - F_{nt}^c)$, while the opposite is true for the EU.

Since we expect that the measured FCT is aligned with the predicted FCT – an expectation which is also going to be tested – we expect a positive value for F_{dt}^c for the US and a positive value for F_{nt}^c for the EU. This relates to the absolute concept of factor abundance, in this case as revealed in trade. Note that it is quite possible that (in applying the absolute concept of factor abundance) a country is revealed to be abundant in both factors.

As alluded to above, in addition to the hypotheses related to assumed US digital leadership, we also perform a formal test for the HOV theorem following Bowen et al. (1987). This test compares the sign of the measured FCT with that of the predicted FCT for each of the countries included in the sample, that is, the US and all EU member states. Given the results obtained in Guarascio and Stöllinger (2022), we expect a fit of this sign test for approximately 90% of the cases.

3.3. DATA

The high level of granularity of the analysis means that we need to rely on several sources of data, for both the EU and the US. In principle, three main types of data had to be collected: employment data at the country-industry-occupation level; data on the digital task content of occupations and finally, international input-output data in order to trace factor endowments in international trade flows.

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[22] One reason is that the assumption of homothetic demand implicit in the predicted FCT is not borne out in the data, among other things, because of home market bias and the existence of non-tradable goods (Trefler, 1995; Trefler and Zhu, 2010; Stehrer, 2014).

Employment data. As in Guarascio and Stöllinger (2022), we rely on the European Labour Force Survey (LFS) for employment data at the country-industry level. The European LFS is a collection of national LFSs conducted by the national statistical offices of the member states[23] and constitutes the largest European household National LFSs that are harmonised at the EU level. In particular, they use the same concepts and definitions (in line with ILO guidelines) and the same classifications, e.g. for industries (NACE) and occupations (ISCO).

From the European LFS we obtain the number of employed persons, which is currently available at the level of 1-digit NACE Rev.2 industries (sections) and 3-digit ISCO-08 occupations. For the year 2012 we can make use of a former version of the European LFS which provided this data at the 2-digit NACE Rev.2 level (divisions). This is extremely valuable because the international input-output data uses a mixture of 1-digit and 2-digit NACE Rev. 2 industries. For the year 2018, we do not have these details available. Therefore the 2-digit industry-3-digit occupations data for 2018 is estimated by exploiting information from the year 2012. More specifically, we regress 2-digit industry-3-digit occupation cells on industry-level employment data (without occupation structure) from the OECD ICIO (see below) and the 3-digit occupation-1-digit industry level data from the LFS. Details of the panel regression model and the methodology are provided in Gschwent et al. (2023). The obtained (out-of-sample) predictions for 2018 are benchmarked against the actual 3-digit occupation-1-digit industry level data for 2018. This ensures that the 2018 data may contain some measurement error at the level of 2-digit industry-3-digit occupation cells but the 1-digit industry and aggregate employment data are fully aligned with European LFS data.

Since the occupation-industry-level data from the LFS is combined with the international input-output table and gross output data from the OECD ICIO, we benchmark the LFS data against the industry level employment of each country from the OECD's trade employment data accompanying the OECD ICIO database[24].

For the US, the compilation of the necessary employment data was more complicated. While the Bureau of Labour Statistics' (BLS) Occupational Employment and Wage Statistics (OEWS) survey provides very detailed US employment data at the combined occupation and industry level, the classifications follow the NAICS industry classification for industries and the SOC occupational classification. Hence crosswalks between the NAICS and NACE Rev.2 industries and the ISCO-08 and SOC 2010 occupations had to be used to bring the US data to the NACE Rev.2 industry classification. All data is transformed to NACE Rev.2 industries because this is the classification used in the OECD ICIO database[25]. With respect to occupations, we bring the SOC level data to ILO's categorisation of occupations (ISCO-08), which is also used in the European LFS.

Unfortunately, none of these crosswalks are unique so that some assumptions regarding the assignment of NAICS industries and SOC occupations had to be made (see Gschwent et al., 2023). Also, since the OEWS is very detailed but not complete (some occupations are only partially covered), the OEWS data was supplemented with data from the US Labor Force Statistics (LFS) from the Current Population Survey (CPS). The latter survey has a less detailed industry and occupation structure but (in most

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

24 The data is available at: https://stats.oecd.org/Index.aspx?DataSetCode=TIM_2021.

25 The OECD ICIO database refers to the ISIC Rev.4 classification but at this level of aggregation it is equal to the NACE Rev. 2 classification.

industries) better coverage. Therefore, the OEWS data was first benchmarked against the (CPS) and some imputations, mainly for missing agricultural occupations, were made. Analogously to the European data, we benchmark the US employment data against the 2-digit (NACE-based) industry-level employment data from the OECD ICIO database.

Digital task indicators. The Survey of Italian Occupations (*Indagine Campionaria sulle Professioni,* ICP) is a unique dataset compiled by the National Institute for Public Policy Analysis of Italy (INAPP). Following the US O*Net approach,[26] 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 inequality (Cetrulo et al., 2022).

To measure digital comparative advantages, we rely on the ICP-based digital tasks indicator (DTI), which is defined at the 4-digit level of occupations according to the CP (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 to match the European LFS data. As mentioned, we assume that the 3-digit ISCO-08 occupations are comparable across EU member states in terms of tasks involved. In this case it is appropriate to apply the ICP-based DTI to all EU countries[27]. It should also be mentioned that the ICP-based DTI is defined at the level of occupations without consideration of the industry (which is also the case in the O*NET database). As a result, a secretary (ISCO 412) employed at a steel company is assumed to perform the same tasks as a secretary working at a university and for this reason has the same digital task content. In other words, the data does not feature any cross-industry variation at the level of occupations.

The ICP-based indicators allow for 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. As we are primarily interested in the latter task, we exploit the digital task indicator (DTI), which is a narrow and more fine-grained measure of digitalisation (Cirillo et al., 2021)[28]. It is derived from a free-form section included in the 2012 wave of the ICP wherein each worker describes – using their own words in a lightly coordinated manner – 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’ in order 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

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

27 In fact, the description of all ISCO-08 occupations (at different levels) are accompanied by a list of typical tasks involved as well (ILO, 2012).

28 The alternative would be the digital use indicator (DUI) which is a ‘broader’ digitalisation indicator, intended to also capture more basic digital tasks (Cirillo et al., 2021).

each occupation, the weighted average, i.e. the 'importance score', of the digital tasks compared to all tasks used to describe the occupation. As Cirillo et al. (2021) underline, the DTI allows one to measure the digitalisation of tasks at both the extensive – 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.

One of the main objectives of this paper, and a major extension of Guarascio and Stöllinger (2022) is to allow for differences in digital task contents across EU member states and the EU. Therefore, we turn to the US Occupational Information Network (O*NET) database as a distinct but in many respects comparable source of data for descriptions of occupational tasks. The O*NET database is the logical choice for defining the digital task content of US occupations because it is based on US occupations and has also been widely used for developing all sorts of indicators, with the routine-task (Autor et al., 2003) and offshoring indicators (Firpo et al., 2011) being the most famous ones.

O*NET is a publicly available electronic list[29] of all existing occupations in the United States, recorded at the Standard Occupational Classification (SOC) System. It contains a large set of variables that describe work and worker characteristics in each occupation[30]. Of the numerous worker and job-oriented data categories, the file containing the 'Detailed Work Activity' of occupations is used, in combination with the 'Task Ratings' and the 'Task Statements' files. The Task ratings file provides information on the relative importance of the tasks performed by individual occupations on a scale ranging from 0 to 100, while the 'Task Statements' file holds descriptions of the tasks associated with each of the occupations and is used to perform a keyword search for 'digital tasks' within the core tasks. The files 'Task Ratings' and 'Task Statements' are combined in order to construct a DTI that mirrors – to the extent possible – the ICP digital task index. The latter is the result of a count index resulting from a digital keyword search over the up to 15 core tasks for each of the 796 5-digit ISCO occupation groups. If one of the digital keywords (e.g. computer) is included in the description of a core task, this core task is considered to be a digital task and is assigned a 1. The digital task score of each individual occupation is then simply the ratio of digital to non-digital tasks. This way, out of the resulting over 6200 tasks, Cirillo et al. (2021) classified 131 tasks as digital.

While the ICP digital task indicator serves as guidance, some adjustments were made to the way the indicator is constructed. First, the list of keywords had to be adjusted to ensure that the descriptions in the 'Task Statements' in the O*NET database were appropriately captured. Second, the 'Task Ratings' could be used to replace the binary (1 or 0) classification of tasks as digital or not digital with a score that ranges from 0 to 100[31] which reflects the importance of the respective task for an occupation.

Since the number of core tasks of an occupation is unrestricted in the O*NET database[32], the number of core tasks and the number of digital core tasks is higher than for the ICP data: Out of the number of core tasks (12,197 in O*NET 17.0 corresponding to 2012 and 13,161 in O*NET 26.0 corresponding to 2018), we heuristically classify 486 respectively 579 tasks as digital (between 4% and 4.15% of core tasks, in comparison to around 2.1% for ICP). The classification is established by defining a list of digital

29 See: https://www.onetcenter.org.

30 See: https://www.onetcenter.org/database.html#individual-files.

31 In principle this score ranges from 0 to 100 but because the analysis focusses on core tasks these importance scores are typically high, with a mean between 88 and 90 and a minimum value of 67 across all O*NET database versions used in the analysis.

32 The maximum number of core tasks in the sample is 38 (for Special Education Teachers).

keywords. The result, that is, the tasks classified as digital, are manually checked and further exclusions are made in case the keywords pick up tasks that are clearly not digital in nature. For example, the naïve search using the keyword 'computer' would also include the task 'Inspect, test, and listen to defective equipment to diagnose malfunctions, using test instruments such as handheld computers, motor analysers, chassis charts, or pressure gauges.' Furthermore, core tasks of highly digital occupation groups (e.g. Programmers) that were not identified as digital by the keywords were checked.

Finally, instead of calculating the share of digital tasks out of total tasks per occupation group – as is done with the ICP index – the 'Task Ratings' allow to weight the importance of each task. Therefore, the final digital task index using O*NET data is calculated as the share of digital task ratings out of total task ratings per occupation group.

A clear advantage of the O*NET database over the ICP data is that it is regularly updated. While these updates do not occur simultaneously for all occupations at one point in time, it is still possible to use different versions of O*NET to capture changes in the digital task content of occupations. In this vein, we use the O*NET 17.0 published in July 2012 to capture digital task contents of occupations as of 2012, while for the year 2018 we turn to the O*NET 23.3 version from May 2019[33]. This allows us to compare the digital task contents of US and European occupations for the year 2012. Given the piecemeal update of occupations' profiles in the O*NET repository, the identifiable within-occupation changes must be seen as the lower bound of actual changes in the task contents of occupations. Hence, we consider this inter-temporal to be only a first attempt to approach the question of changes over time and we do not put it into the focus of the analysis.

Comparing the outcomes of the ICP-based DTI and the O*NET-based DTI for 2012, one finds that the former assigns a positive DTI value to 70 ISCO-08 occupations, while in the latter the corresponding number is 69. Of those, 54 occupations have positive values in both DTIs. Overall, the correlation coefficient between the two indicators is 0.89 which is a remarkably high value given that the DTIs were not only retrieved using different data sources but that these data sources also work with different task descriptions and even different classifications of occupations, i.e. ISCO-08 for EU countries and SOC for the US. Table 2 lists the top ten occupations ranked by digital task content.

Among the occupations with the highest index values according to the ICP-based DTI, five are also found among the top ten in the O*NET-based DTI (Table 2, panel a) and vice versa (panel b). However, there are also some occupations which are top-ranked only in the ICP-based DTI, such as telecommunication and broadcasting technicians (ISCO-08 352), which ranked only 28th in the O*NET-based DTI. Conversely, finance professions (ISCO-08 241), for example, occupy rank 10 in the O*NET-based DTI but are found in position 21 in the ICP-based DTI.

[33] The O-NET surveys cannot be perfectly assigned to any particular year because the surveys for all occupations are updated on a regular basis but not all occupations at the same time.

Table 2 / Occupations with the highest digital task contents, 2012

(a) Top ten occupations in the EU, based on ICP digital task index

Rank	isco3d	isco3d_desc	DTI (ICP)	Employment	Rank in US
1	351	Information and communications technology operations and user support technicians	65.609	1,314,995	2
2	211	Physical and earth science professionals	52.464	333,586	6
3	212	Mathematicians, actuaries and statisticians	52.464	110,240	14
4	251	Software and applications developers and analysts	52.464	2,726,292	1
5	252	Database and network professionals	52.464	547,211	3
6	352	Telecommunications and broadcasting technicians	32.848	343,340	28
7	313	Process control technicians	20.212	714,925	41
8	413	Keyboard operators	18.379	564,841	22
9	214	Engineering professionals (excluding electrotechnology)	10.241	2,912,962	26
10	215	Electrotechnology engineers	10.241	853,344	7

(b) Top ten occupations in the US, based on O*NET digital task index

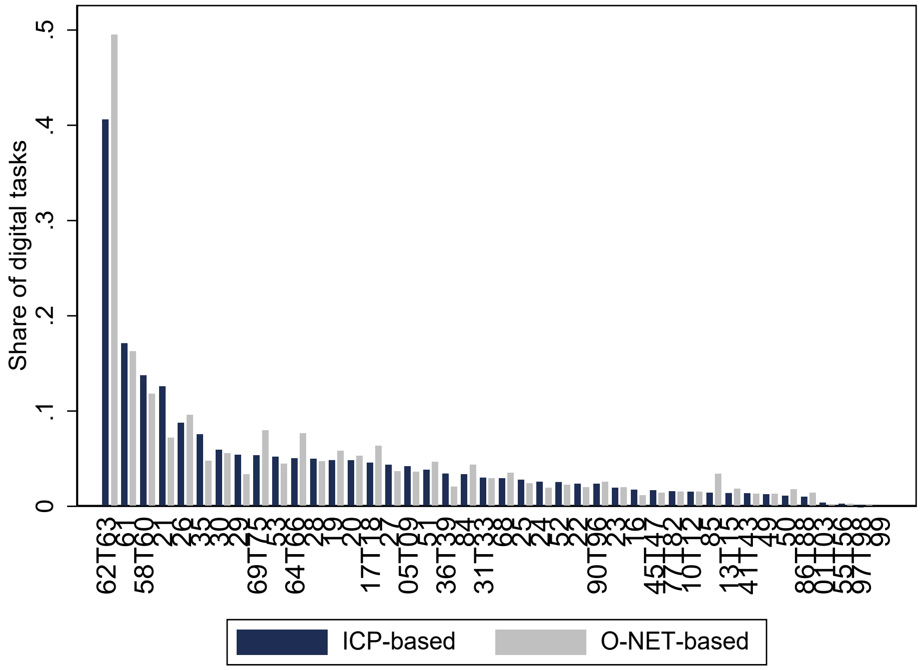
Rank	isco3d	isco3d_desc	DTI (O-NET)	Employment	Rank in EU
1	251	Software and applications developers and analysts	76.989	2,159,741	4
2	351	Information and communications technology operations and user support technicians	73.762	963,907	1
3	252	Database and network professionals	63.460	834,331	5
4	216	Architects, planners, surveyors and designers	19.431	548,053	38
5	133	Information and communications technology service managers	17.732	360,454	66
6	211	Physical and earth science professionals	17.449	211,915	2
7	215	Electrotechnology engineers	16.128	407,630	10
8	411	General office clerks	14.668	2,961,343	17
9	431	Numerical clerks	12.884	2,588,099	20
10	241	Finance professionals	11.940	2,127,195	21

Note: Codes refer to the ISCO-08.
Source: European LFS, OEWS; LFS CPS; Survey of Italian Occupations (ICP); O*NET database; OECD ICIO 2021.

While we cannot entirely rule out that a part of the differences in the digital task content of ISCO-based occupations in the US and the EU are due to the methodology employed, it is much more plausible that the differences in the task structure of occupations reflect actual differences in the job profiles in the two economies. In fact, the high probability that such differences exist, is the very reason that since the existence of the ICP data, researchers have developed new indicators based on the ICP data, such as the recent teleworkability and social interaction indices by (Sostero et al., 2020), or they opt for ICP-based indicators when analysing European countries (Flisi and Santangelo, 2022).

Overall, the two DTI indicators deliver highly plausible results. Figure 1 shows the DTI of Italian industries for both the ICP-based DTI and the O*NET-based DTI, ranked by the former. While there are marked differences, especially in the industries with high digital task intensity, the ranking of the industries is quite consistent across the two DTIs. Computer programming and information service activities (J62_J63) is by far the most task-intensive industry, with a digital task score of 41 (ICP) respectively 50 (O*NET), followed by *Telecommunications services* (J61) with a score of 17 (ICP) respectively 16 (O*NET). The most digital task-intensive manufacturing industry is the *Computer,* *electronic and optical products industry* (C26), found in 5th position in the ICP-based indicator and 4th in the O*NET-based indicator.

Figure 1 / Digital task indicator, Italy, 2012



Note: Codes refer to industries in the OECD ICIO database (based on ISIC Rev. 4). See Appendix for details.
Source: European LFS, Survey of Italian Occupations (ICP); O*NET database; OECD ICIO 2021.

We read Table 2 and Figure 1 as evidence that both indicators yield not only plausible results but also comparable results, while still allowing for within-occupation variation between EU countries and the US in digital task content. For this reason, we apply the ICP-based DTI to EU countries and the O*NET-based DTI to the US economy in the main analysis. We are convinced that this is a very interesting extension of previous work as it allows one to investigate not only differences in digital task intensities resulting from differences in the occupational employment structure but also from differences in the digital task content at the level of individual occupations. Admittedly, we cannot rule out that parts of the differences in the DTIs are due to measurement error.

International input-output data. For the measured factor contents of trade calculations, international input-output data is needed; here we turn to the OECD Inter-Country Input-Output (ICIO) Database. The input-output table of the OECD ICIO Database captures national and international inter-industry flows of intermediate goods and well as final demand flows. The OECD ICIO comprises 45 industries – based on the NACE Rev.2 classification – which are a mixture of divisions (2-digit industries) and sections (1-letter industries). The main advantage of the OECD ICIO over alternative international input-output data (such as the WIOD) is the larger country coverage (63 plus the rest of the world), though this is of lesser relevance for our purposes, and the comparatively long period covered which ranges from 1995 to 2018 and therefore allows for the analysis of more recent structural developments. For the purpose of analysis, the industry structure of the OECD ICIO is mildly adjusted by merging some industries, notably the three separate mining and quarrying industries in the database, resulting in 41 industries[34]. The details of the resulting adjusted OECD ICIO industry structure are provided in the Appendix. While this has a less detailed industry classification compared to the WIOD Version 2016, the longer time span – until 2018 – allows for a more recent analysis of comparative advantages.

The OECD ICIO database is a complete dataset so that no imputations were necessary. Also, since all employment data was rescaled to match the OECD ICIO industry-level data, no adjustment in this respect was necessary either. The sole adjustment to be made was to 'trim down' the (adjusted) OECD ICIO input-output table featuring 64 reporters to the 26 economies (25 EU countries plus the US) which form part of the analysis of this paper. In other words, the EU 25 plus the US are considered to be the world economy for the purpose of this analysis.

34 We do this mainly to ensure better comparability with the results in Guarascio and Stöllinger (2022) which is based on data from the World Input-Output Database (WIOD).

4. Results

The results are presented in two parts. Section 5.1 contains the descriptive results of digital task intensities in the EU and the US, existing differences in these intensities and their underlying reasons. These results relate to hypothesis 1 and hypothesis 2 put forward in the previous section. Section 5.2 is dedicated to the results on digital task abundance in the HOV framework and will test the appropriateness of hypotheses 3 and 4.

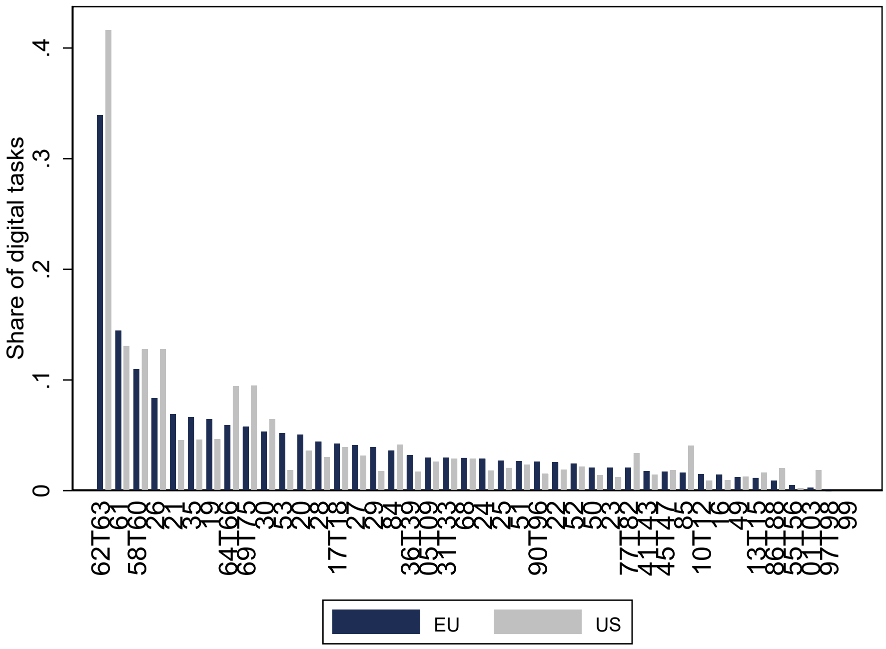
4.1. DIGITAL TASK INTENSITIES

We start the discussion of the results with the presentation of the core analysis which uses the ICP DTI for the EU and the O*NET DTI for the US. These results are confined to the year 2012 because this is the only year for which both the Italian (which we treat as European) DTI and the DTI for the US economy are available.

Core results

As was already shown for Italy, IT and other information services (62T63) is the industry with the highest digital task intensity (Figure 2).

Figure 2 / Digital task shares across industries, EU and US, 2012

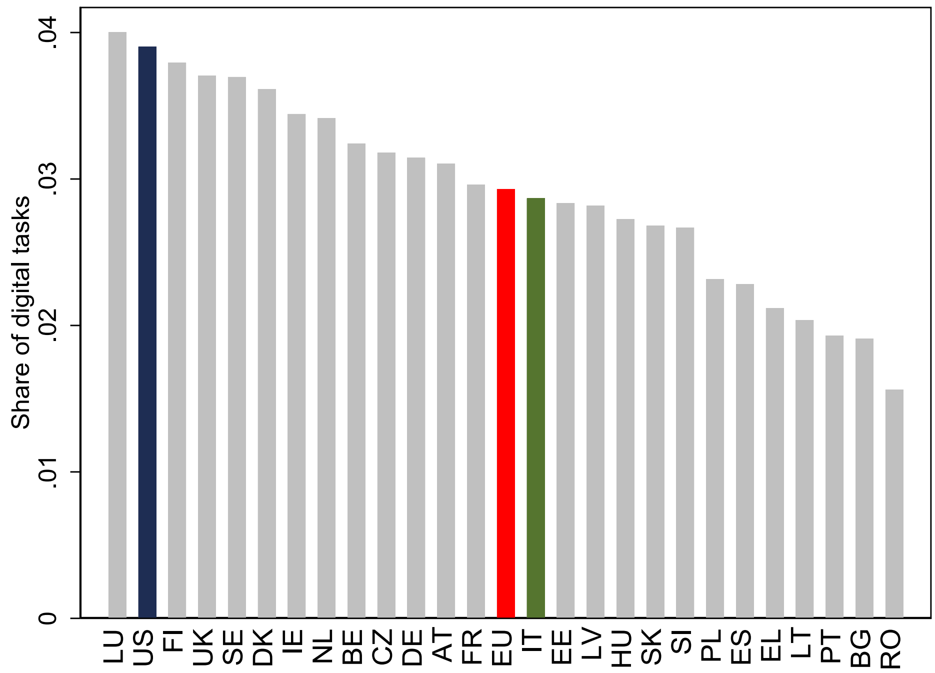


Note: NACE Rev.2 industry code as used in the OECD ICIO database 2021. For a list of the industry descriptions corresponding to the NACE Rev.2 industry codes, see Appendix. EU based on ICP DTI, US based on O*NET DTI.
Source: European LFS, OEWS; LFS CPS; Survey of Italian Occupations (ICP); O*NET database; OECD ICIO 2021.

This is true for the EU but even more so for the US. The digital task intensity in this important industry exceeds 0.4 for the US, compared to 0.34 in the EU. And while there are several industries in which the US has a higher digital task intensity, for example publishing, audiovisual and broadcasting activities (58T60) or computer, electronic and optical equipment (26), this is not a universal rule as evidenced by the telecommunications service industry (61). The same is true for the wood and industry (16) or the basic metals industry (24), which are both industries in which European companies are known to be comparatively innovative and use advanced technologies[35].

At the economy level, the share of digital tasks in total labour services performed in the US (3.9%) exceeds that of the EU (2.9%) by a full percentage point (Figure 3). At first sight this difference may appear to be small. However, considering that digital tasks, because of the intentionally restrictive definition, account for less than 3% of persons employed, a 1 percentage point difference implies that the digital task intensity in the EU is one third lower than in the US. Irrespective of the magnitude of this 'digital gap', we can clearly confirm our first hypothesis which was that the US economy, as the presumed digital leader, features a higher digital task intensity than the EU.

Figure 3 / Digital task shares by countries, 2012



Note: EU based on ICP DTI, US based on O*NET DTI. Digital tasks as shares of total tasks performed in the respective economy
Source: European LFS, OEWS; LFS CPS; Survey of Italian Occupations (ICP); O*NET database; OECD ICIO 2021.

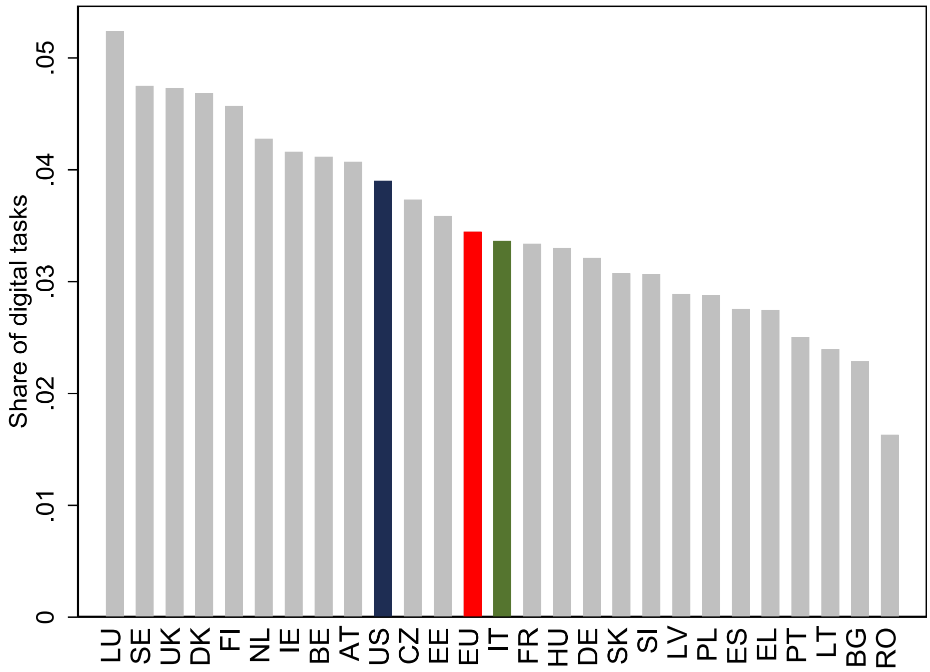
Moreover, the digital task content of the US economy is also higher than that in any EU member state, with the exception of Luxembourg. Italy – the country to which we attach particular importance because the ICP DTI data refers to the Italian economy – has a very similar digital task content to the EU as a whole so that the EU-US comparison is also similar to the comparison between Italy and the US shown before.

[35] An example would be the application of nanotechnologies in the Finnish paper industry (Foray, 2013).

Results based purely on the O*NET DTI

The results become more nuanced when we calculate the digital task intensity of the EU and individual member states with the O*NET-based DTI, that is, with the same DTI as for the US. The digital task content of the US economy, of course, remains the same and is still higher than that of the EU economy, which now records a digital task content of 3.44% (Figure 4). Hence, the relative difference is approximately halved. Moreover, the O*NET-based digital task content of several EU member states exceeds that of the US, including Finland, Sweden, Denmark and the United Kingdom. Note, however, that by applying the DTI of US occupations to EU countries, we have essentially eliminated the occupation-intensive margin.

Figure 4 / Digital task share by countries, O*NET based digital task scores, 2012



Note: EU and US based on O*NET DTI.
Source: European LFS, OEWS; LFS CPS; O*NET database; OECD ICIO 2021.

This result is at the same time plausible and surprising. It is plausible because one would expect the Nordic countries and the United Kingdom to be the ‘most digital’ economies in the EU; and it is surprising because our prior expectation is that the US clearly holds digital leadership vis-à-vis the EU. Appendix 2 shows that this result is in line with existing evidence using data from the OECD Survey of Adult Skills (PIAAC).

Sources of the EU-US digital task gap

The comparison of the core results in Figure 3 (ICP-based DTI for the EU; O*NET-based DTI for the US) with the results using a common DTI (Figure 4), allows us to identify the sources of the gap in digital task intensity between the EU and the US economy. This is because the former reflects the entire difference in digital task intensity, while the latter only reflects structural differences between the EU and the US.

The occupation-intensive margin can therefore be easily retrieved as the difference between the overall EU-US digital gap and the structural gap (Table 3).

This exercise, which addresses hypothesis 2, shows that the US's digital leadership – to the extent that it is detectable in digital labour services – is grounded as much in the occupation-intensive margin of occupations as in structural differences. Remember that the structural component comprises two elements: (i) differences in the composition of occupations within an industry and (ii) differences in the relative importance of the industries. In any case, both effects are negative – from the viewpoint of the EU – which is in line with our expectations. Admittedly, we were agnostic with regard to the relative importance of the intensive margin and the structural effect but the key proposition was that both are working in the same direction.

Table 3 / Digital task share of EU member states and differences to the US, 2012

	Digital task share based on		Difference to US (in p.p.)		
	ICP-DTI	O*NET-DTI			
Country	**(1)**	**(2)**	**Overall**	**Structural effect**	**intensive margin effect**
EU	*2.93%*	*3.45%*	*-0.97*	*-0.46*	*-0.52*
LU	4.00%	5.24%	0.10	1.34	-1.24
FI	3.79%	4.57%	-0.11	0.67	-0.78
UK	3.70%	4.73%	-0.20	0.83	-1.03
SE	3.70%	4.75%	-0.21	0.85	-1.05
DK	3.61%	4.69%	-0.29	0.78	-1.07
IE	3.44%	4.16%	-0.46	0.26	-0.72
NL	3.42%	4.28%	-0.49	0.38	-0.86
BE	3.24%	4.12%	-0.66	0.21	-0.88
CZ	3.18%	3.73%	-0.72	-0.17	-0.56
DE	3.14%	3.21%	-0.76	-0.69	-0.07
AT	3.10%	4.07%	-0.80	0.17	-0.97
FR	2.96%	3.34%	-0.94	-0.56	-0.38
IT	2.87%	3.36%	-1.04	-0.54	-0.50
EE	2.84%	3.59%	-1.07	-0.32	-0.75
LV	2.82%	2.89%	-1.08	-1.01	-0.07
HU	2.73%	3.30%	-1.18	-0.60	-0.58
SK	2.68%	3.07%	-1.22	-0.83	-0.39
SI	2.67%	3.06%	-1.24	-0.84	-0.40
PL	2.32%	2.88%	-1.59	-1.03	-0.56
ES	2.28%	2.76%	-1.62	-1.15	-0.48
EL	2.12%	2.75%	-1.79	-1.15	-0.63
LT	2.04%	2.39%	-1.87	-1.51	-0.36
PT	1.93%	2.50%	-1.97	-1.40	-0.57
BG	1.91%	2.29%	-1.99	-1.62	-0.38
RO	1.56%	1.63%	-2.34	-2.27	-0.07
US		*3.90%*			

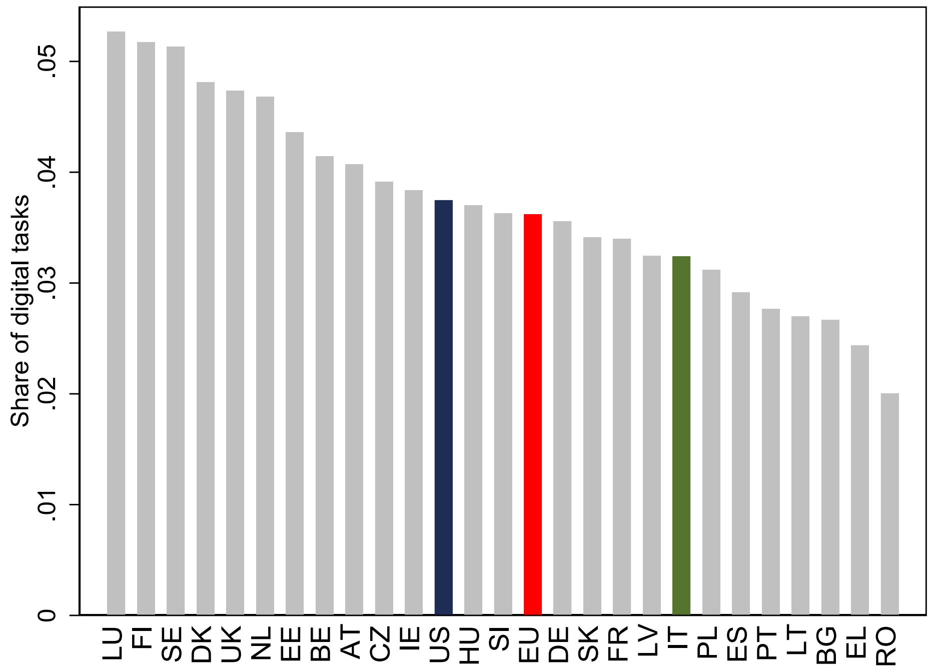
Note: In column (1) the DTI of the EU is based on the ICP data; in column (2) it is based O*NET data. All differences are relative to the digital task content of the US economy based on the O*NET DTI (3.90%). The intensity effect is retrieved as the residual between the overall effect and the structural effect.
Source: European LFS, OEWS; LFS CPS; Survey of Italian Occupations (ICP), O*NET database; OECD ICIO 2021.

This decomposition of the overall gap in digital task intensity vis-à-vis the US can be equally calculated for each of the EU member states. This shows that the occupation-intensive margin for the EU is always negative. As a reminder, this means that on average, occupations in the US are more digital task intensive than corresponding occupations in the EU[36]. Moreover, the effect of the occupation-intensive margin is larger for those EU member states which have comparatively high digital task intensity. In contrast, for the countries at the lower end of the ranking, the structural effect typically exceeds the effect of the occupation-intensive margin. As we have already noted, for the EU as a whole, the structural effect and the intensive margin effect contribute in equal parts – 0.46 percentage points (p.p.) and 0.52 p.p. respectively – to the overall (negative) effect. These relative contributions are very similar for the Italian economy which, for methodological reasons, still serves as the benchmark EU country.

Developments over time, 2012–2018

The O*NET-based DTI also allows for a comparison over time. Hence, one can compare the ranking of countries by their digital task intensity in 2018 (Figure 5) with that in 2012, which was already shown in Figure 4.

Figure 5 / Digital task shares by country, O*NET based digital task scores, 2018



Note: EU and US based on O*NET DTI.
Source: European LFS, OEWS; LFS CPS; Survey of Italian Occupations (ICP); O*NET database; OECD ICIO 2021.

[36] One may argue that this raises a conceptual issue because, in principle, occupations in the ISCO classification are standardised and supposed to be comparable across countries with regard to the tasks and responsibilities associated with the respective occupation. However, it is also obvious that, for example, teachers, nurses or waiters do not perform exactly the same tasks as these tasks depend, inter alia, on legislation (e.g. whether nurses are legally entitled to take blood) and the physical environment (e.g., whether the ordering system in a restaurant is digitised or paper-based).

There are three main insights to be gained from this comparison over time. First, in 2018 the US economy still had a higher digital task content (3.75) than the EU (3.62). However, as in 2012, the US is found behind a series of EU member states which all have a superior digital task intensity, with Luxembourg, Finland and Sweden surpassing the 5% threshold. Second, the structural part of the 'digital distance' between the US and the EU, as measured by digital tasks in labour services, narrowed to 0.13 p.p. in 2018 compared to 0.46 p.p. in 2012[37].

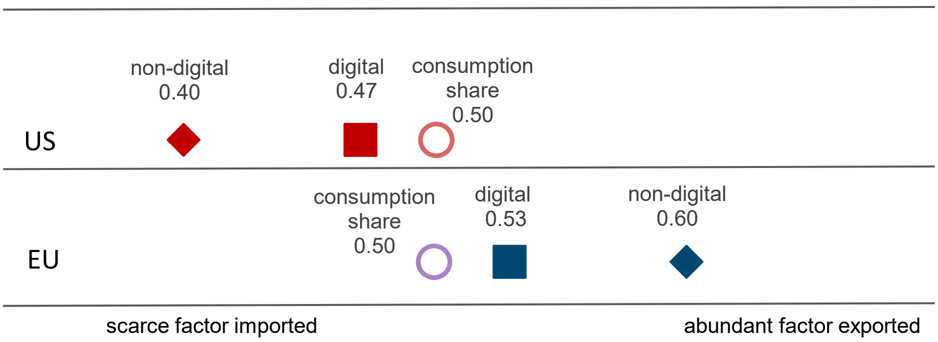
Third, digital task content declined in both the US and the EU between 2012 and 2018. This is a rather unexpected result in a period which may be considered as the onset of the digital transformation. Our data does not allow us to give an ultimate explanation for this development, but it is compatible with the finding of a polarisation of occupations (Goos et al., 2007 for the EU; Autor and Dorn, 2013 for the US). It is, however, also compatible with the more drastic hypothesis by Braverman (1974) that digitalisation and technological progress in general is always geared towards increasing efficiency and rationalising, which more often than not results in simplifying and standardising the tasks to be performed by workers. Therefore, even if some of the top digital-intensive jobs become even more digital, overall the digital task content of occupations may go down. Finally, it should also be mentioned that updating the characteristics of the occupations in the O*NET database is undertaken only partially from one version to the next. Hence, between 2012 and 2018 not all occupations have been updated so that this analysis does not capture the entire within-occupation dynamics which has happened in the US economy during the period considered.

In a next step, we discuss the digital task content of the EU and the EU in the HOV framework, which means we look at the factor endowments and factor contents of trade.

4.2. DIGITAL TASK ABUNDANCE IN THE HOV FRAMEWORK

We start the discussion with the ranking of our two factors in the EU and in the US as suggested in Trefler (1995) and using the relative factor abundance definition of Leamer (1980) (Figure 6).

Figure 6 / Relative factor abundance and factor scarcity, EU and US, 2012



Note: The figures for digital and non-digital trade are the shares of the respective factor and country in the worldwide endowment with that factor. Ranking following Trefler (1995). EU based on ICP DTI, US based on O*NET DTI.
Source: Ranking of factors following Trefler (2015).

[37] Since for 2018 we can only calculate the digital task content based on the O-NET-DTI, we can only identify the change in the structural effect but not the overall difference.

Since the EU and the US add up to the world in our analysis their share in world endowments adds up to 1 (as do the consumption shares, s^c). We find that digital tasks (with a ratio of 0.40 relative to worldwide digital tasks) are abundant in the US relative to non-digital tasks in labour services (ratio of 0.47). The opposite is true for the EU. In comparison to the consumption share, however, the US is scarce in both digital tasks and non-digital tasks. In contrast, the EU is abundant in both these factors.

These rankings are based on the direct factor endowments and the theoretical consumption shares, which are derived by assuming identical and homothetic preferences. They reflect the predicted FCT. The actual factors embodied in trade flows, however, are reflected in the measured FCT. Both types of FCTs are presented in Table 4 for the US, the EU and individual member states.

Looking first at the EU-US comparison, it is reassuring that the predicted FCT confirms the ranking of factors in comparison to the consumption shares: the US is scarce in both factors and therefore records negative predicted FCTs for both factors. In contrast, the EU is abundant in both factors and correspondingly has positive predicted FCTs. This pattern is confirmed by the measured FCT, which is a comforting result.

Table 4 / Measured and predicted factor content of trade, 2012

	Measured factor content of trade		Predicted factor content of trade	
Country	**Digital tasks**	**Non-digital tasks**	**Digital tasks**	**Non-digital tasks**
US	*-45,332*	*-2,013,710*	*-382,611*	*-37,201,730*
EU	*45,332*	*2,013,711*	*382,611*	*37,201,730*
AT	-12,003	-433,285	-15,091	-167,019
BE	-13,884	-436,843	-42,083	-1,119,842
BG	10,352	636,635	43,409	2,723,409
CZ	25,519	799,149	84,364	2,670,862
DE	15,055	-500,026	110,259	5,425,937
DK	-10,358	-360,729	-11,601	-583,302
ES	10,348	837,913	-58,168	4,012,427
EE	1,385	60,998	7,706	310,821
FI	-6,659	-226,848	438	-352,178
FR	-44,541	-1,219,671	-160,815	-1,758,302
UK	31,797	-661,666	121,339	87,009
EL	-2,962	41,155	-2,254	1,500,305
HU	16,661	659,091	62,830	2,542,984
IE	-14,981	-292,100	-11,563	-405,608
IT	-5,127	-286,711	-38,694	2,245,251
LT	1,139	152,177	9,211	762,507
LU	-5,013	-103,650	-6,100	-255,566
LV	2,267	56,369	13,600	527,207
NL	2,404	151,771	11,587	79,591
PL	37,157	1,968,107	170,858	9,658,126
PT	-198	318,922	10,596	2,225,473
RO	10,246	892,461	71,209	6,650,818
SK	11,230	429,258	19,927	1,005,720
SI	1,847	99,632	8,528	432,593
SE	-16,347	-568,400	-16,882	-1,017,492

Note: In column (1) the DTI of the EU is based on the ICP data; in column (2) it is based O*NET data. All differences are relative to the digital task content of the US economy based on the O*NET DTI (3.90%). The intensity effect is retrieved as the residual between the overall effect and the structural effect.
Source: European LFS, OEWS; LFS CPS; O*NET database; OECD ICIO 2021.

There are also a large number of cases in which the measured and predicted FCT have the same sign, which hints at good performance of the sign tests. Note that in the overwhelming majority of cases, EU member states have either positive or negative FCT in digital and non-digital tasks in labour services. However, this is not a mechanical result as evidenced by Germany, the United Kingdom and Portugal (measured FCT) as well as Spain, Finland, Greece and Italy (predicted FCT).

The results in Table 4 contain several features that are well-documented in the HOV literature. First, it is not necessarily the case that the countries which score high in terms of digital task intensity also record a positive net FCT in digital tasks (indicative of absolute factor abundance). Finland is a case in point among EU member states. The country has a negative measured FCT in digital tasks despite having the second highest digital task intensity after Luxembourg.

Most importantly, the US is such an example as it also combines high digital task intensity with a negative measured FCT in digital tasks. This is evidence of the 'endowment paradox' (Trefler, 1995), which refers to the common finding that countries with high GDP per capita tend to be scarce in most factors, while countries with comparatively lower GDP per capita are found to be abundant in most factors. A prime example of the latter in our sample is Bulgaria. Another factor that influences the measured FCT reported in Table 4 is the overall trade balance position, which for the US has been persistently negative over the entire time span considered. Thus, while the HOV literature provides good explanations for the results, it nevertheless means that hypothesis 3 is not confirmed. Taken together, it seems that the endowment paradox combined with the US trade deficit dominate the higher digital task endowment of the US economy so that the US ends up also being scarce in digital tasks when applying the absolute notion of factor abundance.

We conclude the discussion of the net FCT by noting that the predicted FCT are, in general, much larger than the measured FCT which points to the phenomenon of 'missing trade' (Trefler, 1995). The missing trade phenomenon refers to the fact that trade flows (and hence resulting net balances) are lower than predicted by differences in endowment structures. The main explanation for this is typically home market bias (and hence implicitly a violation of the assumption on homothetic preferences).

The fact that countries may be abundant in both factors – in terms of absolute factor abundance – signals that this metric may not be the most suitable indicator for comparative advantage. More informative is relative factor abundance as revealed in trade (see Leamer, 1980). Revealed relative factor abundance can be derived with the help of factor endowments, which can be considered as the factor use in production, and the net FCT. For any country *c*, the factors used in production (V_{dt}^{c}) less the factors embodied in net FCT (F_{dt}^{c}) equal consumption ($V_{dt}^{c} - F_{dt}^{c}$). The relative factor abundance revealed in trade can be determined by taking the ratio of both our factors - V_{dt}^{c} and V_{nt}^{c} and then comparing this ratio for production and consumption. This comparison shows that the US is relatively abundant in digital tasks as the ratio between digital and non-digital tasks is higher in production than in consumption (Table 5).[38] However, revealed relative digital task abundance in US production exceeds that of consumption only by a small margin. This has at least two reasons. First, the net FCT is small compared to the factor endowment. Secondly, the share of digital tasks relative to non-digital tasks is small to begin with.

[38] It is this sort of comparison with which Leamer (1980) solved the 'Leontief Paradox' (Leontief, 1953), by showing that US production has a higher capital/labour ratio than its consumption.

Table 5 / Relative factor abundance as revealed in trade, EU vs US, 2012

	Ratio Digital tasks/Non-digital tasks in…			
	Production	**Net FCT**	**Consumption**	**Production > Consumption**
US	0.04062	0.02251	0.04036	yes
EU	0.03020	0.02251	0.03028	no

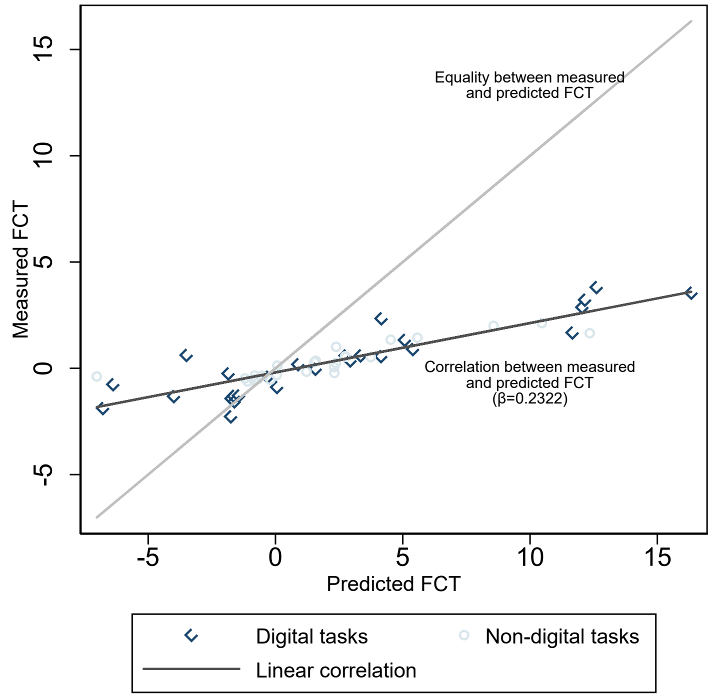
The finding that the US is abundant in digital tasks relative to non-digital tasks, with the opposite being true for the EU, is in line with our hypothesis regarding relative factor abundance (hypothesis 4). This result for relative factor abundance is an important piece of evidence for the digital leadership of the US as it allows us to conclude that the US holds comparative advantages in digital tasks.

To conclude the analysis, we briefly report the results of the sign test for the two factors (Table 6). The result is very satisfactory, with 88% of cases showing the same sign for the measured and predicted FCT. This number is very close to that identified in Guarascio and Stöllinger (2022), and close to earlier results in the literature for the factor labour alone (e.g. Trefler and Zhu, 2010; Stehrer, 2014).

Table 6 / Sign test of the HOV theorem- digital and non-digital tasks, 2012

	Sign test	Slope coefficient	t-statistics	R-square	Obs.
All factors	0.8846	0.2323	(13.611)	0.787	46

Figure 7 / Correlation between measured and predicted factor content of trade, 2012



Note: FCT = Factor content of trade.
Source: Regression output reported in Table 6.

The slope coefficient is highly significant suggesting that the endowments have predictive power for the actual FCT as measured in trade flows, which can be read as evidence in favour of the HOV theorem. The fact that this estimated coefficient (0.2322) resulting from a regression of the measured FCT on the predicted FCT is far below 1, is evidence of the the ‘missing trade’ phenomenon mentioned earlier.

5. Conclusion

In this paper we investigated the comparative advantage in digital and non-digital tasks embodied in labour services in the EU and the US. Most of our prior expectations laid down in four hypotheses are largely confirmed: the US economy is characterised by a higher digital task intensity than the EU (hypothesis 1). The digital task gap between the EU and the US is explained to an equal extent by a within-occupation effect and a structural effect (hypothesis 2). Importantly, we also find that this digital task gap translates into a comparative advantage of the US in digital tasks meaning the US is abundant in digital tasks relative to non-digital tasks (hypothesis 4), leaving the EU with comparative advantage in non-digital tasks.

However, we do not find a positive net FCT for the US which contradicts our prior expectation (hypothesis 3). This result can be rationalised by the HOV literature with the endowment paradox and the chronic US trade deficit. Nevertheless, the rejection of this hypothesis, to some extent, is surprising in view of the large digital gap between the EU and the US that is identified by alternative digital indicators such as digital patents.

The finding that the digital gap as revealed by digital tasks as a central endowment factor is important in itself, but also has policy implications. First of all, it could be seen as evidence for the widespread view that the EU is performing reasonably well in terms of skills and capabilities but underperforms when it comes to turning research excellence into marketable products (and also patents). Second, it is also compatible with the view that the digital gap between the US and the EU is great in highly visible domains such as the internet, artificial intelligence or big data, but at the same time maintains a competitive edge in areas such as communications infrastructure. Whether in the long run these pockets of excellence within the digital domain will suffice for the EU to keep up with the US (and China) in the race for technological leadership is to be seen. The EU may take some comfort from the fact that its satisfactory trade performance makes it a net exporter of digital tasks. This could signal that in principle, the digital skills and capabilities necessary to compete successfully in international markets do exist. This is also an essential basis for improving performance in digital technologies and related products.

Finally, we should also point out some limitations to this study. First, due to data constraints resulting from the massive data requirements for the FCT calculations, our analysis is limited to EU member states and the US. While we believe that the restricted sample does not cause any biases in the results obtained, since it is reasonable to assume that the production technologies of the countries in the sample used for producing output for export to other countries in the sample is not entirely different from that used for producing exports to countries not covered. Nevertheless, it would certainly be interesting to compare the EU to other major economies, notably China as the prime challenger of the US. At the same time, it would be equally insightful to see how big the gap is in terms of digital tasks of developing countries. Such a comparison would also help to put into perspective the differences found for the EU-US comparison. Finally, it would be important to have information of the kind analysed here for more recent years as digitalisation is under way and arguably gaining momentum such that the relative positions may have changed considerably since 2012. Given the current data situation we have to leave this for future work.

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Appendix

APPENDIX 1: INDUSTRY CLASSIFICATIONS

Appendix Table A.1 / List of industries

Industry code	Industry name
01T03	Agriculture
05T09	Mining
10T12	Food products, beverages and tobacco
13T15	Textiles, textile products, leather and footwear
16	Wood and products of wood and cork
17T18	Paper products and printing
19	Coke and refined petroleum products
20	Chemical and chemical products
21	Pharmaceuticals, medicinal chemical and botanical products
22	Rubber and plastics products
23	Other non-metallic mineral products
24	Basic metals
25	Fabricated metal products
26	Computer, electronic and optical equipment
27	Electrical equipment
28	Machinery and equipment, nec
29	Motor vehicles, trailers and semi-trailers
30	Other transport equipment
31T33	Manufacturing nec; repair and installation of machinery and equipment
35	Electricity, gas, steam and air conditioning supply
36T39	Water supply; sewerage, waste management and remediation activities
41T43	Construction
45T47	Wholesale and retail trade; repair of motor vehicles
49	Land transport and transport via pipelines
50	Water transport
51	Air transport
52	Warehousing and support activities for transportation
53	Postal and courier activities
55T56	Accommodation and food service activities
58T60	Publishing, audiovisual and broadcasting activities
61	Telecommunications
62T63	IT and other information services
64T66	Financial and insurance activities
68	Real estate activities
69T75	Professional, scientific and technical activities
77T82	Administrative and support service activities
84	Public administration and defence; compulsory social security
85	Education
86T88	Human health and social work activities
90T96	Arts, entertainment and recreation; Other service activities
97T98	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use

Note: Industries are based on industries as defined in OECD inter-country input-output database with some aggregations
Source: OECD ICIO.

Appendix Table A.2 / Correspondence - OECD ICIO to ISIC Rev 4 industries.

Industry code	Industry name	ISIC Rev4 2.digit code
01T03	Agriculture	01
01T03	Agriculture	02
01T03	Agriculture	03
05T09	Mining	05
05T09	Mining	06
05T09	Mining	07
05T09	Mining	08
05T09	Mining	09
10T12	Food products, beverages and tobacco	10
10T12	Food products, beverages and tobacco	11
10T12	Food products, beverages and tobacco	12
13T15	Textiles, textile products, leather and footwear	13
13T15	Textiles, textile products, leather and footwear	14
13T15	Textiles, textile products, leather and footwear	15
16	Wood and products of wood and cork	16
17T18	Paper products and printing	17
17T18	Paper products and printing	18
19	Coke and refined petroleum products	19
20	Chemical and chemical products	20
21	Pharmaceuticals, medicinal chemical and botanical products	21
22	Rubber and plastics products	22
23	Other non-metallic mineral products	23
24	Basic metals	24
25	Fabricated metal products	25
26	Computer, electronic and optical equipment	26
27	Electrical equipment	27
28	Machinery and equipment, nec	28
29	Motor vehicles, trailers and semi-trailers	29
30	Other transport equipment	30
31T33	Manufacturing nec; repair and installation of machinery and equipment	31
31T33	Manufacturing nec; repair and installation of machinery and equipment	32
31T33	Manufacturing nec; repair and installation of machinery and equipment	33
35	Electricity, gas, steam and air conditioning supply	35
36T39	Water supply; sewerage, waste management and remediation activities	36
36T39	Water supply; sewerage, waste management and remediation activities	37
36T39	Water supply; sewerage, waste management and remediation activities	38
36T39	Water supply; sewerage, waste management and remediation activities	39
41T43	Construction	41
41T43	Construction	42
41T43	Construction	43
45T47	Wholesale and retail trade; repair of motor vehicles	45
45T47	Wholesale and retail trade; repair of motor vehicles	46
45T47	Wholesale and retail trade; repair of motor vehicles	47
49	Land transport and transport via pipelines	49
50	Water transport	50
51	Air transport	51
52	Warehousing and support activities for transportation	52
53	Postal and courier activities	53

contd.

Appendix Table A.2 / (Contd.) Correspondence - OECD ICIO to ISIC Rev 4 industries.

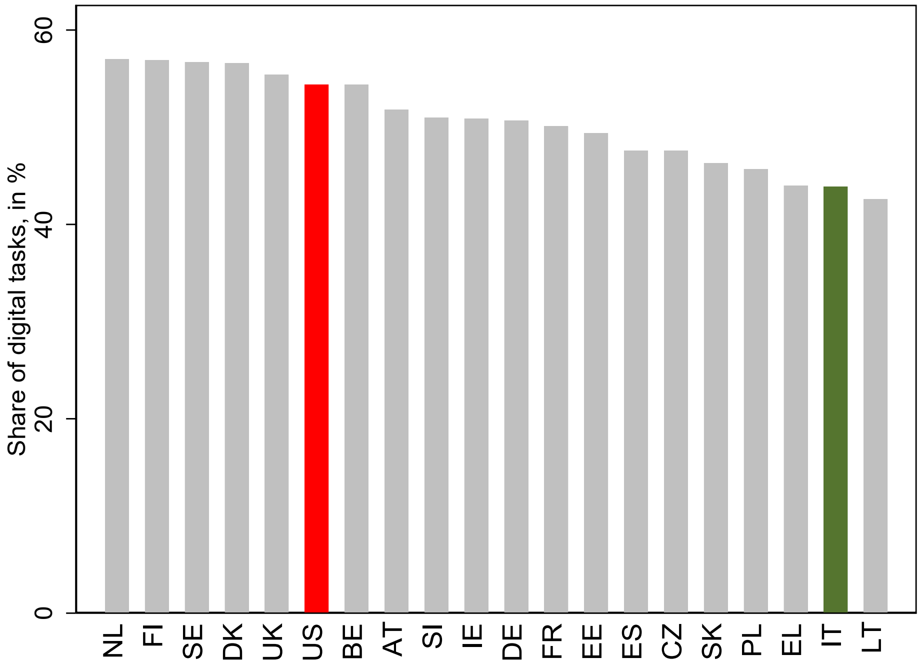
Industry code	Industry name	ISIC Rev4 2.digit code
55T56	Accommodation and food service activities	55
55T56	Accommodation and food service activities	56
58T60	Publishing, audiovisual and broadcasting activities	58
58T60	Publishing, audiovisual and broadcasting activities	59
58T60	Publishing, audiovisual and broadcasting activities	60
61	Telecommunications	61
62T63	IT and other information services	62
62T63	IT and other information services	63
64T66	Financial and insurance activities	64
64T66	Financial and insurance activities	65
64T66	Financial and insurance activities	66
68	Real estate activities	68
69T75	Professional, scientific and technical activities	69
69T75	Professional, scientific and technical activities	70
69T75	Professional, scientific and technical activities	71
69T75	Professional, scientific and technical activities	72
69T75	Professional, scientific and technical activities	73
69T75	Professional, scientific and technical activities	74
69T75	Professional, scientific and technical activities	75
77T82	Administrative and support service activities	77
77T82	Administrative and support service activities	78
77T82	Administrative and support service activities	79
77T82	Administrative and support service activities	80
77T82	Administrative and support service activities	81
77T82	Administrative and support service activities	82
84	Public administration and defence; compulsory social security	84
85	Education	85
86T88	Human health and social work activities	86
86T88	Human health and social work activities	87
86T88	Human health and social work activities	88
90T96	Arts, entertainment and recreation; Other service activities	90
90T96	Arts, entertainment and recreation; Other service activities	91
90T96	Arts, entertainment and recreation; Other service activities	92
90T96	Arts, entertainment and recreation; Other service activities	93
90T96	Arts, entertainment and recreation; Other service activities	94
90T96	Arts, entertainment and recreation; Other service activities	95
90T96	Arts, entertainment and recreation; Other service activities	96
97T98	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	97
97T98	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	98

Note: Industries are based on industries as defined in OECD inter-country input-output database with some aggregations
Source: OECD ICIO.

APPENDIX 2: ICT TASK INTENSITY OF JOBS ACCORDING TO PIAAC

The OECD, using a different approach based on the OECD Survey of Adult Skills (PIAAC), provides information on the ICT task intensity of jobs across economies (Grundke et al., 2017). This measure for the ICT task intensity of jobs yields a similar picture (Appendix Figure A.1) to what we obtain for our measure of digital tasks in labour services when using uniquely the O*NET-based DTI (see Figure 4 in the main text). In both cases, the Nordic countries, the United Kingdom, and the Netherlands emerge as the countries with the highest ICT task intensity, ahead of the US.

Appendix Figure A.1 / OECD ICT task intensity of jobs, 2012/2015



Note: Task intensity ranges from 0 to 100 and relies on 11 items from the OECD Survey of Adult Skills (PIAAC) ranging from simple use of the internet to the use of a word processor, spreadsheet software, or a programming language. A simple average of male and female scores is reported in the OECD data.
Source: OECD Digital Economy Outlook 2020; based on Grundke et al. (2017).

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