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Mind the Digital Gap: The Role of Regional-Level General and Digital Human Capital in Shaping ICT Use of Different Types of Entrepreneurs

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Abstract
We investigate determinants of the frequency of ICT usage of three types of self-employed workers—*self-employed with employees*, *independent own-account self-employed*, and *dependent self-employed workers*—in 305 European NUTS-2 regions. Besides individual-level determinants, we also investigate the role of regional-level *general* human capital and of regional-level *digital* human capital, which capture distinct sources of regional knowledge spillovers. Our results show clear evidence for both types of spillover effects to exist. Moreover, we find that these effects also contribute to a convergence process in ICT use frequency (i) among the three types of self-employed within a given region and (ii) among regions.

Keywords ICT usage frequency · Regional knowledge spillovers · Entrepreneurs' types · Europe

JEL Classification J24 · L26 · L53 · O30 · O52

Introduction

Efficient usage of information and communications technology (ICT) has become an increasingly important element of firm competitiveness in modern economies (Gómez-Sánchez et al., 2023). However, there are great differences among firms in access to and implementation of ICT. This is highly relevant as ICT usage positively affects firm performance (Yunis et al., 2018). Although ICT usage is widely researched in the realm of large firms (Lee et al., 2011), investigation of ICT use in (very) small firms is less common. ICT usage in small firms may be different from larger firms, in part due to resource constraints (Lucchetti & Sterlacchini,

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2004). Increasing our understanding of approaches to ICT in small firms (including micro firms) is also important because micro businesses (i.e., firms with less than 10 employees) account for a large proportion (between 70 and 95%) of total firms in all OECD countries (OECD, 2021).

In this paper, we investigate determinants of ICT use frequency of European self-employed workers while taking a regional perspective. However, self-employment forms a vastly heterogeneous group of workers (Cieslik & Dvouletý, 2019; Dvouletý, 2018). Attributes such as having employees or working mainly for a specific client generate important heterogeneity in self-employment. Based on these dimensions, a relatively recent stream of literature (see, e.g., Muehlberger & Pasqua, 2009; Román et al., 2011; Lyalkov et al., 2020; Barrientos-Marín et al., 2021; Burke et al., 2021; Carrasco & Hernanz, 2022; Block et al., 2022; Dvouletý & Nikulin, 2023; Van Stel et al., 2023) has found important differences (e.g., reason to start-up, earnings, job satisfaction, stress at work, skills, working hours, working time flexibility) among *self-employed with employees* (SEwEs), *independent own-account self-employed* (IOAs), and *dependent self-employed workers* (DSEWs). At the macro level, the importance of accounting for different entrepreneurs' types is emphasized by Audretsch and Belitski (2021) who observed different impacts of self-employed with and without employees and new-firm birth rates on regional economic development.

Millán et al. (2021) explored how ICT usage at work varies among these different types of self-employment among 35 European countries. They found structural differences among the three groups of self-employed, where the frequency of ICT usage at work was highest among SEwEs, followed by IOAs. ICT usage at work was lowest among the group of DSEWs. However, their analysis did not consider the role of regional context. The regional context—both across and within countries—in which these self-employed individuals perform their activities is expected to be of great importance in explaining their ICT use frequency. This may be the case not only because of regional differences in wealth and resources, which may impact ICT use frequency of the region's entrepreneurs, but also because of regional knowledge spillovers that may stimulate ICT usage by individual entrepreneurs. In this paper, we distinguish between two types of knowledge spillovers originating from regions' *general* and *digital* knowledge stocks.

More specifically, we investigate determinants of ICT usage frequency of the three types of self-employed workers in NUTS-2 regions across 35 European countries. In total, we use 4822 observations for self-employed workers distributed over 305 NUTS-2 regions. Our methodology is to estimate multilevel ordered logit models where ICT usage frequency of the self-employed workers in our data base forms the dependent variable. To measure ICT usage frequency, respondents in our sample are asked to rate on a seven-point Likert scale how often they use smartphones, laptops, and other electronic devices in their daily work. Such a scale of ICT usage by entrepreneurs is similar to the four clusters of digital maturity identified by Henderson et al. (2018) where firms vary from "digitally disengaged" (lowest level) to "digitally embedded" (highest level). Besides individual-level determinants of the extent of ICT usage by self-employed workers, we also investigate the role of *regional-level general human capital* (proxied by the percentage of the regional population with tertiary education) and of *regional-level digital human capital* (average ICT usage by workers in the region), while controlling for regional GDP per capita. These two indicators capture regional knowledge spillovers originating from the regions' general and digital knowledge stocks, respectively. Moreover, we also investigate whether these regional spillover effects contribute to convergence processes in the frequency of ICT usage at work among (1) the three types of self-employed (within a given region) and (2) regions with different average levels of ICT usage by their entrepreneurs.

Because our dependent variable, i.e., ICT use frequency at work, is of a discrete ordered nature (as the variable is measured on a seven-point Likert scale), ordered logit models are used. Moreover, since we have observations at the level of self-employed individuals which are nested in regions, we use multilevel (hierarchical) models (Guo & Zhao, 2000). Our results show clear evidence for both examined types of regional knowledge spillover effects to exist, i.e., both general and digital knowledge spillovers. Moreover, we find that these effects also contribute to a convergence process in ICT use frequency (i) among the three types of self-employed within a given region and (ii) among regions.

Two of our contributions to extant literature are that we study ICT usage in (very) small firms rather than large firms and that we study this topic using the individual person level as the unit of observation rather than the firm level (see Millán et al., 2021 for a similar approach). However, our third and most important contribution is that we investigate the role of regional factors in shaping ICT use by individual entrepreneurs. In particular, we investigate whether the general and digital knowledge stocks of the region generate positive spillover effects to individual entrepreneurs in that region, increasing their frequency of ICT usage in their daily work. The analysis of the role of regional context is also the main contribution of the current paper relative to Millán et al. (2021) who did not study regional-level determinants of ICT use frequency. To the best of our knowledge, no study has yet explored regional spillover effects influencing ICT usage by individual entrepreneurs. Fourth and finally, our paper also makes a theoretical contribution, as the next section will show. In particular, we extend the *absorptive capacity theory of knowledge spillover entrepreneurship* (Qian & Acs, 2013) by adding an explicit role for digital human capital and ICT knowledge and skills.

Theoretical Framework and Hypotheses

In modern economies, frequent usage of ICT, including Internet and digital technology platforms, by entrepreneurs and SMEs, becomes ever more common (Kossaï et al., 2020). Globalization, the information revolution, cheaper personal computers and ICT equipment, and the expansion of the (knowledge-based) service sector since the beginning of this century are some of the explanations for this development (Thurik et al., 2013). However, it may be argued that incentives for entrepreneurs to increase their ICT use intensity are even greater in regions characterized by regional populations with high levels of *general human capital endowment* (including tertiary education; Van Praag et al., 2013) and/or *digital human capital endowment* (including implementation and high-frequency usage of ICT; Millán et al., 2021).

The Absorptive Capacity Theory of Knowledge Spillover Entrepreneurship

Following the absorptive capacity theory of knowledge spillover entrepreneurship (Qian & Acs, 2013), a region's human capital endowment is a key determinant of individuals' *entrepreneurial absorptive capacity*, defined as "the ability of an entrepreneur to understand new knowledge, recognize its value, and subsequently commercialize it by creating a firm" (Qian & Acs, 2013, p. 191). The theory is an extension of the knowledge spillover theory of entrepreneurship (KSTE), which recognizes entrepreneurship as a mechanism of knowledge spillovers (Acs et al., 2009). In a typical illustration of the KSTE, an inventor working as an employee in an incumbent firm, unable to convince the decision makers in the firm of the value of her invention, will decide to start her own business in an attempt to appropriate (i.e., commercialize) the value of her invention. In this framework, new knowledge creation is a source of entrepreneurial opportunity which is exploited by former employees of incumbent firms who start their own businesses. The knowledge thus spills over from the incumbent firm to the new business (Audretsch & Keilbach, 2007).

However, in the KSTE, knowledge creation is exogenous, and new firms are assumed to be started by inventor entrepreneurs. These two limitations are being solved in the absorptive capacity theory of knowledge spillover entrepreneurship by introducing a role for entrepreneurial absorptive capacity. New knowledge creation does not automatically lead to more entrepreneurship in a region, but entrepreneurial absorptive capacity (EAC) is needed to actually discover and exploit the entrepreneurial opportunities that emerge from new knowledge creation (see Kirschning and Mrożewski, 2023, for empirical support at the country level, and Kastelli et al., 2023, for empirical support at the individual level). According to Qian and Acs (2013), EAC comprises both scientific knowledge and business knowledge. The explicit role of business knowledge introduces the possibility of entrepreneurship by non-inventors and interpersonal knowledge spillovers between inventors and non-inventor entrepreneurs. A final key characteristic of the absorptive capacity theory of knowledge spillover entrepreneurship concerns the role of human capital. This is not only the main source of new knowledge creation and hence of entrepreneurial opportunity, but also the key determinant of EAC.

Departing from the above framework introduced by Qian and Acs (2013), we will first argue that the concept of EAC is particularly useful for our paper. Second, we will make a small adjustment to the framework by (1) adding a third component of entrepreneurial absorptive capacity, viz., ICT knowledge and skills, and (2) introducing a distinction between a region's general and digital human capital stock in influencing an individual's EAC ("Adding an Explicit Role for ICT" section).

Absorptive capacity is an important determinant of a firm's competitiveness (Proeger, 2020). It is defined not only by the ability to recognize valuable outside knowledge but also by the ability to assimilate this knowledge (Cohen & Levinthal, 1990). However, as noted by Qian and Acs (2013), management literature has mainly focused on the role of absorptive capacity in established firms and organization, but not on absorptive capacity in the context of individual entrepreneurs. In the present paper, we focus on self-employed workers. In order for them to thrive, they will actually need to have a high level of absorptive capacity themselves, i.e., personally, rather than making sure there is a good absorptive capacity at the level of the organization. Hence, when studying self-employed workers, the concept of entrepreneurial absorptive capacity, involving the capability of the entrepreneur to discover and exploit entrepreneurial opportunities, is especially relevant.

Adding an Explicit Role for ICT

In this subsection, we will make a small variation to the absorptive capacity theory of knowledge spillover entrepreneurship by adding an explicit role for digital human capital and ICT knowledge and skills.

In Qian and Acs (2013), human capital is not only an important source of entrepreneurial opportunities but also an important determinant of EAC. This holds both for the human capital of the entrepreneur herself (individual level) and also for human capital at the regional level, which may be viewed as the knowledge stock of the region. If, at the regional level, the level of human capital is high (i.e., the knowledge stock is large), there is a lot of room for knowledge spillover entrepreneurship to occur. First, inventors in incumbent firms may decide to start (knowledge-based) firms of their own, in line with the KSTE. For instance, Murphy and Siedschlag (2013) find that in countries with higher *ex-ante* human capital stocks, ICT-intensive industries grow relatively faster. Second, in regions with high human capital stocks, there will also be more non-inventor entrepreneurs with sufficient levels of EAC who are able to benefit from interpersonal spillovers from inventors.

Such interpersonal spillovers are consistent with the more classic use of the term knowledge spillovers in the sense of knowledge flowing between different persons who are usually affiliated with different (incumbent) firms (Jacobs, 1969). As knowledge is complex and tacit, geographic proximity has been found to be crucial for interpersonal knowledge spillovers (Raspe & Van Oort, 2011). Thus, as high human capital (high-HC) regions have higher knowledge stocks, it is also more likely that more inventions and innovative ideas circulate among the firms in high-HC regions. In turn, possibilities for regional knowledge spillovers to occur are also bigger, in part because high-HC employees may move from one firm to another (Noack et al., 2018). For the average micro firm or one-man business/own-account worker—who is more dependent on knowledge spillovers (relative to performing in-house R&D activity) to keep in touch with the latest technology than larger firms—it may then be attractive to be located in a high-HC region, as regional knowledge spillovers may be more frequent. Still, it will be important that the entrepreneurs have a sufficient level of EAC in order to actually benefit from such spillovers.

The impact of human capital, both at the individual level of the entrepreneur herself and at the regional level, on the individual-level entrepreneurial absorptive capacity, is pictured in Fig. 1. First, through formal education, entrepreneurs may have obtained a certain level of knowledge and skills relevant for EAC. Second, such relevant knowledge may also be obtained via knowledge spillovers. Such knowledge spillovers may involve knowledge flows between coworkers in an incumbent firm and where one worker decides to start her own business (knowledge flow from incumbent firm to new firm, consistent with the KSTE), but also knowledge flows between existing firms, where the receiving entrepreneur may benefit from knowledge obtained from customer firms, supplier firms, and even competitor firms. Since for micro firms and solo entrepreneurs, stakeholders (customers, suppliers, and competitors) are more likely (compared to larger firms) to be located in the same region (Cowling et al., 2019), regional proximity is key for the latter type of spillovers to occur (Jacobs, 1969).

So far, we followed the absorptive capacity theory of knowledge spillover entrepreneurship (Qian & Acs, 2013). We will now add two variations to their framework. First, we add a third element of entrepreneurial absorptive capacity, viz., ICT knowledge and skills. Second, we make a distinction between general and digital human capital at the regional level, representing two related but distinct stocks of knowledge and sources of knowledge spillovers.

Regarding the first variation, Qian and Acs (2013) identify two components of EAC, scientific knowledge and business knowledge. We argue that a third component, ICT knowledge and skills, is a third component of EAC, required to absorb knowledge spillovers from regional actors. Knowledge spillovers may benefit receiving firms by means of imitation but also by means of new inventions emerging from the initial act of imitation (Barry & Thrift, 2007). As knowledge is often complex, it is by no means straightforward that knowledge spilling over from one firm to another is fully appropriated by the receiving firm (Arendt, 2008; Barba-Sánchez et al., 2007). Indeed, in order to actually benefit from such spillovers, firms must make sure that their absorptive capacity is high enough. As mentioned earlier, a firm's absorptive capacity is defined not only by the ability to recognize valuable outside knowledge but also by the

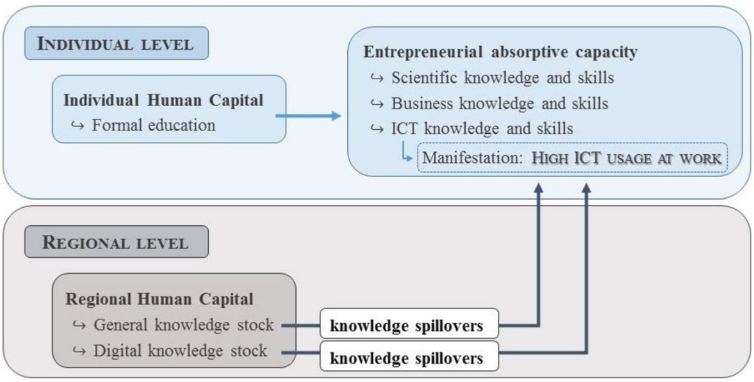

Fig. 1 Conceptual framework. Source: own elaboration, adapted from Qian and Acs (2013)

ability to assimilate this knowledge (Cohen & Levinthal, 1990). In modern knowledge-based economies, the ability to assimilate new knowledge into the own firm increasingly depends on the ability to deal with ICT, as new knowledge is often embodied in ICT applications (Al-Mahaseneh & Harb, 2023). Sufficient experience and daily routine in using ICT at work, which stimulates the learning process in effectively and efficiently making use of ICT, are therefore a prerequisite to benefit from knowledge spillovers (Yang & Andersson, 2018). In regions where such spillovers are more likely to occur, i.e., high-HC regions, it is therefore especially important to frequently use ICT at work, to ensure that the absorptive capacity to benefit from potential knowledge spillovers is and remains at a sufficiently high level. We thus argue that, at the level of individual entrepreneurs, ICT knowledge and skills form an important element of EAC.

The second variation is related to the first. In Qian and Acs (2013), but also in knowledge production function theory more generally, a region's level of human capital is typically interpreted as the region's knowledge stock (Ahmed, 2017). In our paper, we make a distinction between a region's general and digital human capital endowments, representing the region's general and digital knowledge stocks. Although the two concepts partly overlap, we believe this distinction is useful. A first reason for this is the ever increasing importance of ICT knowledge and skills in nowadays' economies (Lechman & Anacka, 2022). A second reason is that ICT knowledge and skills are far more dynamic in the sense that developments in this area follow each other with a rapid pace, so that ICT knowledge is quickly outdated (Lechman, 2017). This is in contrast to general knowledge and skills (e.g., scientific knowledge) which is more static in nature. As an example, scientific knowledge of chemical processes, once obtained, will remain relevant because the nature of the chemical processes will not change. In contrast, ICT knowledge can be quickly outdated. Hence, regional variations in the general knowledge stock may be very different than regional variations in the digital knowledge stock. Allowing for a separate role of the digital knowledge stock is in line with a recent study by Zahra et al. (2023) who highlight the important role of digital technologies in modern entrepreneurial ecosystems, where digital technologies stimulate the birth, development, and growth of new ventures. Similarly, Proeger and Runst (2020) advocate a separate conceptual role for what they call "digitization-related knowledge spillovers" (p. 1509).

Figure 1 presents our complete conceptual framework.

Hypotheses

In this paper, we are interested in the relationship between regional human capital and the intensity of ICT usage by individual entrepreneurs. In terms of our conceptual framework, we view the latter as a manifestation of ICT knowledge and skills, i.e., as a manifestation of one specific component of EAC (see Fig. 1). On the one hand, a higher usage of ICT at work tends to increase the user's ICT knowledge and skills via learning by doing. On the other hand, an entrepreneur with high ICT knowledge and skills will also tend to make more use of these skills by applying ICT in her daily work practice. Hence, the two are closely related and therefore, we feel that ICT usage frequency is a good indicator of ICT knowledge and skills.

As explained above, and pictured in Fig. 1, regional levels of human capital (both general and digital human capital) facilitate knowledge spillovers which in turn increases the level of EAC of individual entrepreneurs in the region, including their ICT knowledge and skills. Thus, via this route, ICT use frequency of entrepreneurs, as a manifestation of their ICT knowledge and skills, is positively influenced by a region's level of human capital. In this regard, the mechanisms behind the two types of knowledge spillovers originating from the general knowledge stock and the digital knowledge stock (see Fig. 1) are slightly different. While the latter type of spillovers directly increases the ICT knowledge and skills of the receiving entrepreneurs (Proeger & Runst, 2020), the former type, i.e., general knowledge spillovers, may lead to a broader application of ICT within the firm. Higher levels of general human capital (formal education) facilitate spillovers allowing for increased understanding of complex matters, including matters related to the efficient organization of a business. This may also include an increased understanding of how ICT use may increase efficiency in various domains within the business, e.g., human resources, marketing, and acquisition (Proeger & Runst, 2020). So, while digital knowledge spillovers directly increase ICT skills leading to a deeper use within a given business domain, general knowledge spillovers may lead to a broader application of ICT by the entrepreneur across various business domains. In short, the general type of knowledge spillovers may lead to a broader use of ICT within the firm while digital knowledge spillovers may lead to a deeper use of ICT.

Besides keeping up entrepreneurial absorptive capacity to benefit from regional knowledge spillovers, a second incentive for intensive ICT usage is related to competition. In regions with high levels of human capital (HC) among the working population, it is likely that incumbent firms in such regions are of a higher quality, because the average worker has a higher human capital level compared to the average worker in a region with lower human capital endowments. Because of their higher quality, firms in high-HC regions will also be more competitive, on average, than firms in low-HC regions. For an individual firm or entrepreneur, this means that local competition will be stronger (Raspe & Van Oort, 2011), and hence, she needs to keep up to date with the latest technologies in order to survive in a competitive market (Jacobs, 1969). In modern knowledge-based economies, the ability to routinely use ICT will be a prerequisite for keeping up to date.

In summary, in high-HC regions (both general and digital human capital), there are higher incentives for entrepreneurs to frequently use ICT at work, both to maintain absorptive capacity to be able to benefit from regional knowledge spillovers (pull factor) and because of the sheer necessity to survive in a competitive local market (push factor). Both arguments lead to the following hypothesis.

H1: In regions with higher levels of general human capital, entrepreneurs on average have a higher frequency of ICT usage at work.

H2: In regions with higher levels of digital human capital, entrepreneurs on average have a higher frequency of ICT usage at work.

It may be argued that regional spillover effects on ICT usage may be stronger for those entrepreneurs that lag behind in their ICT usage at work. For them, there is still a lot of ground to make up in terms of ICT usage and hence, it may be easier to increase their ICT use frequency, relative to entrepreneurs that already have a high level of ICT usage. Moreover, it may be especially attractive for lagging entrepreneurs in regions with high human capital levels (with large knowledge stocks) to catch up, because of the stronger knowledge spillover effects from which they can benefit. In other words, the regional spillover effects may inspire lagging entrepreneurs to catch up, in terms of their ICT usage.

H3: The magnitude of the regional spillover effects is stronger for entrepreneurs' types that lag behind in the frequency of ICT usage at work.

To test H3, we will first establish which of our three entrepreneurial types (DSEWs, IOAs, or SEwEs) lags behind in terms of ICT use frequency and then test H3 in relation to that group.

Using the same logic as with H3, it may also be argued that regional spillover effects are stronger in those regions where the average entrepreneur has a lower ICT usage at work, compared to regions with higher ICT usage. This is again because in such regions, there is more potential improvement in ICT use frequency resulting from a low starting point (i.e., a low initial ICT use frequency).

H4: The magnitude of the regional spillover effects is stronger in regions that lag behind in the frequency of ICT usage at work by the region's entrepreneurs.

To test H4, we will first establish which type of region (in terms of higher or lower GDP per capita values) lags behind in terms of ICT use frequency and then test H4 in relation to those regions.

Data and Methods

Data and Sample

Our data is drawn from the Sixth European Working Conditions Survey (EWCS) 2015 (Eurofound, 2016, 2018). This sixth wave is the first in the EWCS series that allows the identification of the workers' region of residence (at the NUTS-2 level). This feature is crucial for the purpose of this study. The institution in charge of carrying out this survey since 1991 is the EU Agency Eurofound (*European Foundation for the Improvement of Living and Working Conditions*). The EWCS 2015 interviewed about 44,000 workers (including both employees and self-employed individuals) in 305 NUTS-2 regions across 35 countries: the EU-27 member states, the UK, five candidate countries (Albania, Montenegro, North Macedonia, Serbia, and Turkey), and two EFTA countries (Norway and Switzerland). This survey provides comprehensive information on several work-related issues, including exposure to physical and psychosocial risks, work organization, work–life balance, and health and well-being. After filtering the sample, our final dataset consists of 4822 full-time (i.e., working at least 15 h per week) self-employed workers aged 18 to 65.

Dependent Variable

ICT Use Frequency at Work

Respondents in the EWCS are asked to rate how often they use smartphones, laptops, and other electronic devices in their workplace. This Likert scale varies from level 1 (*non-ICT user*) to 7 (*very intensive ICT user*). The discrete ordered nature of this variable is used to operationalize ICT use frequency in our analysis.

Focal Variables

Macroeconomic Indicators at the Regional Level (NUTS-2)

The regional context—both across and within countries—in which these self-employed individuals perform their activities is expected to be of great importance in explaining their ICT use frequency. For instance, in lower developed regions, some low-income self-employed workers may be especially disadvantaged in terms of ICT use due to a generally lower availability of financial resources in such regions. Hence, including regional GDP per capita seems crucial in order to control for the existing differences in terms of economic development, especially taking into consideration that entrepreneurs in our sample belong to 305 different NUTS-2 regions across 35 European countries. Data on GDP per capita (in purchasing power standards (PPS)) at the NUTS-2 regional level are provided by Eurostat.

Besides regional GDP per capita, we aim at investigating the role of two regional indicators that capture knowledge spillover effects: (i) general human capital endowment of the regional population and (ii) digital human capital endowment of the regional population.

Concerning the general human capital endowment of the regional population, we strictly consider highly skilled human capital, proxied by the percentage of the regional population with tertiary education (Millán et al., 2014). Thus, ICT usage by individual entrepreneurs may be positively influenced by the number of highly educated individuals (*knowledge spillovers originating from the region's general knowledge stock*) in their region. In particular, Eurostat provides information at the NUTS-2 level on the proportion of population aged 25–64 with at least first stage of tertiary education.[1]

[1] Tertiary education comprises levels 5 and 6 in the ISCED-1997 classification and levels 5 to 8 in the ISCED-2011 revision.

Concerning the digital human capital endowment of the regional population, we operationalize this as the *ICT use at work* for the whole regional workforce. This variable may capture how usual it is in a region to use ICT and may also generate spillovers to individual-level ICT use (knowledge spillovers originating from the region's digital knowledge stock). Specifically, average ICT use frequency at work for the regional workforce is calculated for each of the 305 NUTS-2 regions in our sample, by using EWCS 2015 data.[2]

Some figures on these indicators for the 35 European countries included in our study are presented in Table 1 below.[3]

Importantly, our two spillover effect variables at the regional level may also cause interaction effects with the type of self-employment (i.e., SEWE, IOA, and DSEW). In other words, the impact of the general and digital knowledge stocks on the ICT use frequency of individual entrepreneurs may be moderated by the type of entrepreneur. In particular, it is not unlikely that groups that are lagging behind in ICT usage, such as DSEW (Millán et al., 2021), are influenced more strongly by regional spillover effects and hence catch up in ICT usage with their peer entrepreneurs. Stated otherwise, the moderating role of the type of entrepreneur may be such that the magnitude of the regional spillover effects is stronger for entrepreneurs' types that lag behind in the frequency of ICT usage at work (see Hypothesis 3). The interaction terms enable to test this hypothesis. Accordingly, these individual-level variables (i.e., our three types of self-employment) also belong to the set of focal variables in this study.

To the end of capturing the existing heterogeneity within entrepreneurs, we use the dimension *professional status within self-employment*, which is described below.

Professional Status Within Self-employment

We empirically distinguish among three types of self-employment. Respondents are asked about the number of employees in their firm, and those self-employed who indicate to have one or more employees are identified as self-employed with employees (SEwEs). To self-employed respondents indicating to have no employees, an additional question is asked about the number of clients. Self-employed individuals with more than one client are identified as independent own-account self-employed workers (IOA). In contrast, self-employed individuals with only one client are economically dependent on this client (Román et al., 2011) and hence, they are labeled dependent self-employed worker (DSEW). The 2015 wave of the EWCS is the first wave that allows identification of dependent self-employed workers.

[2] In order to avoid a correlation by construction between individual-level ICT use of entrepreneurs and regional-level ICT use, we also computed the average ICT use frequency at work for the regional workforce while excluding the entrepreneurs. This exclusion did not alter our main results in a significant manner.

[3] A correlation matrix for our macroeconomic indicators at the regional level is presented in Table 8 in the Appendix. Moreover, the spatial distribution of our macroeconomic indicators at the regional level is also represented by means of maps in Figs. 2, 3, and 4.

Table 1 Descriptive statistics on macroeconomic indicators at the NUTS-2 level

Group	COUNTRY	# Regions (NUTS-2)	# Obs.	GDP '000 PPS per inhabitant Rank#	mean	sd	Share of population with tertiary education Rank#	mean	sd	Average ICT use frequency at work Rank#	mean	sd
EU28 (2013-2020) / EU27 (2007-2013) / EU25 (2004-2006) / EU15 (1995-2004) / EU12 (1993-1994)	Belgium	11	250	8	36.5	12.1	11	37.7	5.8	8	4.00	0.50
	Denmark	5	39	9	34.5	8.0	13	34.6	7.6	1	4.68	0.38
	France	9	98	12	33.0	11.5	15	34.5	7.7	7	4.11	0.38
	Germany	16	167	11	34.1	6.4	20	27.8	3.5	23	3.07	0.34
	Greece	13	174	25	20.2	5.5	18	28.8	6.7	29	2.67	0.52
	Ireland	4	159	2	47.4	15.1	1	44.3	4.8	11	3.76	0.35
	Italy	16	249	14	28.8	6.1	32	17.9	2.5	25	2.91	0.42
	Luxembourg	5	69	1	78.0	0	5	41.1	0	3	4.47	0.57
	Netherlands	12	106	6	37.5	7.6	12	35.0	5.7	5	4.27	0.36
	Portugal	7	126	22	21.3	3.8	28	21.7	5.0	32	2.63	0.46
	Spain	17	441	17	25.5	5.7	14	34.5	6.7	18	3.24	0.47
	United Kingdom	12	182	10	34.4	13.4	3	42.7	6.8	6	4.22	0.32
EU15 (1995-2004)	Austria	9	97	7	37.3	5.9	17	30.2	4.5	15	3.60	0.46
	Finland	4	142	13	31.8	6.8	4	42.5	5.8	13	3.63	0.47
	Sweden	8	55	5	37.7	9.0	7	39.8	6.2	4	4.38	0.29
EU25 (2004-2006)	Cyprus	5	139	19	23.8	0	6	40.5	0	14	3.61	0.45
	Czech Republic	8	101	15	28.3	13.3	24	23.8	9.3	20	3.13	0.35
	Estonia	16	67	21	22.1	0	9	38.1	0	12	3.71	0.69
	Hungary	7	81	24	20.7	6.7	23	25.9	9.1	24	2.96	0.25
	Latvia	6	68	28	18.6	0	16	31.6	0	19	3.20	0.34
	Lithuania	10	76	23	20.9	5.7	10	37.8	6.9	28	2.76	0.64
	Malta	6	90	16	27.1	0.0	29	21.6	0	9	3.86	0.27
	Poland	16	101	27	19.3	5.2	21	27.4	4.7	26	2.90	0.39
	Slovakia	4	84	18	23.9	13.7	27	21.9	6.8	22	3.11	0.36
	Slovenia	6	140	20	22.3	4.0	19	28.8	4.2	10	3.76	0.31
EU27 (2007-2013)	Bulgaria	6	126	30	13.6	5.6	22	27.0	7.3	27	2.86	0.36
	Romania	8	66	31	13.3	5.1	34	14.4	4.2	33	2.48	0.57
EU28 (2013-2020)	Croatia	6	69	29	17.3	0.4	26	22.9	1.4	17	3.47	0.45
EU candidates	Albania	12	319	35	8.4	1.3	35	12.9	0	35	2.18	0.71
	Macedonia	8	135	34	10.4	0	31	18.8	0	21	3.12	0.62
	Montenegro	3	138	32	12.3	0	25	23.5	0	30	2.65	0.14
	Serbia	4	132	33	11.1	4.0	30	20.5	6.4	31	2.64	0.39
	Turkey	12	390	26	19.7	7.1	33	16.4	3.6	34	2.44	0.34
EFTA countries	Norway	7	61	4	38.7	9.0	2	43.4	7.3	2	4.48	0.33
	Switzerland	7	85	3	45.8	0	8	38.9	4.1	16	3.51	0.56
	TOTAL	305	4822		27.3			30.0			3.38	

Countries are ranked from higher to lower (i) GDP PPS per inhabitant, (ii) share of population with tertiary education, and (iii) average ICT use frequency at work. Country figures are unweighted means of the pool of observations in each particular country. Total figures are calculated as unweighted means of country figures. Data source: Eurostat and EWCS 2015

For clarification purposes, this classification will be referred to hereafter as professional status within self-employment. From this information, the following set of dummy variables is generated and used as focal predictors for ICT use frequency at work: (i) a dummy equalling 1 for SEwE; (ii) a dummy equalling 1 for IOA; and (iii) a dummy equalling 1 for DSEW.

Control Variables

We control for several covariates known to affect ICT use frequency at work (see, e.g., Millán et al., 2021): job characteristics including years of experience, weekly hours of work, and activity sector and demographic indicators including gender, born-abroad resident, age, level of education—basic, secondary, or tertiary[4]—type of cohabitation, children in the household, and health perception. Further control variables are the household ability to make ends meet and the degree of urbanization of the entrepreneurs' area of residence (urban, intermediate, rural).

Estimation Methods

To handle the discrete ordered nature of the dependent variable, i.e., ICT use frequency at work, ordered logit models are used. As stated previously, we use 4822 observations for self-employed workers distributed over 305 NUTS-2 regions. Thus, to control for biases resulting from region grouping, we use multilevel (hierarchical) models (Guo & Zhao, 2000; Hedeker, 2008).[5] In the framework of ordered discrete choice models, a different set of results for each frequency of ICT use is generated. However, for brevity and focus, we only present results on the probability that the entrepreneur's ICT frequency (i) equals 1 (being a non-ICT user) and (ii) equals 7 (being a very intensive ICT user).

Comparing Our Empirical Approach to Approaches Used in the Knowledge Spillover Literature

Knowledge spillovers are difficult, if not impossible to measure. The general approach in the literature is to capture certain characteristics of regions or cities, which may then serve as sources of knowledge spillovers. A positive and significant relation between a variable capturing such sources (e.g., regional-level human capital or the number of patents, as indicators of the knowledge stock), and some target variable of regional performance (typically economic growth or new firm formation) is then interpreted as support for the existence of knowledge spillovers. Examples of this approach include Glaeser et al. (1992), Van Stel and Nieuwenhuijsen (2004), Frenken et al. (2007), Lasch et al. (2013), and Qian et al. (2013). We also follow this approach. However, while studies in this field are typically fully defined and operated at the macro (region, city, or sometimes region-sector or city-sector) level, an innovation of our approach is that the receiving end of the knowledge spillovers is defined at the individual level (individual entrepreneurs) (see Fig. 1). This addresses a call for research by Qian and Acs (2013) who note that the ideal unit for analysis to study the absorptive capacity theory of knowledge spillover entrepreneurship "… is the individual instead of the region." (p. 196).

[4] Just as our macroeconomic indicator on general human capital endowment of the regional population, these individual level variables definitions are based on the ISCED-1997 classification. Thus, basic education comprises levels 0 and 1, secondary education comprises levels 2 to 4 and tertiary education comprises levels 5 and 6.

[5] The intraclass correlation (ICC) coefficient equals 21.7% and, therefore, shows that the region-level variance for ICT use frequency at work is non nontrivial and highly significant, which legitimates using multilevel models (Bliese, 2000).

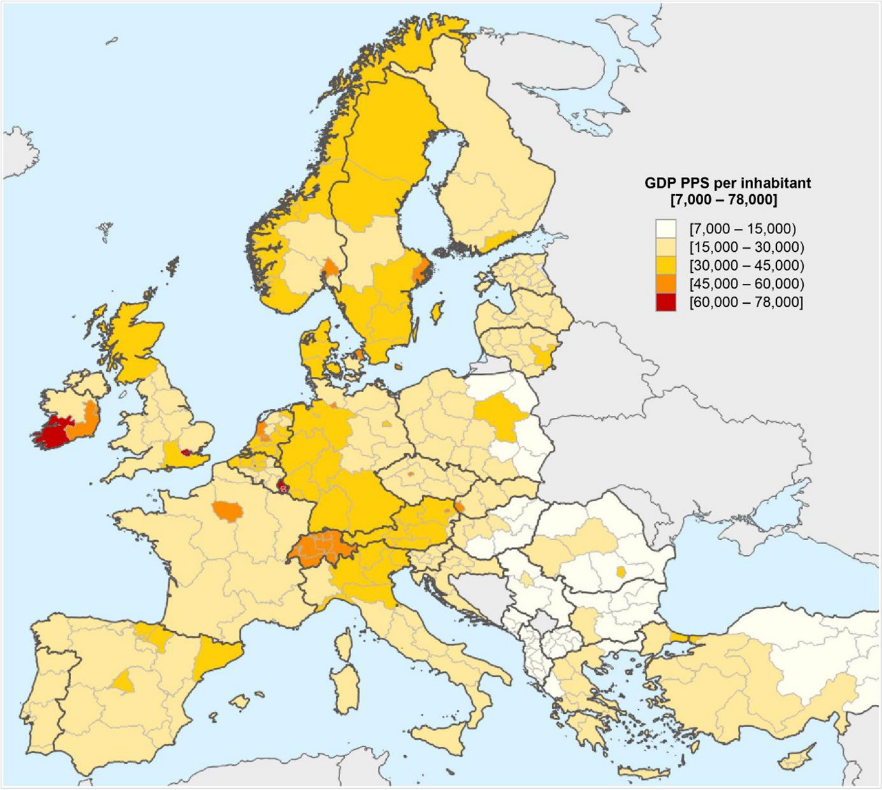

Fig. 2 GDP PPS per inhabitant at the NUTS-2 level. Data source: Eurostat

Results

Descriptive Analysis

Firstly, we analyze how professional status within self-employment affects ICT usage frequency and how these figures vary for low and high values of our three regional macroeconomic indicators: (i) regional GDP per capita, (ii) portion of regional population with tertiary education, and (iii) average ICT use at work for the whole regional workforce.

Confirming earlier results by Millán et al. (2021), Table 2 shows that ICT use frequency is highest among SEwE, followed by IOA and DSEW. Furthermore, we observe how, irrespective of the professional status, ICT usage frequency at self-employment work rises (decreases) for high (low) values of our three regional macroeconomic indicators. These figures hence support the importance of the regional context in explaining ICT usage frequency at work.

Table 3 below shows some descriptive statistics from our sample, distinguishing among professional statuses.

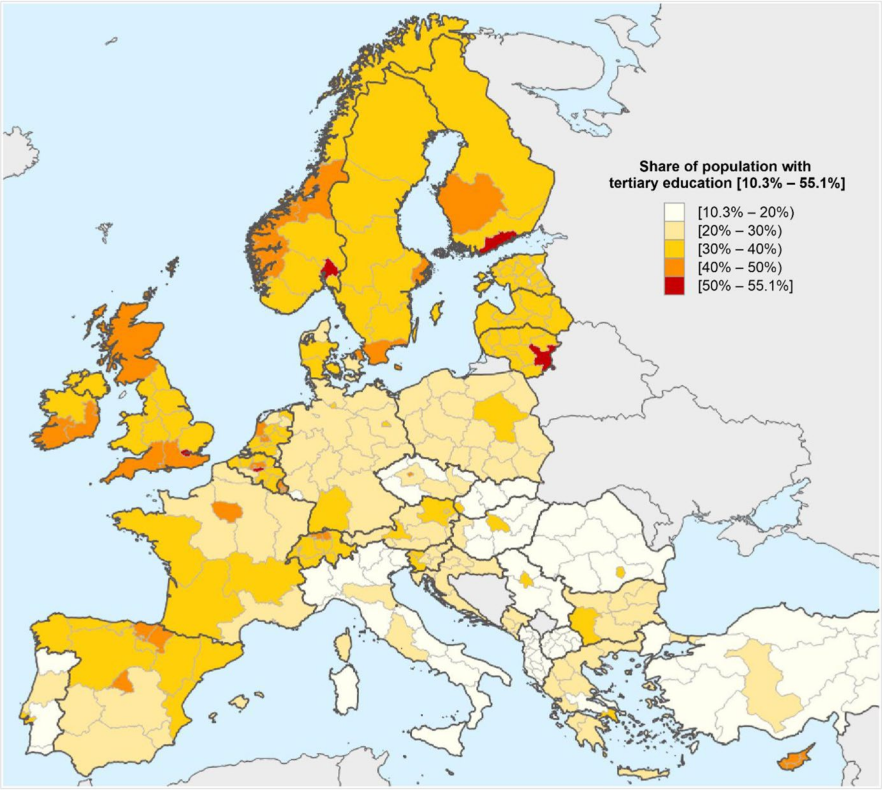

Fig. 3 Share of population with tertiary education at the NUTS-2 level. Data source: Eurostat

When comparing the frequency distribution of ICT use among professional statuses, we observe how 26.7% of SEwEs use ICT at work almost all of the time or all the time (ICT use frequency at work equals 6 or 7). This figure drops to 20.5 and 8.3% for IOA and DSEW, respectively. On the contrary, 36.4% of SEwEs never or almost never use ICT at work (ICT use frequency at work equals 1 or 2) whereas this figure rises to 53.0 and 79.2% for IOA and DSEW, respectively.

Compared to IOA and DSEW, we also observe how SEwEs tend to have more formal education, work longer hours, be male, cohabitate, have children, experience better health, and make more easily ends meet. Conversely, compared to SEwE and IOA, DSEWs are less formally educated, work shorter hours, have less children, experience worse health, and make ends meet with more difficulty. In addition, they are older, have more years of experience in present job, are less likely to have a migration background, and more likely to work in the agricultural sector. Finally, compared to SEwE and DSEW, IOAs have less years of experience in present job and live more often without partner.

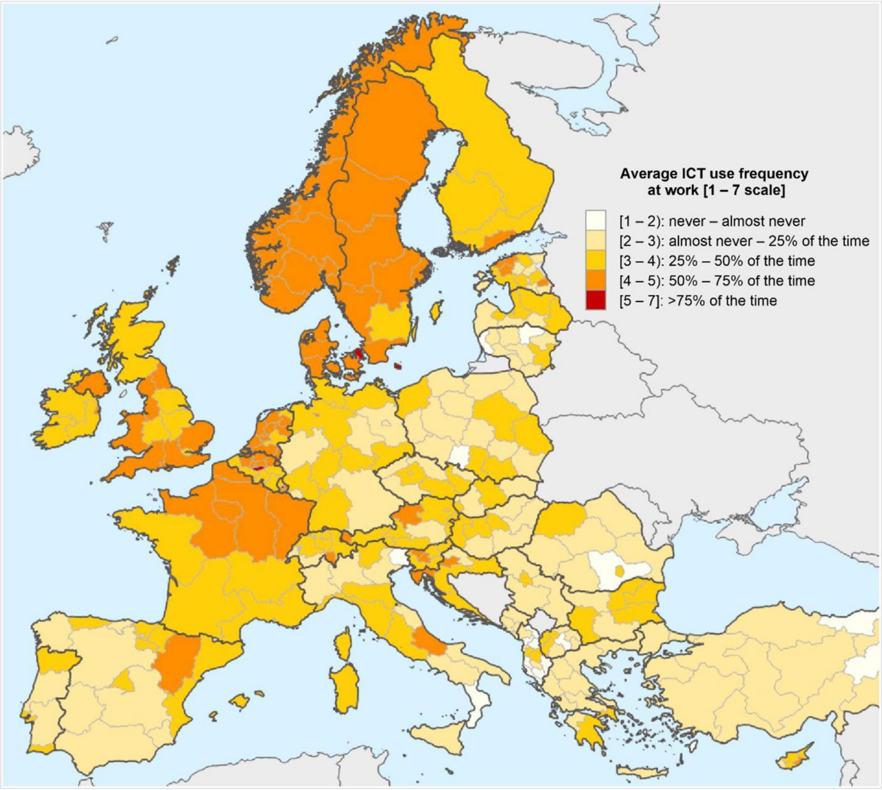

Fig. 4 Average ICT use frequency at work at the NUTS-2 level. Data source: EWCS 2015

Multivariate Analysis

This section will present the results of our multivariate regression analysis. "The Role of the Regional Context in Explaining ICT Usage Frequency" section will present our main results as to the importance of the regional context in explaining ICT usage frequency in self-employment work whereas the "Interaction Effects Between Regional Macroeconomic Indicators and Individual-Level Variables" section explores the existence of interaction effects between our regional macroeconomic indicators and professional status within self-employment. The "Differentiated Effects of the Regional Context for Regions with Low and High GDP Per Capita" section analyzes how our main results can vary for regions with low and high GDP per capita. Finally, some robustness checks are presented in the "Robustness Checks" section.

Table 2 Descriptive statistics on ICT usage frequency for different groups within self-employment and low/high values of macroeconomic indicators

	Total		GDP '000 PPS per inhabitant				Share of population with tertiary education				Average ICT use frequency at work			
			Low (≤ 23.5)		High (> 23.5)		Low (≤ 27.5)		High (> 27.5)		Low (≤ 3.22)		High (> 3.22)	
	N	Mean (SD)	*N*	Mean (SD)	*N*	Mean (SD)	N	Mean (SD)	*N*	Mean (SD)	*N*	Mean (SD)	*N*	Mean (SD)
Professional status within self-employment														
Self-employed with employees	1583	3.61 (2.14)	726	3.40 (2.19)	857	3.79 (2.08)	729	3.29 (2.10)	854	3.89 (2.14)	743	3.10 (2.04)	840	4.06 (2.13)
Independent own-account self-employed	2604	2.99 (2.18)	1264	2.46 (2.02)	1340	3.48 (2.20)	1279	2.42 (1.98)	1325	3.53 (2.22)	1259	2.39 (1.93)	1345	3.55 (2.25)
Dependent self-employed worker	635	1.93 (1.74)	428	1.52 (1.30)	207	2.78 (2.19)	407	1.52 (1.29)	228	2.67 (2.15)	408	1.50 (1.31)	227	2.69 (2.12)
Total	4822	3.05 (2.18)	2418	2.57 (2.07)	2404	3.53 (2.18)	2415	2.53 (2.01)	2407	3.57 (2.21)	2410	2.46 (1.95)	2412	3.64 (2.23)

Individuals in our sample are assigned to areas with low (high) values of each macroeconomic indicator if the value of each macroeconomic indicator in his/her area of residence is below (above) each unweighted median of the pool of observations in the sample. Data source: Eurostat and EWCS 2015

Table 3 Descriptive statistics on ICT usage frequency and main covariates for different groups within self-employment

	Self-employed with employees		*Independent own-account self-employed*		*Dependent self-employed worker*		*Total*	
# observations	1583		2604		635		4822	
% observations	32.8%		54.0%		13.2%		100%	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ICT use frequency at work								
1 Never [a]	0.224		0.391		0.683		0.375	
2 Almost never [a]	0.140		0.139		0.109		0.135	
3 Around ¼ of the time [a]	0.205		0.153		0.063		0.158	
4 Around half of the time [a]	0.095		0.066		0.028		0.071	
5 Around ¾ of the time [a]	0.069		0.045		0.033		0.052	
6 Almost all of the time [a]	0.104		0.071		0.024		0.076	
7 All of the time [a]	0.163		0.134		0.060		0.134	
Educational attainment								
Basic education [a]	0.039		0.079		0.197		0.082	
Secondary education [a]	0.599		0.631		0.658		0.624	
Tertiary education [a]	0.362		0.290		0.145		0.294	
Job characteristics								
Tenure *(1–53)*	14.0	10.0	12.6	10.5	14.6	12.4	13.3	10.7
Working hours (*15–120*)	49.2	13.0	44.5	14.7	43.5	16.7	45.9	14.6
Demographic characteristics								
Female [a]	0.302		0.390		0.392		0.361	
Immigrant [a]	0.107		0.107		0.094		0.105	
Age (*18–65*)	45.4	10.3	45.3	11.2	46.5	11.5	45.5	11.0
Cohabiting [a]	0.777		0.690		0.729		0.724	
Children under 14 [a]	0.330		0.285		0.236		0.294	
Health (1–5)	4.09	0.73	3.98	0.77	3.85	0.76	4.00	0.76

Table 3 (continued)

	Self-employed with employees		*Independent own-account self-employed*		*Dependent self-employed worker*		*Total*	
# observations	1583		2604		635		4822	
% observations	32.8%		54.0%		13.2%		100%	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Ends meet (1–6)	4.23	1.18	3.64	1.30	3.27	1.37	3.79	1.31
Business sector dummies								
Agriculture [a]	0.104		0.146		0.506		0.180	
Industry [a]	0.126		0.091		0.071		0.100	
Construction [a]	0.107		0.108		0.060		0.101	
Commerce and hospitality [a]	0.340		0.254		0.124		0.265	
Transport [a]	0.035		0.043		0.043		0.041	
Financial services [a]	0.026		0.033		0.016		0.029	
Public administration and defence	0.001		0.001		0.002		0.001	
Education [a]	0.011		0.017		0.011		0.014	
Health [a]	0.039		0.048		0.024		0.042	
Other services [a]	0.211		0.260		0.145		0.229	
Degree of urbanization								
Urban[a]	0.394		0.388		0.265		0.374	
Intermediate[a]	0.296		0.254		0.170		0.257	
Rural[a]	0.311		0.358		0.565		0.370	

$N=4822$. [a]Dummy variable

The Role of the Regional Context in Explaining ICT Usage Frequency

The results of two regression models explaining ICT usage frequency in self-employment work are shown in Table 4. The first specification focuses on the percentage of the regional population with tertiary education (as a source of regional-level general knowledge spillovers) as our main predictor, while the second specification focuses on the average ICT use frequency at work (of the whole regional workforce, including employees) in the region (representing a source of regional-level digital knowledge spillovers). Both specifications include regional GDP per capita in order to account for regional variations in economic development.[6]

The top row of Table 4 shows predicted probabilities for the lowest and highest level of ICT usage frequency (1 and 7, respectively), as evaluated in the sample means. Furthermore, the table presents marginal effects of our covariates on these predicted probabilities. These marginal effects are expressed both in absolute terms (first column) and in relative terms (second column). The third column shows the associated *p*-value and significance level.

Our findings indicate that there is a positive relationship between the portion of regional population with tertiary education and ICT usage frequency. In particular, when focusing on the predicted probability of being a non-ICT user, this probability is observed to decrease by about 1.09% with each additional 1% of the regional population with tertiary education (specification 1, left panel). Analogously, the predicted probability of being a very intensive ICT user increases by about 1.65% with each additional 1% of the regional population with tertiary education (specification 1, right panel).

Our results also show the existence of a positive association between the average ICT use at work for the whole regional workforce and ICT usage frequency. More concretely, the predicted probability of being a non-ICT user is observed to decrease by about 28.7% with each additional unitary increase (on the 1–7 ICT use frequency scale) in the average ICT use at work for the whole regional workforce. Similarly, the predicted probability of being a very intensive ICT user increases by about 44.6% with each additional unitary increase in the average ICT use at work for the whole regional workforce (specification 2, right panel). Both of these results are in line with positive regional spillover effects stimulating ICT usage by entrepreneurs in the region (Hypotheses 1 and 2).

Regarding our control variables, our findings indicate that SEwEs are the most likely to use ICT at work, followed by IOA and DSEW. We also observe a positive association between education and ICT usage frequency. By and large, results for our remaining covariates are in line with the findings of Millán et al. (2021). In short, we observe how different socio-economic characteristics (such as education, gender, age, or income) are key to understand digital inequalities for entrepreneurs, which is consistent with findings obtained by the general digital divide literature for the whole population (see, e.g., Chinn

[6] The correlations between GDP per capita and (i) the percentage of population with tertiary education and (ii) the average ICT use at work are, respectively, 0.70 and 0.63 (see Table 8 in the Appendix). Despite these correlations which are high, removing GDP per capita from our specifications is not an option since we are interested in identifying the regional spillover effects, once free from the effect of differences in regional levels of economic development.

Table 4 Determinants of ICT use frequency at work—ordered discrete choice models; multilevel ordered logit

# Specification	1						2					
Average predicted probability (y)	P[ICT use freq. = 1] = 0.363			P[ICT use freq. = 7] = 0.141			P[ICT use freq. = 1] = 0.369			P[ICT use freq. = 7] = 0.138		
Independent variables (x)	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value
Macroeconomic indicators at the NUTS-2 level												
GDP '000 PPS per inhabitant (7–78)	-1.8E-03	-0.51	0.017**	1.1E-03	0.77	0.018**	-3.0E-04	-0.08	0.639	1.7E-04	0.13	0.639
Share of population with tertiary education (10.3–55.1)	-0.004	-1.09	0.000***	0.002	1.65	0.000***						
Average ICT use frequency at work (1.35–5.58)							-0.106	-28.7	0.000***	0.062	44.6	0.000***
Professional status within self-employment												
Self-employed with employees -SEwE- [a]	-0.057	-15.6	0.000***	0.034	24.2	0.000***	-0.059	-15.9	0.000***	0.035	25.1	0.000***
Independent own-account self-employed -IOA- [a] (*ref.*)												
Dependent self-employed worker -DSEW- [a]	0.104	28.7	0.000***	-0.051	-36.3	0.000***	0.100	27.1	0.000***	-0.049	-35.1	0.000***
Educational attainment												
Basic education -BASIC- [a] (*ref.*)												
Secondary education -SEC- [a]	-0.163	-44.8	0.000***	0.048	34.4	0.000***	-0.158	-42.8	0.000***	0.047	33.74	0.000***
Tertiary education -TERT- [a]	-0.350	-96.5	0.000***	0.173	123.5	0.000***	-0.344	-93.1	0.000***	0.168	121.4	0.000***
Job characteristics												
Tenure *(1–53)*	0.002	0.49	0.002***	-0.001	-0.74	0.002***	0.002	0.45	0.003***	-0.001	-0.70	0.003***
Working hours (*15–120*)	-0.005	-1.30	0.000***	0.003	1.98	0.000***	-0.005	-1.29	0.000***	0.003	2.01	0.000***
Working hours (squared)	4.5E-05	0.01	0.000***	-2.7E-05	-0.02	0.000***	4.5E-05	0.01	0.000***	-2.6E-05	-0.02	0.000***
Demographic characteristics												
Female [a]	0.069	19.1	0.000***	-0.040	-28.1	0.000***	0.066	17.8	0.000***	-0.037	-26.8	0.000***
Immigrant [a]	-0.002	-0.50	0.907	0.001	0.77	0.907	0.005	1.26	0.764	-0.003	-1.94	0.763
Age (*18–65*)	-0.013	-3.49	0.000***	0.007	5.32	0.000***	-0.013	-3.41	0.000***	0.007	5.30	0.000***
Age (squared)	1.5E-04	0.04	0.000***	-8.9E-05	-0.06	0.000***	1.5E-04	0.04	0.000***	-8.8E-05	-0.06	0.000***
Cohabiting [a]	0.012	3.35	0.282	-0.007	-5.16	0.287	0.012	3.25	0.286	-0.007	-5.09	0.291

Table 4 (continued)

# Specification	1						2					
Average predicted probability (y)	P[ICT use freq. = 1] = 0.363			P[ICT use freq. = 7] = 0.141			P[ICT use freq. = 1] = 0.369			P[ICT use freq. = 7] = 0.138		
Independent variables (x)	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value
Children under 14 [a]	-0.002	-0.59	0.858	0.001	0.90	0.858	0.001	0.37	0.909	-0.001	-0.57	0.909
Health (1–5)	-0.005	-1.38	0.454	0.003	2.10	0.455	-0.004	-1.05	0.559	0.002	1.63	0.559
Ends meet (1–6)	-0.034	-9.31	0.000***	0.020	14.2	0.000***	-0.032	-8.66	0.000***	0.019	13.5	0.000***
Business sector dummies [e]												
Agriculture [a]	0.042	11.5	0.080*	-0.013	-9.52	0.079*	0.032	8.66	0.175	-0.010	-7.36	0.174
Industry [a]	-0.102	-28.1	0.000***	0.044	31.1	0.000***	-0.104	-28.3	0.000***	0.044	31.8	0.000***
Construction [a] (*ref.*)												
Commerce and hospitality [a]	-0.131	-36.2	0.000***	0.060	42.9	0.000***	-0.135	-36.7	0.000***	0.061	44.2	0.000***
Transport [a]	-0.013	-3.67	0.666	0.005	3.37	0.670	-0.021	-5.66	0.493	0.007	5.33	0.502
Financial services [a]	-0.338	-93.3	0.000***	0.291	206.7	0.000***	-0.342	-92.7	0.000***	0.286	206.3	0.000***
Public administration and defence [a]	-0.246	-67.9	0.044**	0.153	109.1	0.243	-0.255	-69.1	0.036**	0.158	114.1	0.229
Education [a]	-0.098	-27.1	0.026**	0.042	29.7	0.057*	-0.104	-28.3	0.017**	0.044	31.8	0.042**
Health [a]	-0.072	-19.9	0.015**	0.029	20.6	0.022**	-0.068	-18.4	0.021**	0.026	19.1	0.029**
Other services [a]	-0.190	-52.4	0.000***	0.101	71.9	0.000***	-0.190	-51.5	0.000***	0.098	71.0	0.000***
Degree of urbanization												
Urban[a]	-0.015	-4.10	0.251	0.009	6.18	0.250	-0.014	-3.70	0.280	0.008	5.73	0.279
Intermediate[a]	-0.010	-2.84	0.429	0.006	4.24	0.429	-0.006	-1.52	0.661	0.003	2.32	0.661
Rural[a] (*ref.*)												
Log likelihood	-7269.3						-7236.7					

N=4822. For continuous variables, *dy/dx* captures absolute marginal effects whereas [(*dy/dx*)/*y*]% refers to marginal effects, but expressed in relative terms with respect to predicted probabilities. In the context of dummy variables, this reflects the impact for a discrete change of the dummy variable from 0 to 1; *$0.1 > p \geq 0.05$; **$0.05 > p \geq 0.01$; ***$p < 0.01$. [a]Dummy variable. The maximum correlation is 0.63 (between GDP '000 PPS per inhabitant and average ICT use frequency at work), and the Variance Inflation Factor (VIF) values (from specification 2) range from 1.08 to 1.83. Thus, multicollinearity does not pose a concern, especially in consideration of the large size of our sample; Data source: EWCS 2015

& Fairlie, 2006; Ono & Zavodny, 2007; Lera-López et al., 2011; Vicente & López, 2011; Campos et al., 2017; Segovia-Pérez et al., 2020; Expósito et al., 2022).

Interaction Effects Between Regional Macroeconomic Indicators and Individual-Level Variables

Table 5 presents the results from two model variants (specifications 3–4) as regards the possible existence of interaction effects between our regional macroeconomic indicators and professional status within self-employment. Specification 3 introduces some interaction terms designed to capture the possibly differentiated effect of the percentage of regional population with tertiary education on ICT usage frequency for SEwE, IOA, and DSEW, i.e., a moderating effect of the type of entrepreneur on the relationship between a region's general knowledge stock and individual ICT use frequency. Similarly, specification 4 includes some interaction terms designed to capture the possibly differentiated effect of the average ICT use at work for the whole regional workforce on ICT usage frequency for SEwE, IOA, and DSEW, i.e., a moderating effect of the type of entrepreneur on the relationship between a region's digital knowledge stock and individual ICT use frequency.

These specifications enable investigation of convergence in ICT usage among different entrepreneurs' types, whereby the type that is lagging in ICT usage (DSEW; see the "The Role of the Regional Context in Explaining ICT Usage Frequency" section) is possibly stimulated in a stronger way; i.e., we test whether regional spillover effects are stronger for DSEW.

Our results from specification 3 show how the positive effect of the percentage of regional population with tertiary education on ICT usage frequency at work is weaker for SEwE than for IOA and DSEW. In particular, we observe that with each additional 1% of regional population with tertiary education, the predicted probability of being a non-ICT user decreases by about 0.63% for SEwE and by about 1.25% for IOA and DSEW (specification 3, left panel). Analogously, the predicted probability of being a very intensive ICT user is observed to increase, with each additional 1% of regional population with tertiary education, by about 0.97% for SEwE and by about 1.92% for IOA and DSEW (specification 3, right panel). Otherwise stated, we observe how a higher percentage of the regional population with tertiary education (regional knowledge spillover effect) contributes to a convergence process in ICT use frequency among the three types of self-employed. Regarding DSEW, the type with the lowest ICT usage, we observe catching up in ICT use frequency relative to SEwE but not relative to IOA.[7]

Focusing on our specification 4, we observe how the positive effect of the average ICT use at work for the whole regional workforce on ICT usage frequency at work is stronger for DSEW than for IOA and SEwE. Furthermore, we also observe how this effect is marginally weaker for SEwE than for IOA. More specifically, we observe that with each

[7] Note that the interaction terms between DSEW and regional tertiary education in specification 3 are not significant.

Table 5 Determinants of ICT use frequency at work—ordered discrete choice models; multilevel ordered logit

# Specification	3						4					
Average predicted probability (y)	P[ICT use freq. = 1] = 0.363			P[ICT use freq. = 7] = 0.140			P[ICT use freq. = 1] = 0.369			P[ICT use freq. = 7] = 0.138		
Independent variables (x)	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value
Macroeconomic indicators at the NUTS-2 level												
GDP '000 PPS per inhabitant (7–78)	-1.8E-03	-0.50	0.018**	1.1E-03	0.77	0.018**	-2.4E-04	-0.07	0.701	1.4E-04	0.10	0.701
Share of population with tertiary education (10.3–55.1)	-0.005	-1.25	0.000***	0.003	1.92	0.000***						
Average ICT use frequency at work (1.35–5.58)							-0.106	-28.7	0.000***	0.063	45.2	0.000***
Professional status within self-employment												
Self-employed with employees -SEwE- [a]	-0.124	-34.2	0.000***	0.077	54.9	0.000***	-0.117	-31.6	0.011**	0.072	51.7	0.016**
Independent own-account self-employed -IOA- [a] (*ref.*)												
Dependent self-employed worker -DSEW- [a]	0.161	44.5	0.002***	-0.073	-51.7	0.000***	0.315	85.4	0.000***	-0.115	-82.8	0.000***
Interactions Macro indicators x Professional status												
Share of population with tertiary education x SEwE	0.002	0.62	0.015**	-0.001	-0.95	0.015**						
Share of population with tertiary education x IOA (*ref.*)												
Share of population with tertiary education x DSEW	-1.8E-03	-0.50	0.216	1.1E-03	0.76	0.217						
Average ICT use frequency at work x SEwE							0.017	4.71	0.194	-0.010	-7.41	0.196
Average ICT use frequency at work x IOA (*ref.*)												
Average ICT use frequency at work x DSEW							-0.061	-16.4	0.007***	0.036	25.9	0.008***

Table 5 (continued)

# Specification	3						4					
Average predicted probability (y)	P[ICT use freq. = 1] = 0.363			P[ICT use freq. = 7] = 0.140			P[ICT use freq. = 1] = 0.369			P[ICT use freq. = 7] = 0.138		
Independent variables (x)	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value
Educational attainment												
Basic education -BASIC- [a] (*ref.*)												
Secondary education -SEC- [a]	-0.159	-43.7	0.000***	0.048	33.9	0.000***	-0.155	-42.1	0.000***	0.046	33.4	0.000***
Tertiary education -TERT- [a]	-0.344	-94.9	0.000***	0.173	122.9	0.000***	-0.339	-91.8	0.000***	0.168	121.4	0.000***
Job characteristics												
Tenure *(1–53)*	0.002	0.49	0.002***	-0.001	-0.75	0.002***	0.002	0.45	0.004***	-0.001	-0.70	0.004***
Working hours (*15–120*)	-0.005	-1.28	0.000***	0.003	1.97	0.000***	-0.005	-1.25	0.000***	0.003	1.97	0.000***
Working hours (squared)	4.4E-05	0.01	0.000***	-2.6E-05	-0.02	0.000***	4.4E-05	0.01	0.001***	-2.6E-05	-0.02	0.001***
Demographic characteristics												
Female [a]	0.068	18.9	0.000***	-0.039	-28.0	0.000***	0.064	17.3	0.000***	-0.037	-26.4	0.000***
Immigrant [a]	-0.002	-0.51	0.905	0.001	0.78	0.906	0.004	1.08	0.794	-0.002	-1.69	0.793
Age (*18–65*)	-0.012	-3.43	0.000***	0.007	5.27	0.000***	-0.012	-3.37	0.000***	0.007	5.30	0.000***
Age (squared)	1.5E-04	0.04	0.000***	-8.8E-05	-0.06	0.000***	1.5E-04	0.04	0.000***	-8.8E-05	-0.06	0.000***
Cohabiting [a]	0.012	3.19	0.303	-0.007	-4.95	0.308	0.012	3.13	0.300	-0.007	-4.97	0.305
Children under 14 [a]	-0.002	-0.48	0.884	0.001	0.73	0.884	0.001	0.30	0.926	-0.001	-0.46	0.926
Health (1–5)	-0.005	-1.30	0.479	0.003	2.00	0.479	-0.004	-0.96	0.590	0.002	1.51	0.590
Ends meet (1–6)	-0.033	-9.16	0.000***	0.020	14.1	0.000***	-0.032	-8.62	0.000***	0.019	13.6	0.000***
Log likelihood	-7349.9						-7231.0					

$N = 4822$; For continuous variables, *dy/dx* captures absolute marginal effects whereas $[(dy/dx)/y]\%$ refers to marginal effects, but expressed in relative terms with respect to predicted probabilities. In the context of dummy variables, this reflects the impact for a discrete change of the dummy variable from 0 to 1; $^{*}0.1 > p \geq 0.05$; $^{**}0.05 > p \geq 0.01$; $^{***}p < 0.01$. [a]Dummy variable; nine business sector dummies are used (ref. construction); three dummies to capture "Degree of Urbanization" are used. The maximum correlation is 0.63 (between GDP '000 PPS per inhabitant and average ICT use frequency at work), and the VIF values (from specification 4) range from 1.08 to 1.83. Thus, multicollinearity does not pose a concern, especially in consideration of the large size of our sample. Data source: EWCS 2015 additional unitary increase in the average ICT use at work for the whole regional workforce, the predicted probability of being a non-ICT user decreases by about 24.0, 28.7, and 45.2% for SEwE, IOA, and DSEW, respectively (specification 4, left panel). Analogously, the predicted probability of being a very intensive ICT user is observed to increase, with each additional unitary increase in the average ICT use at work for the whole regional workforce, by about 37.8, 45.2, and 71.0% for SEwE, IOA, and DSEW, respectively (specification 4, right panel). In other words, we also observe how a higher average ICT use frequency at work in the regional population (regional knowledge spillover effect) contributes to a convergence process in ICT use frequency among the three types of self-employed. In particular, the DSEWs seem to catch up fast in ICT use frequency in regions with high levels of digital human capital as they benefit from regional spillover effects.

Table 6 below shows predicted probabilities of ICT usage frequency for the sample means and simulated values (percentiles 5, 10, 25, 50, 75, 90, and 95) of our regional macroeconomic indicators. Calculation of predicted probabilities is based on specifications 3 and 4 in Table 5. The inspection of this table allows to evaluate the potential effects of variations of different magnitudes and directions in our regional macroeconomic indicators. Thus, the combination of the information in this table with the information provided by the spatial distribution of our macroeconomic indicators at the regional level (which is represented in Figs. 2, 3, and 4) becomes a useful tool to visualize our results on the impact of regional-level general and digital human capital on ICT use among European entrepreneurs.

Simulation for specification 3 shows how the difference in predicted probability of being a non-ICT user between SEwE and IOA decreases from 6.5 to 3.0 percentual points when the percentage of regional population with tertiary education increases from 27.5 (p.50) to 41.6 (p.90), 41.6 being around the mean value observed in those regions belonging to countries like the UK (rank #3), Finland (rank #4), or Luxembourg (rank #5).[8] In contrast, this simulation also indicates how this difference increases from 6.5 to 10.3 percentual points when the percentage of regional population with tertiary education decreases from 27.5 (p.50) to 13.9 (p.10), 13.9 being around the mean value observed in those regions belonging to countries like Romania (rank #34) or Albania (rank #35).[9] When concentrating on the difference in predicted probability of being a very intensive ICT user between SEwE and IOA, we observe how this difference decreases from 3.7 to 2.2 percentual points when the percentage of regional population with tertiary education simulates the average situation of countries like the UK, Finland, or Luxembourg. Finally, when the percentage of regional population with tertiary education simulates the average situation of

[8] The percentage of regional population with tertiary education equals or exceeds 41.6 (p.90) in 23 regions belonging to 12 different countries, including Ireland (rank #1), Norway (rank #2), UK (rank #3), Finland (rank #4), Sweden (rank #7), Switzerland (rank #8), Belgium (rank #11), the Netherlands (rank #12), Denmark (rank #13), Spain (rank #14), and France (rank #15).

[9] The percentage of regional population with tertiary education is equal or lower than 13.9 (p.10) in 23 regions belonging to five different countries, including Czech Republic (rank #24), Italy (rank #32), Turkey (rank #33), Romania (rank #34), and Albania (rank #35).

Table 6 Predicted probabilities of ICT usage frequency for the sample means and simulated values of macroeconomic indicators (based on specifications 3 and 4 in Table 5)

Specification 3	*P*[ICT use freq. = 1]							*P*[ICT use freq. = 7]						
Share of population with tertiary education (percentile)	12.9 (p.5)	13.9 (p.10)	18.8 (p.25)	**27.5 (p.50)**	37.5 (p.75)	41.6 (p.90)	47.8 (p.95)	12.9 (p.5)	13.9 (p.10)	18.8 (p.25)	**27.5 (p.50)**	37.5 (p.75)	41.6 (p.90)	47.8 (p.95)
Professional status within self-employment														
Self-employed with employees (SEWE)	33.7%	33.5%	32.3%	**30.3%**	28.0%	27.1%	25.8%	13.6%	13.8%	14.4%	**15.7%**	17.3%	18.0%	19.1%
Independent own-account self-employed (IOA)	44.3%	43.8%	41.2%	**36.8%**	32.0%	30.1%	27.3%	8.7%	8.9%	10.0%	**12.0%**	14.6%	15.8%	17.8%
Dependent self-employed worker (DSEW)	58.9%	58.2%	54.6%	**48.3%**	41.0%	38.1%	33.8%	4.6%	4.7%	5.6%	**7.4%**	10.1%	11.4%	13.6%
Specification 4	*P*[ICT use freq. = 1]							*P*[ICT use freq. = 7]						
Average ICT use frequency at work (percentile)	1.8 (p.5)	2.2 (p.10)	2.7 (p.25)	**3.2 (p.50)**	3.8 (p.75)	4.3 (p.90)	4.5 (p.95)	1.8 (p.5)	2.2 (p.10)	2.7 (p.25)	**3.2 (p.50)**	3.8 (p.75)	4.3 (p.90)	4.5 (p.95)
Professional status within self-employment														
Self-employed with employees (SEWE)	44.0%	39.8%	35.0%	**30.0%**	24.5%	21.2%	19.1%	8.1%	9.7%	11.9%	**14.7%**	18.7%	21.7%	24.0%
Independent own-account self-employed (IOA)	54.2%	49.0%	43.0%	**36.6%**	29.4%	25.0%	22.2%	5.2%	6.5%	8.5%	**11.1%**	15.1%	18.2%	20.7%
Dependent self-employed worker (DSEW)	74.0%	67.0%	58.1%	**47.7%**	35.5%	28.0%	23.4%	1.9%	2.8%	4.4%	**7.0%**	11.6%	16.0%	19.6%

countries like Romania or Albania, this difference increases from 3.7 to 4.9 percentual points.

Concerning simulation 4, these figures show how the difference in predicted probability of being a non-ICT user between SEwE and IOA decreases from 6.6 to 3.8 percentual points when the average ICT use at work for the whole regional workforce increases from 3.2 (p.50) to 4.3 (p.90), 4.3 being around the mean value observed in regions belonging to countries like Norway (rank #2), Luxembourg (rank #3), Sweden (rank #4), The Netherlands (rank #5), the UK (rank #6), or France (rank #7).[10] When comparing IOA and DSEW, this difference decreases from 11.1 to 3.0 percentual points when the average ICT use at work for the whole regional workforce increases from 3.2 (p.50) to 4.3 (p.90). Conversely, this simulation also shows how the difference between SEwE and IOA increases from 6.6 to 9.2 percentual points when the average ICT use at work for the whole regional workforce decreases from 3.2 (p.50) to 2.2 (p.10), 2.2 being around the mean value observed in regions belonging to countries like Romania (rank #33), Turkey (rank #34), or Albania (rank #35).[11] Similarly, when comparing IOA and DSEW this difference increases from 11.1 to 18.0 percentual points when the average ICT use at work for the whole regional workforce decreases from 3.2 (p.50) to 2.2 (p.90).

Turning our attention on the difference in predicted probability of being a very intensive ICT user between SEwE and IOA, we observe how this difference remains stable around 3.6 percentual points when the average ICT use at work for the whole regional workforce increases from 3.2 (p.50) to 4.3 (p.90). When comparing IOA and DSEW, this difference decreases from 4.1 to 2.2 percentual points when the average ICT use at work for the whole regional workforce increases from 3.2 (p.50) to 4.3 (p.90). Finally, when the average ICT use at work for the whole regional workforce decreases from 3.2 (p.50) to 2.2 (p.10), we only observe a decrease by about 0.4 percentual points in both the difference between SEwE and IOA and the difference between IOA and DSEW.

In summary, our simulation exercises show strong evidence of convergence in ICT usage among different types of entrepreneurs, where the relatively lower-frequency ICT users (DSEW) are lagging behind with a smaller gap in regions with a higher-educated workforce and a higher-frequency ICT use workforce, suggesting that stronger regional spillover effects contribute to closing the gap in ICT use among different entrepreneurs' types. These results support Hypothesis 3.

[10] The average ICT use at work equals or exceeds 4.3 (p.90) in 36 regions belonging to 15 different countries, including Denmark (rank #1), Norway (rank #2), Luxembourg (rank #3), Sweden (rank #4), The Netherlands (rank #5), UK (rank #6), France (rank #7), Belgium (rank #8), Malta (rank #9), Ireland (rank #11), Estonia (rank #12), Finland (rank #13), Austria (rank #15), Switzerland (rank #16), and Germany (rank #23).

[11] The average ICT use at work is equal or lower than 2.2 (p.10) in 30 regions belonging to 12 different countries, including Estonia (rank #12), Czech Republic (rank #20), Macedonia (rank #21), Italy (rank #25), Poland 2 (rank #6), Lithuania (rank #28), Greece (rank #29), Serbia (rank #31), Portugal (rank #32), Romania (rank #33), Turkey (rank #34), and Albania (rank #35).

Differentiated Effects of the Regional Context for Regions with Low and High GDP Per Capita

Finally, Table 7 below presents the results from two models (specifications 5–6) aimed at capturing the possibly differentiated relationship between our regional macroeconomic indicators and ICT usage of entrepreneurs between regions with low and high GDP per capita. In particular, specification 5 introduces an interaction term designed to capture the possibly differentiated effect of the percentage of regional population with tertiary education on ICT usage frequency in regions with low and high GDP per capita. Similarly, specification 6 includes an interaction term designed to capture the possible differentiated effect of the average ICT use at work for the whole regional workforce on ICT usage frequency in regions with low and high GDP per capita.

These specifications enable investigation of convergence in ICT usage of entrepreneurs between regions with low and high GDP per capita, whereby the regions that are lagging in ICT usage (those with low GDP per capita; see Table 2) are possibly stimulated in a stronger way; i.e., we test whether regional spillover effects are stronger in regions with low GDP per capita. These results are presented in a similar manner to those presented in Tables 4 and 5.

Our results from specification 5 show how the positive effect of the percentage of regional population with tertiary education on ICT usage frequency at work is stronger in regions with low GDP per capita. In particular, we observe that, with each additional 1% of regional population with tertiary education, the predicted probability of being a non-ICT user decreases by about 0.66% in regions with high GDP per capita and by about 2.18% in regions with low GDP per capita (specification 5, left panel). Analogously, the predicted probability of being a very intensive ICT user is observed to increase, with each additional 1% of regional population with tertiary education, by about 1.03% in regions with high GDP per capita and by about 3.38% in regions with low GDP per capita (specification 5, right panel). Otherwise stated, we observe how a higher percentage of the regional population with tertiary education (regional spillover effect originating from the general knowledge stock) contributes to a convergence process in ICT usage by individual entrepreneurs in regions with low and high GDP per capita.

When turning our attention to our specification 6, we observe how the positive effect of the average ICT use at work for the whole regional workforce on ICT usage frequency at work is stronger for regions with low GDP per capita. More concretely, we find that, with each additional unitary increase in the average ICT use at work for the whole regional workforce, the predicted probability of being a non-ICT user decreases by about 20.9% in regions with high GDP per capita and by about 43.0% in regions with low GDP per capita (specification 6, left panel). Analogously, the predicted probability of being a very intensive ICT user is observed to increase, with each additional unitary increase in the average ICT use at work for the whole regional workforce, by about 33.2% in regions with high GDP per capita and by about 68.1% in regions with low GDP per capita (specification 6, right panel). In other words, we also observe how a higher average ICT use frequency at work in the regional population (regional spillover effect originating from the digital knowledge

Table 7 Determinants of ICT use frequency at work—ordered discrete choice models; multilevel ordered logit

# Specification	5						6					
Average predicted probability (y)	P[ICT use freq. = 1] = 0.364			P[ICT use freq. = 7] = 0.140			P[ICT use freq. = 1] = 0.369			P[ICT use freq. = 7] = 0.138		
Independent variables (x)	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value
Macroeconomic indicators at the NUTS-2 level												
Low GDP PPS per inhabitant [a, b]	0.192	52.7	0.001***	-0.106	-76.0	0.001***	0.257	69.7	0.000***	-0.140	-101.8	0.001***
Share of population with tertiary education (10.3–55.1)	-2.4E-03	-0.66	0.041**	1.4E-03	1.03	0.042**						
Average ICT use frequency at work (1.35–5.58)							-0.077	-20.9	0.000***	0.046	33.2	0.000***
Interactions main regressors x Low GDP dummy												
Share of population with tertiary education x Low GDP	-0.006	-1.51	0.003***	0.003	2.35	0.003***						
Average ICT use frequency at work x Low GDP							-0.081	-22.0	0.000***	0.048	34.9	0.000***
Professional status within self-employment												
Self-employed with employees -SEwE- [a]	-0.056	-15.3	0.000***	0.034	24.2	0.000***	-0.056	-15.1	0.000***	0.034	24.4	0.000***
Independent own-account self-employed -IOA- [a] (*ref.*)												
Dependent self-employed worker -DSEW- [a]	0.101	27.9	0.000***	-0.050	-36.0	0.000***	0.099	26.8	0.000***	-0.049	-35.3	0.000***
Educational attainment												
Basic education -BASIC- [a] (*ref.*)												
Secondary education -SEC- [a]	-0.156	-42.9	0.000***	0.047	33.5	0.000***	-0.156	-42.3	0.000***	0.046	33.6	0.000***
Tertiary education -TERT- [a]	-0.342	-94.0	0.000***	0.171	122.8	0.000***	-0.341	-92.4	0.000***	0.169	122.4	0.000***
Job characteristics												
Tenure *(1–53)*	0.002	0.50	0.002***	-0.001	-0.77	0.002***	0.002	0.45	0.003***	-0.001	-0.72	0.003***
Working hours (*15–120*)	-0.005	-1.32	0.000***	0.003	2.05	0.000***	-0.005	-1.26	0.000***	0.003	2.00	0.000***
Working hours (squared)	4.6E-05	0.01	0.000***	-2.7E-05	-0.02	0.000***	4.4E-05	0.01	0.000***	-2.6E-05	-0.02	0.000***

Table 7 (continued)

# Specification	5						6					
Average predicted probability (y)	P[ICT use freq. = 1] = 0.364			P[ICT use freq. = 7] = 0.140			P[ICT use freq. = 1] = 0.369			P[ICT use freq. = 7] = 0.138		
Independent variables (x)	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value	$\frac{dy}{dx}$	$\frac{dy/dx}{y}\%$	p-value
Demographic characteristics												
Female [a]	0.070	19.1	0.000***	-0.040	-28.7	0.000***	0.066	17.8	0.000***	-0.038	-27.3	0.000***
Immigrant [a]	-0.006	-1.69	0.688	0.004	2.64	0.691	0.002	0.57	0.889	-0.001	-0.90	0.889
Age (*18–65*)	-0.013	-3.44	0.000***	0.007	5.34	0.000***	-0.012	-3.33	0.000***	0.007	5.28	0.000***
Age (squared)	1.5E-04	0.04	0.000***	-8.9E-05	-0.06	0.000***	1.5E-04	0.04	0.000***	-8.7E-05	-0.06	0.000***
Cohabiting [a]	0.011	3.01	0.330	-0.007	-4.71	0.335	0.012	3.23	0.285	-0.007	-5.16	0.289
Children under 14 [a]	-0.002	-0.54	0.869	0.001	0.84	0.869	-5.6E-06	0.00	1.000	3.3E-06	0.00	1.000
Health (1–5)	-0.006	-1.74	0.344	0.004	2.69	0.345	-0.005	-1.22	0.492	0.003	1.93	0.493
Ends meet (1–6)	-0.034	-9.33	0.000***	0.020	14.5	0.000***	-0.033	-8.85	0.000***	0.019	14.0	0.000***
Log likelihood	-7266.4						-7229.3					

$N = 4822$. For continuous variables, *dy/dx* captures absolute marginal effects whereas [(*dy/dx*)/*y*]% refers to marginal effects, but expressed in relative terms with respect to predicted probabilities. In the context of dummy variables, this reflects the impact for a discrete change of the dummy variable from 0 to 1; $*0.1 > p \geq 0.05$; $**0.05 > p \geq 0.01$; $***p < 0.01$. [a]Dummy variable. [b]Dummy equals 1 for workers living in NUTS-2 regions where the GDP PPS per inhabitant is below the unweighted median of the pool of observations in the sample; nine business sector dummies are used (ref. construction); three dummies to capture "Degree of Urbanization" are used. The maximum correlation is 0.63 (between low GDP PPS per inhabitant and average ICT use frequency at work), and the VIF values (from specification 6) range from 1.07 to 1.84. Thus, multicollinearity does not pose a concern, especially in consideration of the large size of our sample. Data source: EWCS 2015 stock) contributes to a convergence process in ICT use frequency of entrepreneurs in regions with low and high GDP per capita. These results support Hypothesis 4.

Robustness Checks

We tested the robustness of our results in several ways. First, our results are consistent with the inclusion of country dummies in the analysis. Second, our results are robust to the estimation of standard errors that are clustered at both the country and the NUTS-2 levels (Moulton, 1986, 1990). Third, we note that individual use of ICTs contributes to the regional-level use of ICTs, i.e., our regional-level indicator of the digital knowledge stock. Hence, one might argue that the regional-level indicator, which is an independent variable in our model, is in part made up by the dependent variable, namely, the individual-level value of ICT use frequency, causing an endogeneity problem. Even though the contribution of an individual's ICT use frequency is negligible for the average ICT use frequency at the regional level (given the high number of workers at the regional level), we performed a robustness test. Specifically, in order to avoid a correlation by construction between individual-level ICT use of entrepreneurs and regional-level ICT use, we also computed the average ICT use frequency at work for the regional workforce while excluding the entrepreneurs.[12] The exclusion of entrepreneurs from the computation of digital human capital at the regional level did not alter our main results in a significant manner. Fourth, we also included quadratic terms of our regional variables and observed decreasing returns of both general and digital human capital. These results did not affect the main conclusions from our regression analysis though. Finally, our results remain significant to the use of single-level ordered (logit) models.[13]

Conclusions and Policy Implications

Digital transformations have radically changed the competitive landscape in recent decades (Kraus et al., 2021). Accordingly, efficient ICT usage is a key prerequisite for firms and entrepreneurs to remain competitive in today's economy (Beynon et al., 2021). Therefore, it is relevant to know if and how frequent ICT usage can be stimulated (Sassetti et al., 2022) and what role absorptive capacity may play (Barba-Sánchez et al., 2007). In the present paper, we investigated ICT use frequency by individual entrepreneurs, rather than firms. An important difference with the above general management literature on ICT use is that when one-man businesses (solo entrepreneurs) are concerned, the firm's ICT usage coincides with the ICT usage by the entrepreneur personally. Therefore, in the

[12] We emphasize though that conceptually, the digital human capital of entrepreneurs is also part of the region's digital knowledge stock, and hence, in our main exercises, we include the entrepreneurs' digital human capital for computing the digital human capital stock at the regional level.

[13] Detailed results for these robustness checks can be obtained from the authors upon request.

current paper, we followed Qian and Acs (2013) and employed the concept of entrepreneurial absorptive capacity which is defined at the individual level, rather than the general concept of absorptive capacity which is defined at the firm level (Cohen & Levinthal, 1990).

Specifically, we investigated if regional spillover effects exist whereby individual entrepreneurs are stimulated to more frequently use ICT in their daily work while benefiting from regional knowledge spillovers. Conceptually, we applied a small variation to the absorptive capacity theory of knowledge spillover entrepreneurship (Qian & Acs, 2013) by adding an explicit role for digital human capital and ICT knowledge and skills. Empirically, we investigated determinants of ICT usage frequency of three types of self-employed workers—self-employed with employees; independent own-account self-employed; and dependent self-employed workers—in NUTS-2 regions across 35 European countries. In total, we used 4822 observations for self-employed workers distributed over 305 NUTS-2 regions. Besides individual-level determinants of the extent of ICT usage (which we operationalize with a Likert scale) by self-employed workers, we also investigated the role of regional-level general human capital (as measured by the percentage of the regional population with tertiary education) and of regional-level digital human capital (average ICT usage by workers in the region), while controlling for regional GDP per capita. These two human capital indicators capture two related but distinct sources of regional knowledge spillovers.

Our empirical exercises show clear evidence for both types of spillover effects to exist. Moreover, we found that the differences in ICT use frequency at work that exist among the three types of self-employed are smaller in regions with higher levels of general and digital human capital. Hence, these regional spillover effects also contribute to a convergence process in ICT use frequency among the three types of self-employed within a given region. Finally, we also found evidence of stronger knowledge spillovers in regions with lower initial ICT usage by entrepreneurs so that regional spillover effects also contribute to convergence among regions.

Our findings are in line with those found by Raspe and Van Oort (2011). They note a trade-off between bigger opportunities for new firms in regions endowed with high levels of human capital to benefit from knowledge spillovers and stronger competition from higher-quality firms in such regions. Whereas the higher potential for knowledge spillovers may stimulate new firms to grow, the higher competition in high-HC regions may threaten their survival. Accordingly, these authors conclude that “Survival and growth prospects of new firms will depend on their ability to absorb external knowledge and transform it into competitive advantages” (Raspe & Van Oort, 2011, p. 511). The results of our paper clearly suggest that frequent ICT usage is an influential element of this absorptive capacity and that in regions endowed with high levels of human capital, it is even more important for entrepreneurs to develop their ICT skills and keep these skills at a sufficiently high level, in order to remain competitive.

A policy implication of our paper is that ICT use by entrepreneurs—especially those that are lagging behind in ICT use, such as many DSEW—can be stimulated not only by targeting the entrepreneurs directly but also indirectly by stimulating the broader regional population to participate in tertiary education and in the digital society. Our results suggest that in the long term, this may also positively influence more frequent ICT usage at work among a region's entrepreneurs. Increased ICT usage at work, in turn, may increase entrepreneurial performance (Millán et al., 2021). Moreover, our exercises allowing for different magnitudes of knowledge spillovers between low- and high-GDP per capita regions showed that knowledge spillovers from a given knowledge stock are stronger in low-GDP per capita regions. This suggests that increasing the regional stocks of general and digital knowledge in poorer regions may be particularly effective for entrepreneurs in poorer regions to catch up with their counterparts in richer regions, as far as their ICT knowledge and skills are concerned. Increasing the regional stocks of general and digital knowledge is primarily a task for the education sector and can be achieved by stimulating intensive ICT use at all levels of education. In line with this, students should be stimulated to pursue a career in the ICT sector, so as to further increase a region's digital knowledge stock. Such an increased digital knowledge stock, in turn, will lead to a higher amount of (digital) knowledge spillovers.

Our paper is not free from limitations. First, our ICT usage frequency variable is self-reported. Second, because our data base is a cross-section, it is difficult to make a claim on causal effects. Having said that, we also note that a *reversed* causal relationship between our regional-level explanatory variables of interest and our (individual-level) dependent variable is highly unlikely, as individual entrepreneurs cannot normally influence behavior at the aggregate (in this case regional) level.[14] Still, longitudinal analysis is recommended for future research as this would allow tracking ICT usage over time after changes in the regional context take place, thereby allowing to confirm the causality. Longitudinal analysis would also allow for capturing convergence in a more formal manner, i.e., as a process over time where lagging entrepreneurs or regions gradually catch up with their frontrunning counterparts. In the present paper, due to the cross-sectional nature of our data base, we have used the term convergence in a somewhat loose manner, namely, to indicate that the difference (in ICT use frequency) between leading and lagging entrepreneurial types or regions becomes smaller due to regional knowledge spillovers taking place at a single point in time. Another area of interest could be considering different ICT types (Karim et al., 2022) to test whether some sorts of ICT are more prone to regional spillover effects than other types. Finally, future studies may also extend this work by combining the use of data on ICT usage at both the individual person level and the firm level.

[14] The typical exception involves an entrepreneur running a very large firm. Very large firms may influence behavior and policy at the aggregate (regional) level. However, we do not have such entrepreneurs in our data base.

In conclusion, we consider this study is an important contribution to extant literature by investigating the relationship between sources of regional knowledge spillovers and ICT use frequency by different entrepreneurs' types.

Appendix

Table 8 Correlation matrix for macroeconomic indicators at the NUTS-2 level

	2	3
1. GDP PPS per inhabitant		
2. Share of population with tertiary education	0.699	
3. Average ICT use frequency at work	0.635	0.702

$N = 4822$. All correlations are significant with $p < 0.01$. Data source: EWCS 2015

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Declarations

Conflict of Interest The authors declare no competing interests.

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