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ORIGINAL RESEARCH

Assessing Digital Leadership: Is the EU Losing Out to the US?

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Abstract

Since Leontief's (Leontief 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 · Digital technologies · Heckscher-Ohlin-Vanek theorem · Europe · US

1 Introduction

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

With the growing importance of digital technologies, this eternal concern about defending a technological edge has intensified for a number of reasons. First, the digital

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transformation may entail a new technological paradigm (Cimoli et al. 2020) reshaping (and eventually stiffening) 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) innovation often takes place on the factory floor rather than in the R&D lab.[1] Third, the EU's economic structure is comparatively static, meaning that the process of creative destruction is 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 digital leadership. The almost complete lack of EU companies in the platform economy is just one indication of this (EPSC 2019).

In this paper we investigate the EU's readiness for the digital transformation and compare it to the US, by looking at the economies' endowments, 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 one. 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 (Guarascio and Stöllinger 2023). In addition, we use the task descriptions performed across US occupations contained in the O*NET database (Autor et al. 2003), to replicate the methodology of the Italian DTI for the US economy. This allows comparing the digital task content in employment in both EU member states and in the US economy, taking into account the likely variation between the EU and the US.[3] Hence, differences in digital task intensity between the EU and the US economy may 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. To test this prediction empirically, we rely on the approach 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

[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).

[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).

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 data requirements. Data limitations also explain why this analysis is circumscribed to 25 member states and the US and timewise, restricted to two benchmark years, 2012 and 2018.

The paper contributes to the literature in three ways. First, we build a DTI based on the descriptions of occupations in the O*NET database which parallels, to the extent possible, the indicator developed by Cirillo et al. (2021). The implied within-occupation variation adds an additional layer to the analysis.[4] Second, we integrate these indicators into a HOV-framework 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 at least partly 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.

We find that digital task intensity in the US economy is higher than that in the EU, a result driven by both higher digital task contents of occupations as well as by differences in the occupational structures of industries and the industry structure of the economy. The US economy remains more digital task-intensive even when the same DTI 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 former 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 point to a *decline* in the average digital task intensity of occupations. 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.

[4] 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.

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. 2023; Rikap and Lundvall 2021; Caravella et al. 2021; Brattberg et al. 2020; Fanti et al. 2022).

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. 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). 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. 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). This claim is supported by the data. For example, the number of firms from the EU (comprising all member states and including the United Kingdom) in the Forbes list of the 100 top digital companies is only 13, compared to 39 from the US.[5] Another type of indicator, which is more telling about the broader technological capabilities of countries are patent stocks. The Asian Development Bank (ADB) provides very informative statistics about the patent stock in technologies which can be expected to be relevant for the Fourth Industrial Revolution (IR4), where IR4 is just another expression of the digitalisation of the economy. Therefore the IR4-related patent stocks provide a very useful (and consistently collected) measure of the relative positions of the

[5] The list refers to the year 2019 and is available at: https://www.forbes.com/top-digital-companies/list/#tab:rank.

EU and US in the development of (marketable) digital technologies. As revealed in Tables 1 and 2 in 2012 the US possessed a third of the total global IR4 patent stock, which was about 3.5 time as much as all EU countries together. In 2018, this ratio, which can be interpreted as the relative position in digital technologies, increased from 3.5 in 2012 to more than 4.4 in 2018. While these ratios are already high, the relative positions in important technology families such as core AI (5.5) and data management (6) are even more in favour of the US.[6]

The picture emerging from these IR4-related patents is that the US have a significant lead over the EU in terms of digital technologies, which will be reflected in our main hypotheses.

Methodologically, the paper belongs to the factor content of trade literature, revived by the availability of international input–output data (Trefler and Zhu 2010; Stehrer 2014; Guarascio and Stöllinger 2023).

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.[7]

Leontief's paradoxical result fuelled subsequent investigations, many of which confirmed Leontief's original finding, as well as analyses for other countries (for an overview, see Baldwin 2008). Relying on the HOV,[8] Leamer (1980) resolved the paradox by showing that Leontief performed the wrong test for identifying endowment-based comparative advantage. He 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 (1968)'s insights, he 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.[9]

While Leamer (1980) resolved Leontief's paradox, his findings on the relative factor contents of the US did not constitute a formal test of the HOV theorem. This is done by Bowen et al. (1987), proposing a sign and rank test to compare 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.

Among the (non-exclusive) candidate explanations for the poor performance of the HOV-theorem, differences in technology received a lot of attention. Trefler

6 Concerning AI patents, confirmatory evidence is provided by Fanti et al. (2022).

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

8 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).

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

(1993) showed that incorporating differences in technology across countries by adjusting endowments for their relative productivity – yielding 'effective factor endowments' – improves the empirical fit of the HOV-theorem. 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 factor input coefficients using country-level productivity differences[10] reporting a considerably better fit of the data. In particular, it reduces a substantial part of the "missing trade", i.e. measured FCT being smaller than predicted by endowments. This author shows that the missing trade phenomenon may be 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. Using labour as the sole production factor, they find that sign tests were correct in 95% while rank tests in 89% of the cases. Despite such improvements in the fit of the HOV model, the issue of 'missing trade' remained sizeable. According to Trefler and Zhu (2010), this is due to 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'. Following the same approach, Stehrer (2014) tested the HOV theorem for three types of labour and capital showing that the HOV model performs better for labour services than for capital. In a recent work (Guarascio and Stöllinger 2023), we relied on Trefler and Zhu (2010)'s approach to study the FCT of EU countries for digital tasks and ICT capital, confirming the relevance of the HOV theorem. However, we do not find any match between EU innovation leaders and comparative advantage in digital tasks and ICT capital. Both innovation leaders and modest innovators (as classified by the European Innovation Scoreboard[11]) 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.[12]

The use of digital tasks performed by workers in different occupations in Guarascio and Stöllinger (2023) also creates a link between the empirical HOV literature and

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

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

[12] 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.

the literature on routine-biased technological change (Autor et al. 2003; Acemoglu and Autor 2011) and job polarisation (Goos et al. 2009; Autor and Dorn 2013). This stream of literature focuses on skills and tasks embodied in occupations to explain labour market trends related to processes such as automation or offshoring.

One of the key findings of this strand of the literature is that occupations with high routine-task intensity, that is a high degree of the predictability of the activities involved, are more prone to automation – which can be defined as a process of introducing "prediction machines" (Agrawal et al. 2018) – than jobs which involve a large amount of non-routine, cognitive tasks. The close relationship between routine-task intensity (or codifiable tasks) of occupations and the risk of workers losing their job, made Frey and Osborne (2017) develop a new (strongly highly related) indicator which they label automatability index.

These RTI and automatability indicators are defined using detailed job descriptions of the O*Net database.[13] The routine-task hypothesis literature has a strong focus on labour market implications of new technologies, in particular the effects on polarisation, that is the decline in the number of middle-paid jobs relative to high and low-paid jobs and the probability of large scale technological unemployment, a term originally introduced by Keynes (2010, [1930]). While job polarisation was identified for the US in the pioneering study by Autor et al. (2003) and subsequent studies (Acemoglu and Autor 2011; Autor and Dorn 2013; Acemoglu and Restrepo 2022), the results for EU countries are much more mixed (Goos et al. 2009, 2014; Fernández-Macías and Hurley 2017; Oesch and Piccitto 2019; Martinaitis et al. 2021). There is also no consensus on the overall impact of new technologies on labour demand and hence the probability of technological unemployment (Acemoglu and Restrepo 2018, 2019; Aghion et al. 2020, 2023).

In parallel to technological change, task-based approaches were also used to analyse the employment implications of offshoring (Autor and Dorn 2013; Goos et al. 2014). The quantitative results of these studies suggest that the impact of technology on labour demand is larger than that of offshoring. Overall, the task-technology nexus remains an active field of study with new indicators being developed to investigate, for example, the impact of AI on employment (Felten et al. 2018) more specifically. Moreover, attempts are made to consider the role of newly emerging job categories ('new work') in counterbalancing the erosive effect of task-displacing automation (Autor et al. 2024).

Our paper relates to the topics of international trade, labour market compositions and new technologies and is also using a task-based approach. Instead of studying the extent to which jobs are replaced by automation or offshoring, however, we are interested in the differences in the composition of the labour supply, as evidenced by the number of digital tasks performed by workers, and the implications for trade balance in these tasks.

[13] For the automatability index, Frey and Osborne (2017) also used information from expert assessments in combination with machine learning tools and the tasks descriptions of the O*NET database.

Moreover, differently from the studies assessing risks of labour substitution (e.g., Autor et al. 2013), we make no attempt to measure whether an occupation can be *replaced by* new (digital) technologies (or shored to another country) but to what extent persons in different occupation *work with* digital technology, that is, perform digital tasks.

It is also worth mentioning that Muro et al. (2017) suggested a digital task index for the US, which is also constructed using the O*Net database. While the indicator by Muro et al. (2017) is at first sight similar to our DTI, it is constructed using only two O*NET variables and therefore much more generic.[14] In contrast, and as explain in the next section in much more detail, our DTI for the US economy is modelled after the DTI for Italy and hence relying on a larger and more fine-grained set of O*NET-type information.

In Guarascio and Stöllinger (2023), we focus on digital task and ICT capital to assess EU countries digital competitiveness. To measure the digital tasks embodied in labour services, we build on Cirillo et al. (2021). 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. We showed that this index is also suitable for identifying endowment-based digital comparative advantage.

2.2 Main Hypotheses

In this section we spell out the key hypotheses that are tested empirically in what follows. Existing evidence on the US's digital leadership leads to the expectations that such 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.*

With hypothesis 1, we provide an empirical account of something that, despite being common wisdom[15] – i.e. the EU's digital backwardness vis-à-vis the US (UNCTAD 2021; Rikap and Lundvall 2021; Fanti et al. 2022) –, is rather poorly documented in the empirical trade literature, in particular with respect to endowments.

[14] These variables are "knowledge–computer and electronics", intended to capture the overall knowledge of computers and electronics needed in the occupation, and "work activity–interacting with computers", interpreted as a measure for the centrality of computers to the overall work.

[15] 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".*

The second hypothesis relates to the potential sources of such difference in terms of digital task endowments. The two drivers are: a within-occupation (or occupation-intensive margin effect) and a structural effect (i.e. increasing share of digital intensive occupations). The prior expectation is that both dimensions contribute to the digital leadership of the US,[16] whilst remaining agnostic with respect to their relative contributions. Hence, hypothesis 2 is formulated as follows:

> ***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 associated hypotheses. The first (hypothesis 3) assumes that the US are abundant in digital tasks and scarce in non-digital tasks, as measured by a positive net FCT.[17]

> ***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 Sect. 3.2), 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. Therefore, our last hypothesis is:

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

3 Methodology and Data

3.1 Measuring Digital Tasks

Investigating the labour 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),

[16] 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.

[17] This hypothesis relates to the notion of absolute factor abundance as explained in more detail in Sect. 3.2.

offshoreability (Firpo et al. 2011) or viral transmission risk (Chernoff and Warman 2022), we follow a similar methodological approach. More specifically, we define endowments – or production factors – at the level of tasks, distinguishing between digital and non-digital.

For our analysis, tasks are key as the readiness for the digital transformation crucially hinges on human capabilities (Cimoli et al. 2020). This is true both for the development as well as the adoption of new technologies. Moreover, 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 has the required skills and qualifications to perform the usual tasks assigned to this occupation. The same is true for all other occupations.

A simple example can help explaining the logic underlying the measurement of digital factor endowments. We compare mechanic and network professionals (Table 1). In the EU, there are approximately 547,000 database and network professionals performing 52.5% of 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, who are much more numerous (3.5 million persons in the EU) but have a much lower digital task content (2.23).

As a result, the digital tasks performed by this occupation amount to less than 79,000. 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 a reasonable approximation.[18] Conversely, a separate digital task index is used for the US economy, which is derived from the US O*NET database. The comparison shows, for example, that database and network professionals 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 is a within-occupation effect (or intensive margin effect). In the case of machinery mechanics and repairers, there are fewer employed persons in the US and their digital task content is below that of their European counterparts.[19]

[18] 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).

[19] 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.

Table 1 Patent stocks across digital technologies in the EU and US, 2012 and 2018

	2012			2018		
	EU	US	US/EU	EU	US	US/EU
Technology	Share in global patents		Patent ratio	Share in global patents		Patent ratio
3D support systems	5.6%	52.1%	9.27	6.3%	43.5%	6.93
Agriculture	12.6%	39.5%	3.13	4.4%	37.4%	8.50
Connectivity	10.6%	32.1%	3.03	8.7%	33.4%	3.85
Consumer goods	8.8%	32.3%	3.66	7.5%	33.0%	4.42
Core AI	8.3%	45.1%	5.46	3.9%	40.3%	10.43
Data management	6.3%	37.4%	5.98	4.9%	33.9%	6.87
Data security	10.3%	35.4%	3.45	8.0%	37.5%	4.68
Geo positioning	8.1%	37.7%	4.64	6.9%	39.6%	5.74
Healthcare	5.8%	50.0%	8.56	5.2%	41.3%	7.97
Home	10.9%	33.9%	3.12	8.4%	34.8%	4.13
IT hardware	7.7%	33.4%	4.33	6.3%	35.4%	5.67
Industrial	7.2%	38.8%	5.37	4.9%	34.2%	7.00
Infrastructure	7.9%	40.4%	5.11	6.2%	37.8%	6.08
Power supply	7.6%	35.0%	4.59	9.1%	34.6%	3.79
Safety	10.4%	31.2%	3.00	5.7%	34.3%	5.97
Services	6.8%	42.5%	6.23	5.0%	39.2%	7.80
Software	6.6%	41.0%	6.25	5.0%	40.7%	8.14
User interfaces	5.7%	38.1%	6.73	4.4%	33.0%	7.56
Vehicles	8.0%	32.8%	4.08	5.8%	33.6%	5.78
Total	9.3%	33.0%	3.57	7.4%	32.9%	4.44

The Asian Development Bank (ADB) assigns patents which are related to technologies deemed associated with the Fourth Industrial Revolution (IR4) into 'IR4 technology families'. The IR4-related technologies can be interpreted as digital technoilogies. The numbers in the table refer to patent stocks in the respective IR4 technology family and the total of IR4 technologies respectively. Patents are assumed to expire after 10 years and are then deducted from the stock. EU comprises all member states, including the United Kingdom

Source: ADB-ADBI Innovation and Structural Transformation Database; authors own calculations

3.2 Embedding Digital Tasks into the HOV Framework

In order to link digital tasks to the HOV-theorem, we follow a twofold strategy. First, we calculate the predicted factor content of trade (FCT) which can be used to identify countries' factor abundances. For any country c, the predicted net FCT for factor f, $\widetilde{F}_f^c$ 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):

$$\widetilde{F}_f^c \equiv V_f^c - s^c \cdot V_f^W \tag{1}$$

Table 2 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

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 where V_f^W is the 'worldwide' endowment with factor f defined as $V_f^W = \sum_c V_f^c$. The share of country c in world consumption, s^c is defined as $s^c = (Y^c - TB^c)/(Y^W - TB^W)$. In this Y^c and TB^c are the GDP and trade balance of country c respectively and Y^W and TB^W are the 'worldwide' counterparts.[20] Here, the fact that our sample is limited to 25 EU member states and the US leads to a complication. The complication is that country-specific economy-wide endowments, V_f^c, cannot be restricted to the relevant amounts used for trade with countries in the sample. Therefore, we also use 'truly' global GDPs and trade balances: for each EU country and the US the GDP and the overall trade balance also includes exports and imports to countries which are out of the sample.

As long as identical and homothetic demand structures and full employment are assumed, Eq. (1) 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, Eq. (1) can be written individually for the two factor endowments, V_{dt} and V_{nt}:

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

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

Following our hypotheses, we expect a positive $\widetilde{F}_{dt}^c$ for the US and a positive $\widetilde{F}_{nt}^c$ for the EU. Since here we make calculations for each of the factors individually, this is a test of absolute factor abundance.

Equation (1) implies that a country c is abundant in factor f if its endowment of factor f in comparison to that of world endowment (V_f^c/V_f^W) exceeds country c's share of world consumption, s^c (Feenstra 2003). This can be considered as a factor-specific or absolute concept of factor abundance related to a single factor and country.

The endowment ratio (V_f^c/V_f^W) also provides a bridge to the concept of *relative* factor abundance (Leamer 1980). By combining this ratio of two or more factors, one can follow Trefler (1995) and rank them to obtain relative factor abundances and scarcities (Eq. 2):

$$V_{f_S}^c/V_{f_S}^W < V_{f_A}^c/V_{f_A}^W \tag{2}$$

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.

Applied to our factors, this definition implies that country c is abundant in digital 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 and V_{nt} denotes non-digital task endowments.

We expect the US to be relatively digital task abundant $\left(V_{nt}^{US}/V_{nt}^W < V_{dt}^{US}/V_{dt}^W\right)$ and the EU to be relatively non-digital task abundant $\left(V_{dt}^{EU}/V_{dt}^W < V_{nt}^{EU}/V_{nt}^W\right)$. Note

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

that here we make use of the relative concept of factor abundance and apply it to the economy-wide endowments.[21]

Yet, 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.[22] As in Guarascio and Stöllinger (2023), we employ a theory-consistent calculation of the FCT in the presence of cross-country technology differences and trade in intermediate goods, in line with Trefler and Zhu (2010).

The measured FCT requires three elements. First, a vector with the primary factor requirements for each factor of production, D_f. Second, 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. Third, a net trade vector, T^c.[23] The primary factor requirements vector, together with the Leontief Inverse, accounts for differences in production technologies across countries and trade in intermediate goods (Trefler and Zhu 2010). The net FCT, F^c, of country c and factor f is then defined as:

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

where F_f^c is a column vector of dimension $N{\cdot}J \times 1$ 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 a $N{\cdot}J \times 1$ vector containing the country-industry specific amounts of digital, d_{dt}, and non-digital tasks, d_{nt}, per unit of gross output, X, respectively. $\boldsymbol{L}$ is the usual Leontief matrix of dimension $N{\cdot}J\ x\ N{\cdot}J$, 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 $N{\cdot}J \times 1$. 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 Eq. (3) as:

$$F_f^c \equiv \boldsymbol{A_f} \cdot T^c \tag{3.1}$$

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 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.

[21] In this calculation, no actual trade flows are involved.

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

[23] For a detailed exposition of the matrices for a 3-country-2- industry example, see Guarascio and Stöllinger (2023).

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

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

Empirically, the Heckscher-Ohlin-Vanek theorem in its 'trade specification' (Davis and Weinstein 2001), as formulated in Eq. (4), will not hold with equality.[24] 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. This sign test is essentially a test of the validity of these underlying assumptions of the HOV-theorem. Given the results obtained in Guarascio and Stöllinger (2023), we expect a fit of this sign test for approximately 90% of the cases.

3.3 Data

The analysis brings together three different data sources: 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.

[24] 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).

3.3.1 Employment Data

As in Guarascio and Stöllinger (2023), we rely on the European Labour Force Survey (LFS) for employment data at the country-industry level. From the European LFS we obtain the number of employed persons, at the 1-digit NACE Rev.2 industry (sections) and 3-digit ISCO-08 occupation-level. 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, 2-digit industry-3-digit occupations data are estimated exploiting information from the year 2012.[25] 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.[26]

For the US, the compilation of the necessary employment data uses the Bureau of Labour Statistics' (BLS) Occupational Employment and Wage Statistics (OEWS) survey, supplemented with data from the US Labor Force Statistics (LFS) from the Current Population Survey (CPS).[27] It constitutes the most detailed US employment data at the occupation-industry level. Since it is compiled at the NAICS industry classification and the SOC occupational classification, crosswalks[28] to NACE Rev.2 industries respectively ISCO-08 occupations were necessary in order to be compatible with the European data and the OECD ICIO database.[29]

3.3.2 Digital Task Indicators

Digital tasks intensity is defined at the level of occupations using information from the Survey of Italian Occupations (*Indagine Campionaria sulle Professioni,* ICP) for EU countries and from the US Occupational Information Network (O*NET) database for the US.[30] Both datasets provide an extensive amount of information on skills, tasks, work content, technology and organisational characteristics of the workplace.

25 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.

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

27 For details see Gschwent et al. (2023).

28 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).

29 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.

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

As in Guarascio and Stöllinger (2023), we chose the DTI, defined at the 4-digit level of occupation-level (Cirillo et al. 2021) to measure digital comparative advantages. The scores of the digital indicators of each 4-digit 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.[31]

Relying on the DTI, 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.[32] While in the ICP the DTI indicator is readily available (Cirillo et al. (2021), for the US data it had to be replicated using the 'Task Ratings' and 'Task Statements' in the O*Net database. For this, 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. In this way, 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).[33]

The use of two distinct databases capturing the task structure of occupation was necessary in order to allow for differences in digital task contents across EU member states and the US. One of the stated objectives of this paper, and a major extension of Guarascio and Stöllinger (2023).

While the DTI originates from the Italian ICP, 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.[34] 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.

[31] 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).

[32] For details of the construction of the DTI see Cirillo et al. (2021) and for the application to comparative advantages see Guarascio and Stollinger (2023).

[33] Further details are provided in Gschwent et al. (2023).

[34] 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.

3.3.3 Digital Tasks of Occupations in the EU and the US: ICP vs ONET

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 3 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 3, 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.

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.

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.

We read Table 3 and Fig. 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.

3.3.4 International Input–Output Data

To carry out FCT calculations we rely on the OECD Inter-Country Input–Output (ICIO) Database. The OECD ICIO comprises 45 industries – based on the NACE Rev.2 classification – which are a mixture of divisions (2-digit industries) and section (1-letter industries).[35] Moreover, we 'trim down' the (adjusted) OECD ICIO input–output table

[35] 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 (see Appendix 1 for the list of industries). We do this mainly to ensure better comparability with the results in Guarascio and Stöllinger (2023) which is based on data from the World Input–Output Database (WIOD).

Table 3 Occupations with the highest digital task contents, 2012

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

Rank	ISCO code	Occupation	DTI (ICP)	Employment	Rank in US
1	351	ICT 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 & 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 (excl. 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	ISCO code	Occupation	DTI (O-NET)	Employment	Rank in EU
1	251	Software and applications developers and analysts	76.989	2,159,741	4
2	351	ICT 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	ICT 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

Codes refer to the ISCO-08. *ICT* Information and communications technology

Source: European LFS, OEWS; LFS CPS; Survey of Italian Occupations (ICP); O*NET database; OECD ICIO 2021

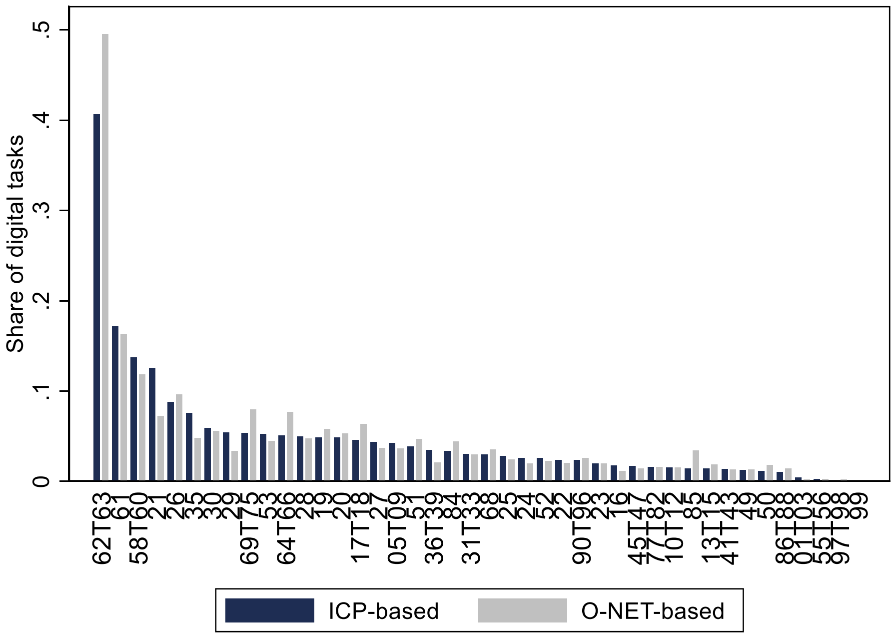

Fig. 1 Digital task indicator, Italy, 2012. Note: Codes refer to industries in the OECD ICIO database (based on ISIC Rev. 4). See Appendix for details. Source: European LFS, Survey of Italian Occupations (ICP); O*NET database; OECD ICIO 2021

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. Limiting the analysis to only 26 countries is of course a potential source of distortions. The sectorial composition of exports influences the amounts of tasks embodied in aggregate exports. This is because industries differ regarding their occupational structure and hence their task intensities. We cannot rule out that the sectorial structure of exports to our EU-US world is different from the truly global sample. In fact, the potential distortion increases with the share of exports covered in our sample. For the EU member states, this share ranges from 47% in Greece to 77% in Luxembourg with an EU-wide average of 62.89%.[36] In general, the export coverage tends to be higher in small EU countries, though the economy with the lowest share of exports covered is certainly the US: only 21% of US exports are destined for EU countries, which is what is covered in the data. However, the problem is less severe than it seems at first sight. Even if the global net factor contents were to be affected by missing exports, the bilateral comparison between the EU and the US would only be slightly concerned. The 'only' omission we have in this comparison is that we do not capture indirect EU exports to the US which reach the US via a country outside the EU-US sample (and vice versa). Therefore, the potential distortion in our results stemming from our restricted sample is unlikely to be significant.

[36] The export coverage for all countries in the sample is provided in Appendix 2.

4 Results

The results are presented in two parts. Section 4.1 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 H1 and H2. Section 4.2 is dedicated to the results on digital task abundance in the HOV framework and will test the appropriateness of H3 and H4.

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 ICP and O*NET-based DTIs are available.

4.1.1 Comparison of Digital Task Intensities Across Industries and Countries

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

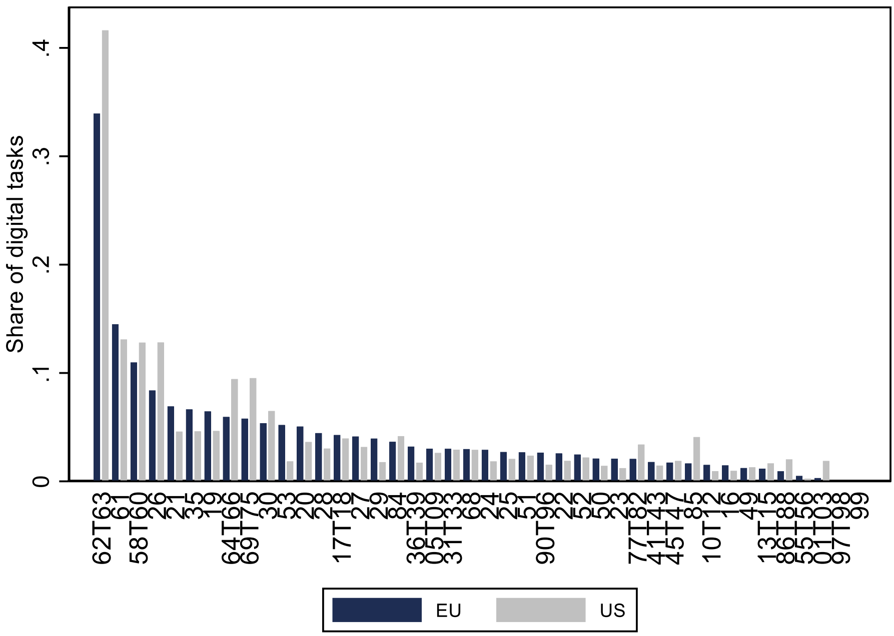

Fig. 2 Digital task shares across industries, EU and US, 2012 Note: NACE Rev.2 industry code as used in the OECD ICIO database 2021. For a list of the industry descriptions corresponding to the NACE Rev.2 industry codes, see Appendix. EU based on ICP DTI, US based on O*NET DTI. Source: European LFS, OEWS; LFS CPS; Survey of Italian Occupations (ICP); O*NET database; OECD ICIO 2021

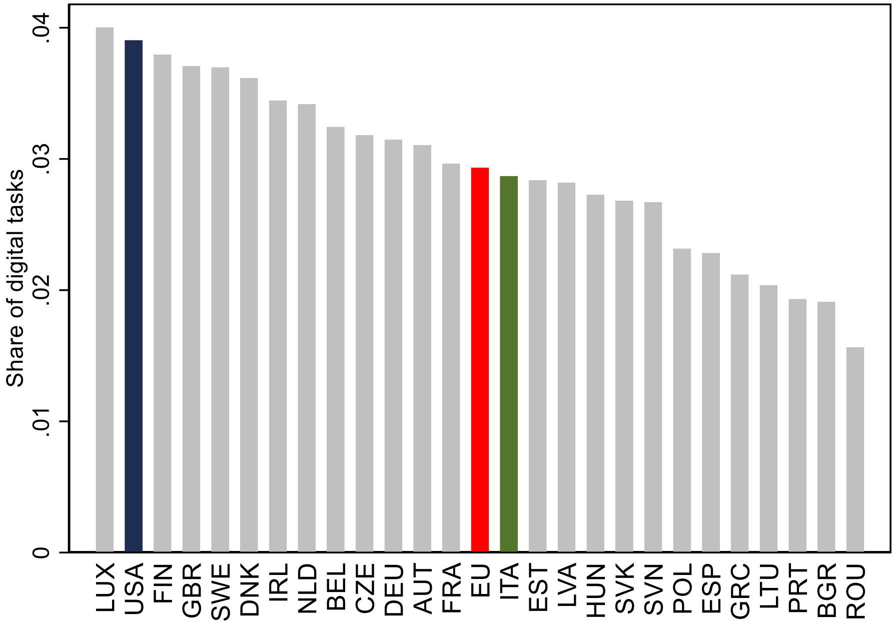

Fig. 3 Digital task shares by countries, 2012. Note: EU based on ICP DTI, US based on O*NET DTI. Digital tasks as shares of total tasks performed in the respective economy Source: European LFS, OEWS; LFS CPS; Survey of Italian Occupations (ICP); O*NET database; OECD ICIO 2021

This is true for the EU but even more so for the US (0.4 for the US, compared to 0.34 in the EU). 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 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.[37]

Moving to the cross-country comparison, the US digital task intensity (3.9%) exceeds that of the EU (2.9%) by a full percentage point (Fig. 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 H1: the US economy, as the presumed digital leader, features a higher digital task intensity than the EU.

Concerning intra-EU differences, Northern member states such as Finland, Sweden and Denmark together with the UK display a relatively higher digital task intensity vis-à-vis the EU average; while Southern and Eastern countries as, for example,

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

Romania, Bulgaria and Portugal are located at the bottom of the ranking. The largest EU economies, i.e., France, Germany and Italy, are positioned around the EU average, the first two above while Italy slightly below.

4.1.2 Results Based 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. The digital task content of the US economy is still higher than that of the EU economy. However, the relative difference is approximately halved as the EU now records a digital task content of 3.44% (Fig. 4). Moreover, when their digital task content is measured relying on the O*NET data, the DTI 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.

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, irrespective the considered member state. Appendix 3 shows that this result, including the ranking of countries, is in line with descriptive evidence on ICT skills across countries as measured by the existing ICT skills index by Grundke et al. (2017) which is based on the OECD Survey of Adult Skills (PIAAC).

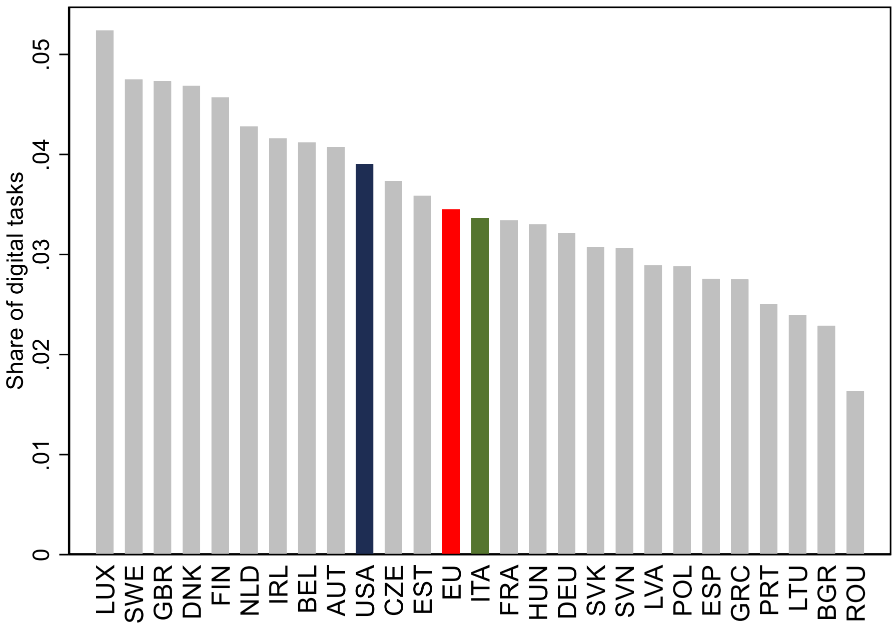

Fig. 4 Digital task share by countries, O*NET based digital task scores, 2012. Note: EU and US based on O*NET DTI. Source: European LFS, OEWS; LFS CPS; O*NET database; OECD ICIO 2021

4.1.3 Assessing the Sources of the EU-US Digital Task Gap

The comparison of the core results in Fig. 3 (ICP-based DTI for the EU; O*NET-based DTI for the US) with the results obtained using a common DTI (Fig. 4), allows us identifying the potential sources of the EU-US ‘digital gap’. 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 4).

This exercise, which addresses hypothesis 2, shows that the US’s digital leadership 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 are 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.

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.[38] 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.

4.1.4 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 (Fig. 5) with that in 2012, which was already shown in Fig. 4.

[38] 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).

Table 4 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
LUX	4.00%	5.24%	0.10	1.34	-1.24
FIN	3.79%	4.57%	-0.11	0.67	-0.78
GBR	3.70%	4.73%	-0.20	0.83	-1.03
SWE	3.70%	4.75%	-0.21	0.85	-1.05
DNK	3.61%	4.69%	-0.29	0.78	-1.07
IRL	3.44%	4.16%	-0.46	0.26	-0.72
NLD	3.42%	4.28%	-0.49	0.38	-0.86
BEL	3.24%	4.12%	-0.66	0.21	-0.88
CZE	3.18%	3.73%	-0.72	-0.17	-0.56
DEU	3.14%	3.21%	-0.76	-0.69	-0.07
AUT	3.10%	4.07%	-0.80	0.17	-0.97
FRA	2.96%	3.34%	-0.94	-0.56	-0.38
ITA	2.87%	3.36%	-1.04	-0.54	-0.50
EST	2.84%	3.59%	-1.07	-0.32	-0.75
LVA	2.82%	2.89%	-1.08	-1.01	-0.07
HUN	2.73%	3.30%	-1.18	-0.60	-0.58
SVK	2.68%	3.07%	-1.22	-0.83	-0.39
SVN	2.67%	3.06%	-1.24	-0.84	-0.40
POL	2.32%	2.88%	-1.59	-1.03	-0.56
ESP	2.28%	2.76%	-1.62	-1.15	-0.48
GRC	2.12%	2.75%	-1.79	-1.15	-0.63
LTU	2.04%	2.39%	-1.87	-1.51	-0.36
PRT	1.93%	2.50%	-1.97	-1.40	-0.57
BGR	1.91%	2.29%	-1.99	-1.62	-0.38
ROU	1.56%	1.63%	-2.34	-2.27	-0.07
US		3.90%			

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

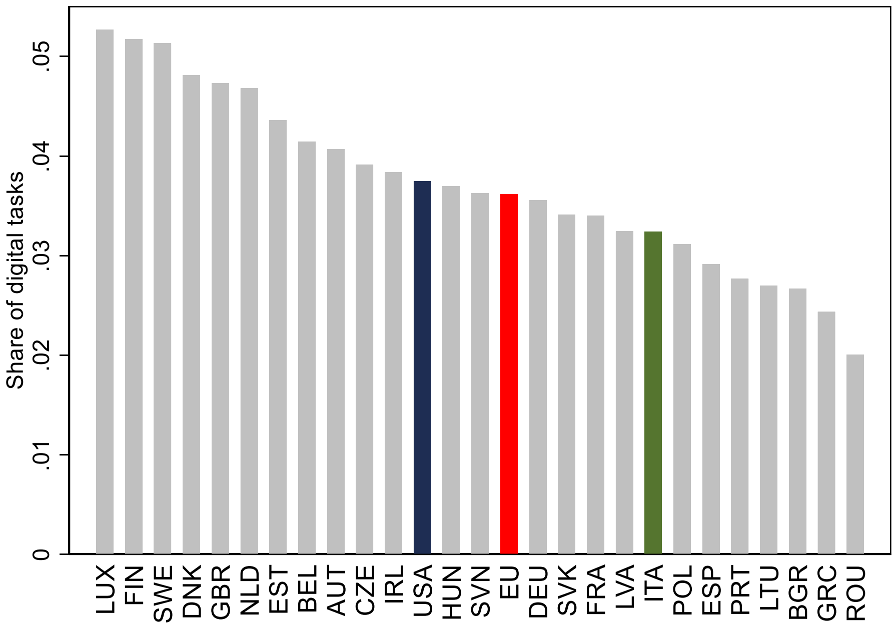

Fig. 5 Digital task shares by country, O*NET based digital task scores, 2018. Note: EU and US based on O*NET DTI. Source: European LFS, OEWS; LFS CPS; Survey of Italian Occupations (ICP); O*NET database; OECD ICIO 2021

There are three main insights to be gained from this comparison. 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.[39]

Third, digital task intensity 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. Nevertheless, there are a number of economics mechanisms which could favour such an outcome.

A first aspect to consider is that digital technologies are embodied in capital goods (e.g., smart robots, Internet of Things, autonomous vehicles, etc.), while often less 'visible' in labour. This is partly related to the fact that digital-related knowledge and competences are to a considerable extent tacit and linked to organizational patterns and 'routines'. Tacit knowledge is much more difficult to formalize or it is also harder to trace it back to specific skills/tasks (Dosi et al. 2021) – even if, with the DTI a

[39] 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.

serious attempt to capture digital tasks. This may affect the share of digital tasks present and measured in an economy. Against this background, the finding of a declining digital task intensity of the economy is compatible with both polarisation at the labour and a structural shift towards a service economy in which new jobs are created predominantly in elementary services which have a low in digital task content.

Secondly, and mostly related to the occupation-intensive margin effect mentioned above, digital technologies are reshaping tasks across all sector of the economy, including industries mostly employing medium and low-skill occupations. In such occupations, workers are increasingly dealing with digital devices (e.g., a typical example are digital tools and apps used in sectors such as restaurants or transports), but they are unlikely to develop specific digital skills or to carry out tasks that are directly related to the design, deployment or transformation of such technologies which we intend to capture in the DTI.

In terms of the task-based literature, our results would therefore imply that for digital tasks, the reinstatement effect, resulting from complementarities between technologies and labour tasks (Acemoglu and Restrepo 2019), is dominated by the displacement effect.

At the same there is considerable empirical evidence that technological change led to an 'upskilling' in the labour force and that occupations became more 'complex', though with some polarisation (Martinaitis et al. 2021). Specific evidence on the evolution of digital skills and task, however, is scarce though. The only relevant contribution we found is that by Muro et al. (2017), who find an increasing digital task content in the US economy between 2002 and 2016. More specifically, what they find is that the share of employment in occupations with high and medium digital task scores increased to the detriment of occupations low digital task scores.[40]

As already mentioned our DTI captures mainly sophisticated digital tasks and is therefore a much more restrictive measure than the broad-brush measure of Muro et al. (2017), which makes results not directly comparable. Despite the methodological differences, there is a noticeable parallel, though, in our finding of a declining digital task intensity and the result in Muro et al. (2017). This parallel is a declining digitalisation score among the high digital task intensive occupations which these authors find during their sample period – which is in contrast to the economy-wide rise of the digitalisation score between 2002–2016 that they find. Now, given the high barrier imposed for considering tasks as digital tasks in our methodology, our digital task contents are, if at all, more comparable to (some of) the task performed by the high digitalisation occupations in the methodology Muro et al. (2017).

Finally, it should also be mentioned that the O*NET database is only partially updated from one version to the next. This may result in an underestimation of the within-occupation change taking place across waves, including changes in terms of digital task intensity. This fact may influence both the results in Muro et al. (2017) and our measured changes in the digital task intensity over time. This is why, as

[40] High digital task occupations are defined as those occupations with a digital score above 60 (out of a maximum score of 100), medium digital task occupations are those with scores between 60 and 33 and low digital task occupations have scores below 33.

pointed out at the beginning of this section, the results for the comparisons over time should be interpreted with caution.

The result of a declining digital task intensity is, also compatible with the more drastic hypothesis by Braverman (1974) that digitalisation and technological progress in general are always geared towards increasing efficiency and rationalising, which more often than not results in simplifying and standardising the tasks to be performed by industrial workers. For sure, the Braverman hypothesis was initially articulated with a view to factory floor workers. Mass production coupled with managerial efforts to routinise and simplify individual tasks of the work process, he associated with a deskilling with regards to their craftsmanship. Whether this argument translates to the activities of 'digital workers' requires further empirical investigation. Yet, our results of a declining digital task intensity is compatible with the notion of a 'digital Braverman' hypothesis.[41]

In what follows, we discuss the digital task content of the US and the EU in the HOV framework, focusing on 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 as suggested in Trefler (1995), using the relative factor abundance definition of Leamer (1980) (Fig. 6).

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 0.4 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

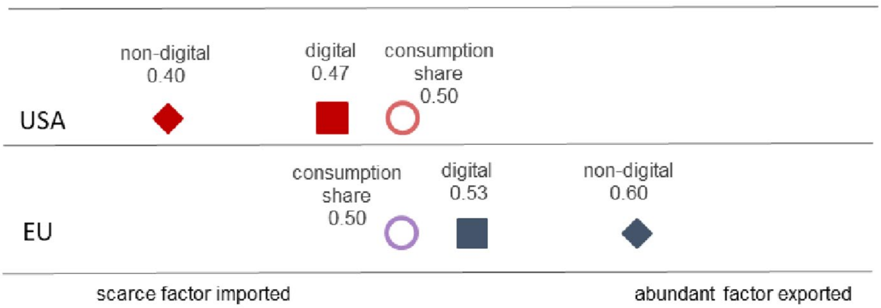

Fig. 6 Relative factor abundance and factor scarcity, EU and US, 2012. Note: The figures for digital and non-digital trade are the shares of the respective factor and country in the worldwide endowment with that factor. Ranking following Trefler (1995). EU based on ICP DTI, US based on O*NET DTI. Source: Trefler (1995)

[41] In that respect it is interesting to note that Eurofound expects an increased demand for higher skills resulting from digitalisation. At the same time, they also point to the risk that some new technologies carry the risk of deskilling as a result of fragmentation of jobs into individual tasks which are then often more routine-tasks and of a low-skilled nature. This very much resembles the Braverman hypothesis. See: https://www.eurofound.europa.eu/en/what-about-skills-digital-age.

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 5 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.

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 5 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 5 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, pointing to the phenomenon of "missing trade" (Trefler 1995). The latter 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, the 'home market' bias (implicitly, a violation of the assumption on homothetic preferences).

Table 5 Measured and predicted factor content of trade (FCT), 2012

	Measured FCT		Predicted FCT	
Country	Digital tasks	Non-digital tasks	Digital tasks	Non-digital tasks
USA	-45,332	-2,013,710	-382,611	-37,201,730
EU	45,332	2,013,711	382,611	37,201,730
AUT	-12,003	-433,285	-15,091	-167,019
BEL	-13,884	-436,843	-42,083	-1,119,842
BGR	10,352	636,635	43,409	2,723,409
CZE	25,519	799,149	84,364	2,670,862
DEU	15,055	-500,026	110,259	5,425,937
DNK	-10,358	-360,729	-11,601	-583,302
ESP	10,348	837,913	-58,168	4,012,427
EST	1,385	60,998	7,706	310,821
FIN	-6,659	-226,848	438	-352,178
FRA	-44,541	-1,219,671	-160,815	-1,758,302
GBR	31,797	-661,666	121,339	87,009
GRC	-2,962	41,155	-2,254	1,500,305
HUN	16,661	659,091	62,830	2,542,984
IRL	-14,981	-292,100	-11,563	-405,608
ITA	-5,127	-286,711	-38,694	2,245,251
LTU	1,139	152,177	9,211	762,507
LUX	-5,013	-103,650	-6,100	-255,566
LVA	2,267	56,369	13,600	527,207
NLD	2,404	151,771	11,587	79,591
POL	37,157	1,968,107	170,858	9,658,126
PRT	-198	318,922	10,596	2,225,473
ROU	10,246	892,461	71,209	6,650,818
SVK	11,230	429,258	19,927	1,005,720
SVN	1,847	99,632	8,528	432,593
SWE	-16,347	-568,400	-16,882	-1,017,492

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

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^c_{dt}) less the factors embodied in net FCT (F^c_{dt}) equal consumption ($V^c_{dt} - F^c_{dt}$). The relative factor abundance revealed in trade can be determined by taking the ratio of both our

Table 6 Relative factor abundance as revealed in trade, EU vs US, 2012

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

Calculations for the EU are based on the ICP data, those for the US on O*NET data

Source: European LFS, OEWS; LFS CPS; O*NET database; OECD ICIO 2021

factors—V^c_{dt} and V^c_{nt}—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 6).[42] 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.

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 (H4). 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.

Table 7 provides a sensitivity analysis for this central of the relative digital task abundance of the US. The sensitivity analysis consists of re-calculating the economy-level relative factor abundance for the EU and the US as in Table 6 but each time omitting one industry.

The sensitivity check is intended to reveal if the aggregate finding is driven by a single large and influential industry. As the results show, though, this is not the case. No matter which industry is exempted from the factor abundance calculation, the US maintains their relative digital task abundance. This includes the omission of the important IT industry (NACE 62T63), the telecommunication sector (NACE 61) or the computer, electronic and optical equipment industry (NACE 26). Since these are industries with high digital task contents, their omission reduces the digital task to non-digital task ratios but it does so both on the production and the consumption side. In no case, the contribution of these industries to the overall result is so decisive as to tilt the result.

To conclude the analysis, we briefly report the results of the sign test for the two factors (Table 8 and Fig. 7). 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 (2023), as well as to earlier results in the literature for the factor labour alone (e.g., Trefler and Zhu 2010; Stehrer 2014).

[42] 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 7 Sensitivity tests for the relative digital task abundance of the US, 2012

Omitted industry	Production (Y)	Net FCT	Consumption (C)	Y > C
Agriculture (01T03)	0.04093	0.02411	0.04071	yes
Mining (05T09)	0.04069	0.02243	0.04044	yes
Food products, beverages, tobacco (10T12)	0.04099	0.02266	0.04074	yes
Textiles, textile products, leather (13T15)	0.04069	0.02291	0.04045	yes
Wood and products of wood and cork (16)	0.04070	0.02256	0.04044	yes
Paper products and printing (17T18)	0.04061	0.02219	0.04036	yes
Coke and refined petroleum products (19)	0.04061	0.02242	0.04036	yes
Chemical and chemical products (20)	0.04063	0.02159	0.04037	yes
Pharmaceuticals, medicinal products (21)	0.04060	0.02130	0.04034	yes
Rubber and plastics products (22)	0.04071	0.02233	0.04046	yes
Other non-metallic mineral products (23)	0.04069	0.02250	0.04044	yes
Basic metals (24)	0.04068	0.02224	0.04043	yes
Fabricated metal products (25)	0.04082	0.02208	0.04057	yes
Computer, electronic and optical Eq. (26)	0.03990	0.02356	0.03967	yes
Electrical equipment (27)	0.04064	0.02188	0.04038	yes
Machinery and equipment, nec (28)	0.04069	0.02052	0.04043	yes
Motor vehicles, trailers and semi-trailers (29)	0.04073	0.02102	0.04047	yes
Other transport equipment (30)	0.04049	0.02306	0.04024	yes
Manufacturing nec; (31T33)	0.04069	0.02195	0.04044	yes
Electricity, gas, steam (35)	0.04059	0.02210	0.04033	yes
Water supply; sewerage, waste mgmt. (36T39)	0.04069	0.02233	0.04043	yes
Construction (41T43)	0.04199	0.02258	0.04172	yes
Wholesale and retail trade (45T47)	0.04456	0.02412	0.0443	yes
Land transport and transport via pipelines (49)	0.04108	0.02319	0.04084	yes
Water transport (50)	0.04063	0.02250	0.04038	yes
Air transport (51)	0.04067	0.02249	0.04041	yes
Warehousing, transp. support services (52)	0.04080	0.02236	0.04054	yes
Postal and courier activities (53)	0.04080	0.02163	0.04052	yes
Accommodation, food services (55T56)	0.04415	0.02266	0.04383	yes
Publishing, audiovisual, broadcasting (58T60)	0.03953	0.02518	0.03932	yes
Telecommunications (61)	0.04003	0.02252	0.03979	yes
IT and other information services (62T63)	0.03481	0.01608	0.03455	yes
Financial and insurance activities (64T66)	0.03808	0.02382	0.03788	yes
Real estate activities (6b)	0.04076	0.02247	0.0405	yes
Professional, scientific, technical services (69T75)	0.03654	0.02541	0.03639	yes
Administrative and supp. Services (77T82)	0.04099	0.02520	0.04075	yes
Public administration and defence (84)	0.04036	0.02248	0.04008	yes
Education (85)	0.04044	0.02354	0.04018	yes
Human health and social work activities (86T88)	0.04350	0.02270	0.04317	yes
Arts, entertainment and recreation (90T96)	0.04223	0.02208	0.04193	yes
Activities of households as employers (97T98)	0.04062	0.02251	0.04036	yes

The results are similar to those in Table 6 only that in each case a single industry is omitted for the calculation of the relative factor abundance (ICIO industry codes are in bracktes). The results are shown for the US only because the results for the production-to-consumption ratio for the EU are simply the opposite. Calculations for the EU are based on the ICP data, those for the US on O*NET data

Source: European LFS, OEWS; LFS CPS; O*NET database; OECD ICIO 2021

Table 8 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

Calculations for the EU are based on the ICP data, those for the US on O*NET data

Source: European LFS, OEWS; LFS CPS; O*NET database; OECD ICIO 2021

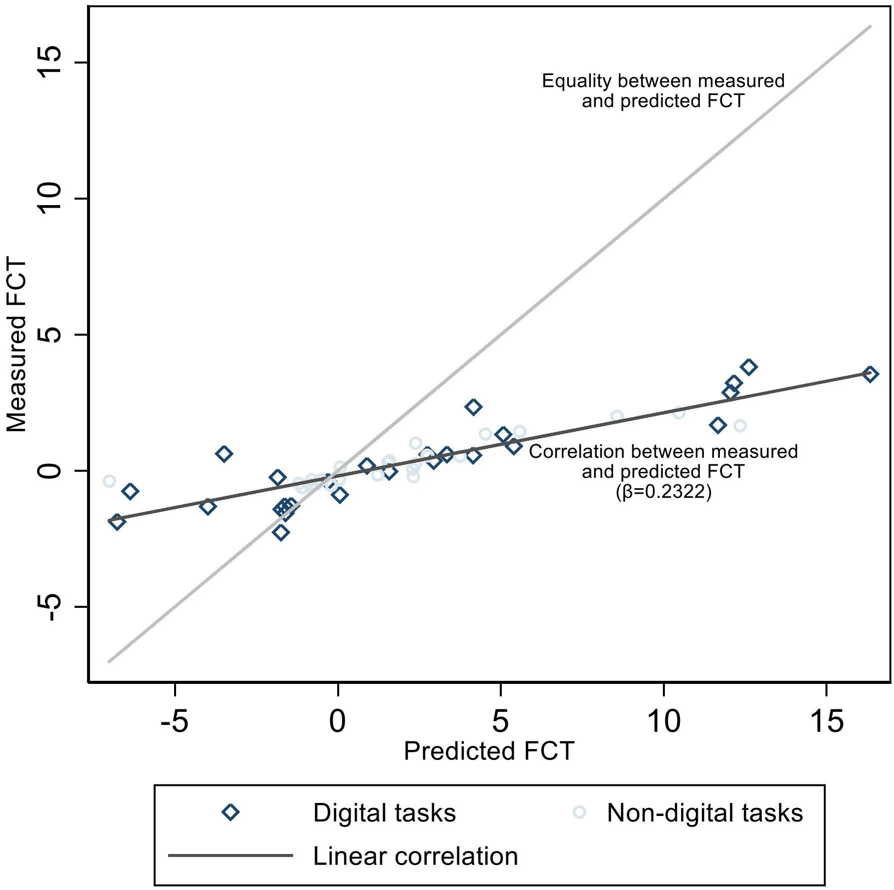

Fig. 7 Correlation between measured and predicted factor content of trade, 2012. Note: FCT = Factor content of trade. Source: Regression output reported in * MERGEFORMAT Table 8

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 (0.23) resulting from a regression of the measured FCT on the predicted FCT is far below 1, is evidence of 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 (H1). 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 (H2). Importantly, we also find that this gap translates into a comparative advantage of the US in digital tasks meaning the US is abundant in digital relative to non-digital tasks (H4), leaving the EU with comparative advantage in non-digital tasks. The within-occupation effect which we identify and show to be quantitatively important, is a major 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.

However, we do not find a positive net FCT for the US which contradicts our prior expectation (H3). This result can be rationalised by the HOV literature, pointing to 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, where it was shown that the US has a lead over the EU by a factor of 3.5 to 1.

The 'digital gap' in digital tasks between the EU and the US per se, but even more so the fact that this task-based gap is possibly smaller than in patents data and similar dimensions of digit has important 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 medium-to-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. A positive interpretation of our results on the comparative advantage in digital tasks from an EU perspective is the following: while the EU is currently lagging behind the US in the development of digital technologies – as revealed by the significant IR4 patent gap between the EU and the US –, it has the necessary digital task endowments on the side of labour to catch up with the US (as well as other competitors such as China) and to close the existing gap in digital technologies. Yet, Europe is also facing the risk of a growing digital gap. In fact, virtually all the companies that are leading the new wave of digital innovation, i.e., the one related to the unfolding of AI, are US or China-based with the few European followers (e.g., the French AI start-up Mistral). As a result, if the EU does not manage to rapidly increase its productive and technological capabilities in this domain, the trajectories of digital-related capabilities could embark on a trajectory that is highly unfavourbale for Europe (Guarascio et al. forthcoming).

Finally, we should also point out some limitations to this study. First, due to data constraints, our analysis is limited to EU member states and the US. While we believe that the restricted sample does not cause a significant distortion in the results obtained, 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 digital gap could be with respect to 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. Given the current data situation we leave this for future work.

Appendix 1: Industry Classifications

Table 9 provides the complete list of industries along with industry codes as used in the OECD inter-country input–output (ICIO) database. Table 10 contains the correspondence between industry codes as used in the OECD ICIO database and ISIC Rev. 4 industry codes.

Table 9 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

Table 9 (continued)

Industry code	Industry name
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 HHas employers; goods- and services-producing activities of HH for own use

Industries are based on industries as defined in OECD inter-country input–output database with some aggregations. *HH* households

Source: OECD ICIO

Table 10 Correspondence—OECD ICIO to ISIC Rev 4 industries

ICIO Industry code	Industry name	ISIC Rev4 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

Table 10 (continued)

ICIO Industry code	Industry name	ISIC Rev4 code
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
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

Table 10 (continued)

ICIO Industry code	Industry name	ISIC Rev4 code
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 HH as employers; producing activities of HH for own use	97
97T98	Activities of HH as employers; producing activities of HH for own use	98

Industries are based on industries as defined in OECD inter-country input–output database with some aggregations. *HH* households

Source: OECD ICIO

Appendix 2: Export Coverage of Countries in the Sample

The overall exports of each country in the sample, that is the 'EU-US world', only covers a certain share of global exports. The calculation of the measured factor content of trade relies on exports of each country. As a consequence, the exports which are covered in our sample, consisting of EU countries and the US, matters. Section 3.3 discussed the implications of the fact that the sample only covers EU countries and the US which amounts to 63% and 21% respectively. Appendix Table 11. presents the export coverage for each individual country. It illustrates the claim made in the main text that the export coverage in general tends to be higher in small EU countries.

Table 11 Export coverage globally and in the EU-US sample

Country	(1) Global sample (in USD mn)	(2) EU-US sample (in USD mn)	(3) share of exports covered
AUT	196,343	136,777	69.66%
BEL	292,081	214,209	73.34%
BGR	30,680	17,942	58.48%
CZE	144,149	109,311	75.83%
DEU	1,372,433	789,237	57.51%
DNK	149,788	86,002	57.42%
ESP	393,647	258,362	65.63%
EST	16,350	10,751	65.76%
FIN	94,669	50,709	53.56%
FRA	709,882	430,233	60.61%
GBR	672,516	409,900	60.95%
GRC	65,657	30,670	46.71%
HUN	101,601	74,754	73.58%
IRL	224,259	156,067	69.59%
ITA	572,071	317,673	55.53%
LTU	25,111	17,261	68.74%
LUX	93,178	71,315	76.54%
LVA	12,973	8,320	64.13%
NLD	415,879	294,103	70.72%
POL	204,395	149,257	73.02%
PRT	76,824	52,127	67.85%
ROU	53,127	36,134	68.01%
SVK	75,778	57,567	75.97%
SVN	28,254	18,610	65.87%
SWE	215,185	125,183	58.17%
EU	6,236,828.0	3,922,472	62.89%
USA	1,965,614	418,502	21.29%

The share of exports covered in column (3) is simply the ratio between global exports and the exports in the EU-US sample Hence, column (3) is calculated as column (2) over column (1)

Source: Authors' own calculations; OECD ICIO

Appendix 3: ICT Task Intensity of Jobs According to PIAAC

In its Digital Economy Outlook, the OECD rely on a ICT task intensity indicator to assess the digitalisation of jobs (OECD 2020). The indicator stems from a factor analysis reducing the numerous tasks included in the Program for the International Assessment of Adult Competencies (PIAAC) survey to six key skills (Grundke et al. 2017), one of them being ICT skills[43]. ICT skills are identified by way of an exploratory factor analysis, making use of the individual questions from the PIACC questions. ICT skills are characterised by having high factor loading, for example, in the 'Frequency of programming language use' (question G_Q05g) or the 'Frequency of email use' (G_Q05a)[44].

These tasks/questions which define the OECD's ICT indicator captures predominantly simple ICT tasks, with the use of email being a good example.

Despite the significant methodological differences and different data source used for the construction of the indicators, though there is an interesting overlap with our results. In both. cases, there are several European countries which have higher scores in the ICT task indicator respectively our digital task indicator than the US. According to the OECD (2020), the Nordic countries, the United Kingdom, and the Netherlands emerge as the countries with the highest ICT task intensity, all ahead of the US (Appendix Fig. 8).

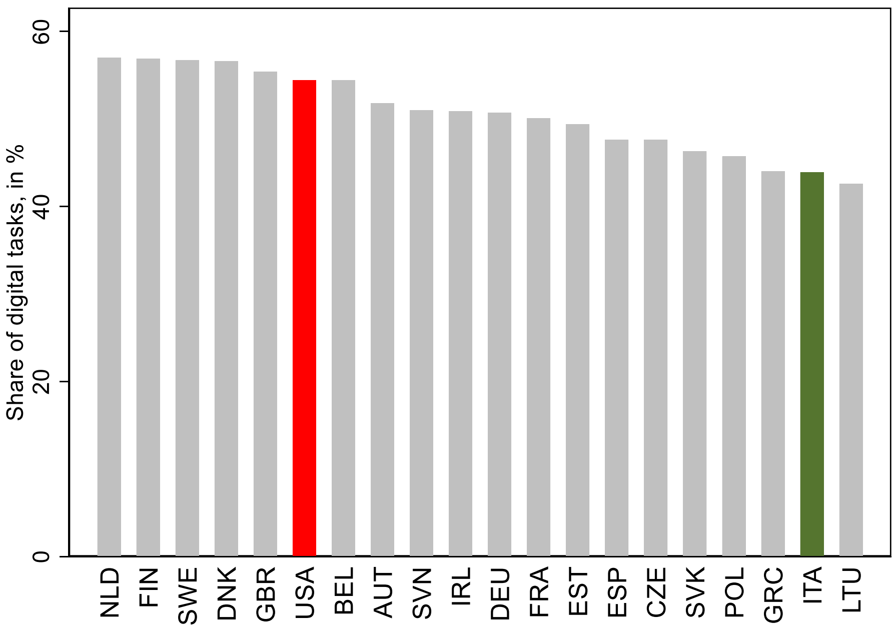

Fig. 8 OECD ICT task intensity of jobs, 2012/2015. Note: Task intensity ranges from 0 to 100 and relies on the 11 items from the OECD Survey of Adult Skills (PIAAC) listed in text. Appendix Fig. 8 shows a simple average of male and female scores is reported separately in OECD (2020, Figure 4.26). Source: OECD Digital Economy Outlook 2020; based on Grundke et al. (2017)

[43] The paper by Grundke et al. (2017) labels the indicator ICT skills while many OECD publications rerer to this indicator as ICT tasks.

[44] For the full set of questions relevant for the ICT skills see Grundke et al. (2017).

Author Contributions D. Guarascio: Introduction, Related Literature and Hypotheses Conclusion Roman Stöllinger Introduction Methodology and Data Results.

Data Availability The data that support the findings of this study are available from the corresponding author, R.S., upon reasonable request.

Declarations

Competing Interests The authors declare that they have no competing interests.

References

Acemoglu D, Autor D (2011) Skills, tasks and technologies: implications for employment and earnings. in: Card D, Ashenfelter O (eds), Handbook of Labor Economic. 4, Part B. Elsevier:1043–1171

Acemoglu D, Restrepo P (2018) The race between man and machine: implications of technology for growth, factor shares, and employment. Am Econ Rev 108(6):1488–1542

Acemoglu D, Restrepo P (2019) Automation and New Tasks: How Technology Displaces and Reinstates Labor. J Econ Perspect 33(2):3–30

Acemoglu D, Restrepo P (2022) Tasks, automation, and the rise in US wage inequality. Econometrica 90(5):1973–2016

Aghion P, Antonin C, Bunel S, Jaravel X (2023) The effects of automation on labor demand. In: Yan L, Grossman GM (eds) Robots and AI: A New Economic Era. Taylor and Francis, pp 15–39

Aghion P, Antonin C, Bunel S, Jaravel, X (2020) What are the labor and product market effects of automation? New evidence from France. CEPR discussion paper 14443. CEPR Press, Paris, London.

Agrawal A, Gans J, Goldfarb A (2018) Prediction machines: The simple economics of artificial intelligence. Harvard Business Review Press, Boston, MA

Arntz M, Gregory T, Zierahn U (2017) Revisiting the risk of automation. Econ Lett 159:157–160

Autor DH, Levy F, Murnane RJ (2003) The Skill Content Of Recent Technological Change: An Empirical Exploration. Quart J Econ 118(4):1279–1333

Autor DH, Dorn D (2013) The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. Am Econ Rev 103(5):1553–1597

Autor DH, Dorn D, Hanson GH (2013) The geography of trade and technology shocks in the United States. Am Econ Rev 103(3):220–225

Autor D, Chin, C, Salomons AM, Seegmiller B (2024) New frontiers: the origins and content of new work, 1940–2018. Q J Econ qjae008. https://doi.org/10.1093/qje/

Baldwin RE (2008) The Development and Testing of Heckscher-Ohlin Trade Models. MIT Press

Bogliacino F, Pianta M (2016) The Pavitt Taxonomy, revisited: patterns of innovation in manufacturing and services. Econ Politica 33(3):153–180

Bowen H, Leamer E, Sveikauskas L (1987) Multicountry, Multifactor Tests of the Factor Abundance Theory. Am Econ Rev 77(5):791–809

Brattberg E, Csernatoni R, Rugova V (2020) Europe and AI: Leading, Lagging Behind, or Carving Its Own Way?, Carnegie Endowment for International Peace working paper, July 2020. Available at: https://www.carnegieendowment.org/files/BrattbergCsernatoniRugova_-_Europe_AI.pdf

Braverman H (1974) Labor and Monopoly Capital. Monthly Review Press, New York
Caravella S, Crespi F, Guarascio D, Tubiana M (2021) Heterogeneity in the demand-growth relationship at the firm level: the role of demand sources and innovation/knowledge characteristics. Econ Innov New Technol 30(5):516–535
Castellacci F (2008) Technological paradigms, regimes and trajectories: Manufacturing and service industries in a new taxonomy of sectoral patterns of innovation. Res Policy 37(6–7):978–994
Chernoff A, Warman C (2022) COVID-19 and implications for automation. Appl Econ 55(17):1939–1957
Cimoli M, Dosi G, Yu X (2020) Industrial policies, patterns of learning, and development. In: Oqubay A, Cramer C, Chang HJ, Kozul-Wright R (eds) The Oxford handbook of industrial policy. Oxford University Press, Oxford, pp 93–124
Cirillo V, Evangelista R, Guarascio D, Sostero M (2021) Digitalization, routineness and employment: An exploration on Italian task-based data. Res Policy 50(7):104079
Davis DR, Weinstein DE (2001) An Account of Global Factor Trade. Am Econ Rev 91(5):1423–1453
Davis DR, Weinstein DE (2004) The Factor Content of Trade. In: Choi EK, Harrigan J (eds) The Handbook of International Trade. Blackwell Publishing, Oxford, pp 119–145
Dosi G (1984) Technical change and industrial transformation: the theory and an application to the semiconductor industry. Springer
Dosi G, Marengo L, Virgillito M (2021) Hierarchies, knowledge, and power inside organizations. Strategy Sci 6(4):371–384
Edler J, Blind K, Kroll H, Schubert T (2023) Technology sovereignty as an emerging frame for innovation policy. Defining rationales, ends and means. Res Policy 52(6):104765
European Political Strategy Centre (EPSC) (2019), EU Industrial Policy after Siemens-Alstom. Finding a new balance between openness and protection, March 2019. Available at: https://www.politico.eu/wp-content/uploads/2019/03/EPSC_Industrial-Policy.pdf
Fanti L, Guarascio D, Moggi M (2022) From Heron of Alexandria to Amazon's Alexa: a stylized history of AI and its impact on business models, organization and work. J Ind Bus Econ 49(3):409–440
Feenstra RC (2003) Advanced International Trade: Theory and Evidence. Woodstock, Princeton University Press, Princeton
Felten EW, Raj M, Seamans R (2018) A method to link advances in artificial intelligence to occupational abilities. AEA Papers Proc 108:54–57
Fernández-Macías E, Hurley J (2017) Routine-biased technical change and job polarization in Europe. Soc Econ Rev 15(3):563–585
Firpo S, Fortin N, Lemieux T (2011) Occupational tasks and changes in the wage structure, IZA Discussion Papers 5542. Institute for the Study of Labor (IZA), Bonn
Flisi S, Santangelo G (2022) Occupations in the European Labour Market During the COVID-19 Pandemic. Intereconomics 57:120–126
Foray D (2013) The economic fundamentals of smart specialisation. Ekonomiaz 83(02):55–82
Frey CB, Osborne MA (2017) The future of employment: How susceptible are jobs to computerisation? Technol Forecast Soc Chang 114:254–280
Goos M, Manning A, Salomons A (2009) Job polarization in Europe. Am Econ Rev 99(2):58–63
Goos M, Manning A, Salomons A (2014) Explaining job polarization: Routine-biased technological change and offshoring. Am Econ Rev 104(8):2509–2526
Greenstein S (2015) How the internet became commercial: Innovation, privatization, and the birth of a new network. Princeton University Press
Grundke R, Jamet S, Kalamova M, Keslair F, Squicciarini M (2017) Skills and global value chains: A characterisation, OECD Science. Technology and Industry Working Papers, 2017/05. OECD Publishing, Paris. https://doi.org/10.1787/cdb5de9b-en
Gschwent L, Guarascio D, Jestl S, Sabouniha A, Stöllinger R (2023) Digital Tasks and ICT Capital: Methodologies and Data, wiiw Statistical Report, 11, January 2023. Available at: https://www.wiiw.ac.at/digital-tasks-and-ict-capital-methodologies-and-data-dlp-6429.pdf
Guarascio D, Reljic J, Cucignatto G, Celi G, Simonazzi A (forthcoming) Between Scylla and Charybdis. Long-term drivers of EU structural vulnerability, Review of Keynesian Economics
Guarascio D, Stöllinger R (2023) Comparative advantages in the digital era–A Heckscher-Ohlin-Vanek approach. Int Econ 175:63–89
ILO (2012) International Standard Classification of Occupations. Structure, group definitions and correspondence tables. International Labour Office, Geneva
Keynes JM (2010, [1930]) Economic possibilities for our grandchildren. Essays in persuasion. Palgrave Macmillan, London, pp 321–334

Leamer E (1980) The Leontief paradox, reconsidered. J Polit Econ 88(3):495–503
Leontief W (1953) Domestic Production and Foreign Trade: The American Capital Position Re-Examined. Proc Am Philos Soc 97(4):332–349
Lewandowski P, Park A, Hardy W, Du Y, Wu S (2022) Technology, Skills, and Globalization: Explaining International Differences in Routine and Nonroutine Work Using Survey Data. World Bank Econ Rev 36(3):687–708
Martinaitis Z, Christenko A, Antanavičius J (2021) Upskilling, Deskilling or Polarisation? Evidence on Change in Skills in Europe. Work Employ Soc 35(3):451–469
Mazzucato M (2018) Mission-oriented innovation policies: challenges and opportunities. Ind Corp Chang 27(5):803–815
McKinsey (2022), Securing Europe's competitiveness. Addressing its technology gap, available at: https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/securing-europes-competitiveness-addressing-its-technology-gap#/
Miller C (2022) Chip War: The Fight for the World's Most Critical Technology. Scribner, New York
Muro M, Liu S, Whiton J, Kulkarni S (2017) Digitalization and the American workforce. Brookings Metropolitan Policy Program. Brookings Institution. November
OECD (2020) OECD Digital Economy Outlook 2020. OECD Publishing, Paris
Oesch D, Piccitto G (2019) The polarization myth: Occupational upgrading in Germany, Spain, Sweden and the UK, 1992–2015. Work Occup 46(4):441–469
O'Mara M (2020) The code: Silicon Valley and the remaking of America. Penguin, New York
Pavitt K (1984) Sectoral patterns of technical change: towards a taxonomy and a theory. Res Policy 13(6):343–373
Rikap C, Lundvall B-Å (2021) The digital innovation race. Conceptualizing the emerging new world order. Palgrave Macmillan, Cham
Stehrer R (2014) Does the home bias explain missing trade in factors? wiiw Working Paper 110
Trefler D (1993) International factor price differences: Leontief was right! J Polit Econ 101(6):961–987
Trefler D (1995) The case of the missing trade and other mysteries. Am Econ Rev 85(5):1029–1046
Trefler D, Zhu S (2010) The structure of factor content predictions. J Int Econ 82:195–207
UNCTAD (2021) Digital Economy Report, 2021 Cross-border data flows and development: For whom the data flow United Nations Geneva
Vanek J (1968) The Factor Proportions Theory: The N-Factor Case. Kyklos 21:749–756

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