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The Effects of Digital Literacy on Wages in Europe and Central Asia

Metin Nebiler
Kyunglin Park

WORLD BANK GROUP
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Abstract

Digital skills are becoming increasingly more important in the labor market as demand for them is increasing in all sectors. This paper explores the determinants of digital skill acquisition and estimates the impact of digital skills on wages in developing countries by using the latest round of the Life in Transition Survey from 30 countries in the Europe and Central Asia region. The results show that acquisition of digital skills is correlated with individual characteristics including age, education, and gender but also with household characteristics such as household income, place of residence, and parents' educational attainment. These disparities translate directly into labor market outcomes: individuals with advanced digital skills earn, on average, 18.9 percent higher wages than those without such skills, with substantial heterogeneity within and between regions. The wage premium for high digital skills is higher in Central Asia, the South Caucasus, Eastern Europe, and Central Europe. Moreover, the results show that larger firms offer significantly higher premiums for digital skills.

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The Effects of Digital Literacy on Wages in Europe and Central Asia

Metin Nebiler*

Kyunglin Park

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* Corresponding author. Metin Nebiler is a Senior Economist and Kyunglin Park is an Economist (consultant) in the World Bank. This paper's findings, interpretations, and conclusions are entirely those of the authors and do not necessarily represent the views of the World Bank, its Executive Directors, or the countries they represent. Email: mnebiler@worldbank.org.

1 Introduction

Human capital is defined as workers' accumulated experience and skills, including education, health, training, and abilities. It is important in determining an individual's productivity and earning capacity, which in turn influences their contribution to economic growth and their capacity to increase their living standards and even escape from poverty. Economic literature shows a strong correlation between an individual's human capital, usually measured with educational attainment, and their earning potential, indicating higher educational levels generally lead to better job prospects, higher labor income, and more stable employment, thereby reducing the risk of poverty (Mincer (1975), Card (1999), Jedwab et al. (2023), Moscarini & Postel-Vinay (2014), Autor et al. (2003)). At the macroeconomic level, developing human capital can play a vital role in increasing productivity, boosting growth, promoting mobility, and ultimately building resilience to reduce poverty and inequality (Acemoglu & Zilibotti (2001), Hall & Jones (1999), Abbott & Gallipoli (2022), Santos (2011)).

Recently, digital skills have been in the forefront of human capital accumulation by offering significant opportunities for those who can utilize them. The rapid diffusion of digital technologies has reshaped production processes, employment prospects, and economic development trajectories by transforming various sectors. It has introduced new ways to achieve innovation, efficiency, and inclusivity, and offers significant benefits and opportunities for individuals, organizations, and countries.

Digital skills can influence one's earnings through multiple channels. First, digital skills can have a significant impact on finding employment. Recent research shows that people with some level of digital skills are more likely to be employed compared to people with no digital skills (Bergson-Shilcock & Taylor (2023), Non et al. (2021)). Second, digital skills can improve the productivity of workers, which may lead to higher earnings in the labor market. In the late 1980s, Krueger's well-known research showed that computer use accounted for a wage premium ranging from 13.9 to 17 percent (Krueger (1993)). Similar research on the wage premium associated with digital skills has found significant effects

(from 6 to 15 percent) (Garcia-Lazaro et al. (2025), Cutuli & Tomelleri (2023), Hanushek et al. (2015)).

This paper investigates the heterogeneity of digital skill acquisition and the associated wage premium of these skills across European and Central Asian (ECA) countries. The findings show statistically significant disparities both within and between these countries. The results show that approximately 43.7 percent of people report a complete absence of digital skills, highlighting almost half of the population lacking fundamental digital competencies. Central Europe and the Baltic States report the highest concentration of individuals with high digital skills, with 47.20 and 47.60 percent of respondents, respectively, while Central Asia has the lowest overall share, with only 23.6 percent of individuals reporting high digital skills. Specifically, the results consistently indicate a positive correlation between the likelihood of digital skill acquisition and several individual-level characteristics, including younger age, male, urban residency, and tertiary educational attainment. Individuals from low-income households demonstrate a lower propensity for digital skill acquisition: being in the bottom 40 of the income distribution reduces the probability of having high digital skills by 16.8–12.4 pp in South Caucasus and Southeast Europe, compared to a smaller effect in Central Asia (8.4 pp). Moreover, parental education emerges as a significant determinant of digital skill acquisition, underscoring the risk of persistent intergenerational inequality in digital capabilities.

These disparities translate directly into labor market outcomes: individuals with advanced digital skills earn, on average, 18.9 percent higher wages than those without such skills, with substantial heterogeneity across countries and regions. The wage premium for high digital skills is higher in Central Asia (47.7 percent), Eastern Europe (26.7 percent), the South Caucasus (23.5 percent), and Central Europe (19.5 percent). On the other hand, digital skills are not associated with significant positive effects in Southeast Europe, the Baltic States and the Western Balkans. Moreover, we find that larger firms offer significantly higher premiums for high digital skills. However, the results do not show any heterogeneity of wage premium for digital skills by occupation and sector of workers.

This paper offers several contributions to the economic literature. First, while a substantial body of literature has investigated the wage premium associated with digital skills in developed economies, empirical evidence from developing countries remains limited. Second, existing research has predominantly focused on the labor market returns to digital skills. In contrast, this study extends the analysis by also examining the determinants of digital skill acquisition. This is particularly important as it provides a valuable assessment of current digital skills development within the context of developing economies in the region.

The remainder of this paper is structured as follows. Section 2 provides a review of the relevant theoretical and empirical literature. Section 3 outlines the econometric methodology employed in the analysis, and Section 4 provides details on the data and presents descriptive statistics. Section 5 presents the empirical findings, and Section 6 offers concluding remarks and discusses potential avenues for future research.

2 Literature Review

The literature on human capital and labor-market outcomes has evolved significantly since the human capital theory of Becker (1962). He discusses in his theoretical paper that investments in education and training enhance an individual's productivity, leading to higher wages. Multiple research has consistently demonstrated a positive correlation between education and earnings, with an average 10 percent earnings increase per additional year of schooling (Pichler & Stehrer (2021), Chetty et al. (2011), Altonji et al. (2016)). However, variations in returns were noted across different contexts, with higher returns in low-income countries, among women, and at lower education levels (Hampf et al. 2017). The most commonly used measures are from the Programme for the International Assessment of Adult Competencies (PIAAC), developed by the OECD covering 33 countries. Using this data, Hanushek et al. (2015) found that a one-standard deviation increase in numeracy skills is associated with an 18 percent wage increase among prime-age workers.

As digital skills are considered a key form of human capital in current economies, the work

of Acemoglu (2002) and Acemoglu & Autor (2011) highlights how technological advancements often complement skilled labor while potentially substituting for less-skilled tasks. The rise of digital technologies is a prime example of skill-based technological change, increasing the demand for workers with the requisite digital skills and potentially widening wage inequality. Acemoglu & Autor (2011) further refine their analysis by focusing on how technology affects specific job tasks. They discuss that digitalization can automate routine tasks, leading to a polarization of the labor market with increased demand for both high-skilled cognitive tasks and low-skilled manual tasks, while middle-skilled routine jobs may decline. They suggest that digital skills are crucial for workers to transition into the growing high-skilled occupations.

Recently, researchers have developed indexes to measure digital skills and explored their impact on labor market outcomes. Using the PIAAC data, Hanushek et al. (2015) find that although the returns of such skills sets on individual income are relatively low compared to literacy and numeracy skills, in a few countries, such as Czechia and the Slovak Republic, they seem to yield significant improvements in average returns. Similarly, Falck et al. (2021) reveal that digital skills are significantly correlated with higher wages, as a one standard deviation increase in digital skills yields a 24 percent increase in log hourly wages. It has been shown to have positive results on employment probabilities, as demonstrated in Hampf et al. (2017) where an increase in one level of PIAAC skills increases employment likelihood by 8 percentage points.

Furthermore, Pichler & Stehrer (2021) use the PIAAC data to show that wages in digital occupations significantly outpace those in low-digital occupations, on average 59 percent higher median gross wage, in the UK. This underscores the value of technical skills in the modern economy, as highlighted by Acemoglu & Autor (2011) on the displacement of routine

jobs and the resulting polarization of the job market, emphasizing the growing importance of high cognitive skills and adaptability.

Another strand of literature focuses on the use of the internet and its returns to earnings. Similarly, using internet use as a proxy for digital skills, Goss & Phillips (2002) discover a 13.5 percent wage premium and Freeman (2002) a 14 percent premium in the U.S. Similarly, Forman et al. (2012) found that there is a positive correlation between internet investment and wage growth. Akerman et al. (2015) found that broadband internet raises the wages of workers with abstract tasks. Yang et al. (2023) find that the higher is the level of digital economy development in a region in China, the larger is the wage gap between high- and low-skilled workers.

More recently, researchers have been working on the impact of artificial intelligence (AI) on labor market outcomes. For instance, Alekseeva et al. (2021) found that AI skills carry a wage premium. In particular, high-skilled workers are the biggest beneficiaries of AI development. Felten & Seamans (2019) found that new advances in AI have a positive impact on wages in high-income occupations. Results by Engberg et al. (2023) indicate a wage growth premium in occupations more exposed to AI, contrasting with a wage growth discount in occupations exposed to robots.

Yet there is a scarcity of literature on developing countries, primarily due to the challenges of collecting data on digital skills (i.e., cognitive, non-cognitive skills). The contribution of this paper to literature is that it is one of the first papers identifying the impact of digital skills on wages in developing countries. The paper presents cross-country evidence from 30 countries in Europe and Central Asia. The data used in the analysis provides consistent cross-country data on the digital skills of the adult population in developing countries.

3 Empirical Strategy

To identify the impact of digital skills in the labor market, we estimate a general Mincerian equation with additional information for digital skills. In particular, the modified Mincerian equation used in the analysis is an individual-level wage regression as follows:

$$log(w_{ic}) = \beta_0 + \beta_1 digi_{j(ic)} + X_{ic}\beta_2 + \delta_c + \epsilon_{ic} (1)$$

where w_{ic} is gross hourly wages earned by individual i living in country c and $digi_{ic}$ is a set of dummy variables where $digi0$ refers to no digital skills, $digi1$ refers to basic digital skills, and $digi2$ refers to high digital skills. X_{ic} is a vector of individual level a range of factors that affect human capital accumulation educational attainment, family inputs measured by parent's education, and other relevant factors that include labor market experience, age, gender, sector and occupation. $delta_c$ is the country-fixed effects that account for any differences in the countries' wage levels and ϵ_{ic} is the error term. To measure the impact of digital skills on wages, we use ordinary least squares (OLS), and β_1 is the coefficient of interest. We only include working-age population (15-64 years old) who reported any wage income in the main analysis.

Our empirical strategy can hardly provide the causal effect of digital skills on wage levels. First, the results could be biased in case of significant measurement errors in accurately estimating the digital skills as the analysis relies on the self-reported question of digital skills in the Life in Transition Survey (LITS). If respondents over-report or under-report their digital skills, the results are going to be biased. The results will lead to a downward bias if individuals underestimate their digital skills and an upward bias if digital skills are over-estimated. Second, our results could have an upward bias if there is a reverse causality generated by higher paid jobs resulting with higher development of digital skills. Finally, omitted variables can lead to biased estimates if these variables affect wage levels and are also related with the digital skill acquisition. Although the analysis

includes a very large set of explanatory variables, omitted variables could still cause bias in the results. However, it is difficult to assess the bias of the omitted variables, including non-cognitive skills, personality, and others.

4 Data

This study draws on data from the LiTS, a collaborative effort with the World Bank and the European Bank for Reconstruction and Development (EBRD). The survey's purpose is to evaluate the socio-economic conditions of households and individuals and their views on a range of socio-economic and political challenges. Initially launched in 2006 in 29 countries, subsequent rounds were carried out in 2010 (35 countries), 2015 (34 countries), and the most recent in 2022, covering 37 countries with a minimum of 1,000 household responses from each. The last round included seven countries in the Middle East and North Africa. This analysis focuses only on 30 countries within Europe and Central Asia, with Germany serving as a reference point for a developed European country.

For evaluating labor market outcomes, we use the individual's monthly income, excluding bonuses and benefits and deducting taxes and social security. We group the countries by their geographical regions. The study categorizes the regions into Central Europe (Bulgaria, Croatia, Czechia, Germany, Hungary, Romania, Poland, the Slovak Republic, and Slovenia), Eastern Europe (Belarus and Moldova), Southeast Europe (Greece, the Russian Federation, and Türkiye), the Western Balkans (Albania, Bosnia and Herzegovina, Kosovo, Montenegro, North Macedonia, and Serbia), the South Caucasus (Armenia, Azerbaijan, and Georgia), and Central Asia (Kazakhstan, Kyrgyz Republic, Tajikistan, and Uzbekistan).

4.1 Digital skills

Returns to skill analysis is scarce in developing countries mainly due to limited availability of data. The LITS provides information on labor market outcomes of respondents as well as their self-assessed digital skills. The digital skills in the survey are grouped into several

categories. We use digital skills based on capabilities like managing files and sending emails, installing software or devices, and programming in a specialized language, with responses categorized as either capable (”Yes”) or not (”No”). Furthermore, we adjust for the overlap in skills to accurately assess the impact of each skill, distinguishing between basic abilities and more sophisticated competencies to avoid overestimating their economic impact. For our analysis, we define digital skills as following[1]:

- *No digital skills:* People reporting to ”No” to all questions in the survey. This category includes people who cannot copy and move files, send emails, install software or devices and write a computer program.
- *Basic digital skills:* People reporting to ”Yes” to basic digital skills questions but ”No” to higher digital skills questions. This category includes people who can copy and move files and send emails, but they cannot install software or devices and write a computer program.
- *High digital skills:* People reporting to ”Yes” to all digital skills questions in the survey. This category includes people who can copy and move files, send emails, install software or devices and write a computer program.

4.2 Descriptive statistics

The incidence of digital skills in developing countries in the ECA region is generally low. The results show that approximately 43.7 percent of people report a complete absence of digital skills, highlighting that almost half of the population lacks fundamental digital competencies. A further 20.8 percent of respondents across the region assess their digital skills as basic. Only 35.5 percent of respondents possesses high digital skills that are necessary for exploiting the benefits of higher demand for digital skills in the labor market.

[1]Are you able to do the following on a computer/laptop, mobile device or tablet? 1. Copy or move files, 2. Send emails with attached files, 3. Install new software or devices, 4. Write a computer program using a specialized programming language.

The distribution of digital skills exhibits significant heterogeneity across regions and countries. Central Europe and Baltic States report the highest concentration of individuals with high digital skills, with 47.20 and 47.60 percent of respondents self-assessing their proficiency at this level. Within this region, Germany leads with 64.3 percent of individuals reporting high digital skills, followed closely by Hungary (57.5 percent), Czechia (56.8 percent), and Poland (52.7 percent). In contrast, Central Asia has the lowest overall share, with only 23.6 percent of individuals reporting high digital skills. The regional average masks significant variation: while Kazakhstan stands out with 41.5 percent, Kyrgyz Republic (15.9 percent) and Tajikistan (10.2 percent) report notably lower levels.

The Baltic States and Southeast Europe also show relatively high shares of digitally skilled populations. Estonia, for example, has 58.0 percent of respondents with high digital skills—among the highest across all countries. Meanwhile, Southeast Europe averages 35.3 percent, with Russia (46.2 percent) outperforming countries like Türkiye, where only 19.9 percent reported high digital skills.

On the other end of the spectrum, the South Caucasus region records the highest share of people with no digital skills, averaging 64.0 percent. Armenia (68.1 percent) and Azerbaijan (66.0 percent) have significantly higher share of people with no digital skills compared to Georgia (58.1 percent). Within the Western Balkans, the range is wide: Montenegro leads with 37.3 percent of high-skilled individuals, more than double Albania's 17.1 percent.

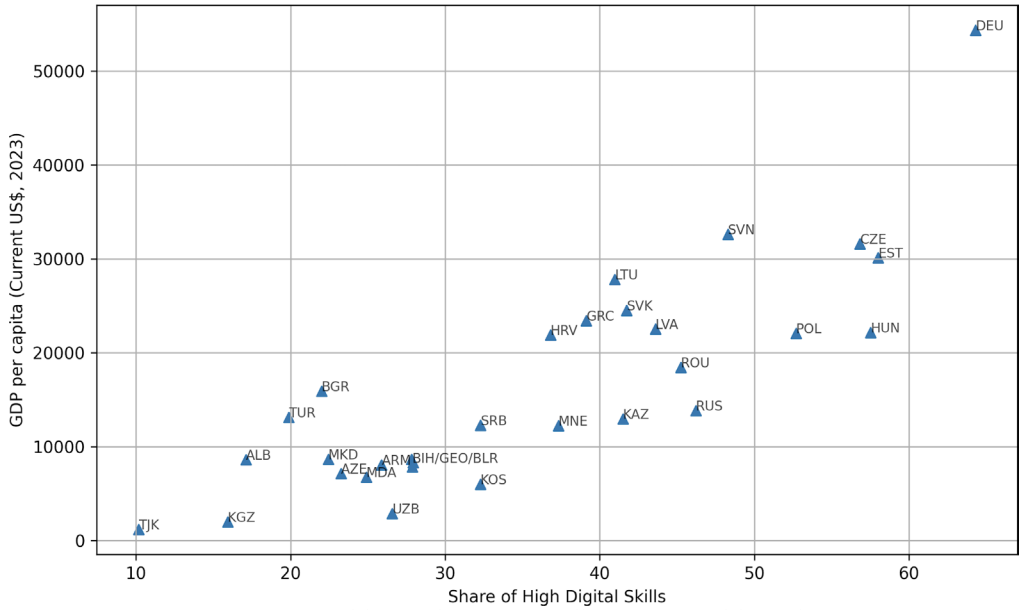
Country-level heterogeneity is even more pronounced. Figure 1 shows that having high skills is positively correlated with GDP per capita. High-income countries such as Germany, Estonia, Hungary, Czechia, and Poland all have more than half of their populations with high digital skills. Correspondingly, the share of individuals with no digital skills in these countries remains below one-third, ranging from 14.5 percent in Czechia to 31.5 percent in Poland. In contrast, low-skill incidence dominates in low-income countries such as Tajikistan (77.9 percent), Kyrgyz Republic (70.8 percent), and Albania (62.6 percent).

Table 1: Summary Statistics by Country and Region

	No digital skills (%)	Basic digital skills (%)	High digital skills (%)
Bulgaria	47.61	30.39	22.00
Croatia	36.18	27.01	36.80
Czechia	14.51	28.66	56.83
Germany	19.25	16.45	64.31
Hungary	25.42	17.06	57.52
Romania	43.29	11.48	45.23
Poland	31.52	15.79	52.69
Slovak Republic	28.14	30.12	41.74
Slovenia	28.26	23.46	48.28
Central Europe	30.45	22.36	47.20
Belarus	24.37	47.77	27.86
Moldova	62.47	12.64	24.89
Eastern Europe	43.39	30.24	26.38
Greece	37.41	23.48	39.11
Russian Federation	31.93	21.86	46.21
Türkiye	56.48	24.27	19.25
Southeast Europe	41.51	23.16	35.32
Estonia	25.49	16.49	58.01
Latvia	33.97	22.44	43.59
Lithuania	21.49	37.54	40.97
Baltic States	26.88	25.52	47.60
Albania	62.57	20.33	17.10
Bosnia and Herzegovina	43.75	28.44	27.81
Kosovo	47.78	19.94	32.28
Montenegro	48.22	14.44	37.33
North Macedonia	56.47	21.08	22.44
Serbia	48.03	19.69	32.29
Western Balkans	51.20	20.64	28.16
Armenia	68.10	6.02	25.88
Azerbaijan	65.99	10.76	23.25
Georgia	58.09	13.99	27.93
South Caucasus	64.02	10.23	25.75
Kazakhstan	32.38	26.12	41.50
Kyrgyz Republic	70.81	13.27	15.92
Tajikistan	77.94	11.91	10.16
Uzbekistan	62.97	10.47	26.56
Central Asia	60.93	15.48	23.59
Total	43.66	20.84	35.51

Notes: *No digital skills:* This category includes people who cannot copy and move files, send emails, install software or devices and write a computer program. *Basic digital skills:* This category includes people who can copy and move files and send emails but they cannot install software or devices and write a computer program. *High digital skills:* This category includes people who can copy and move files, send emails, install software or devices and write a computer program.

Figure 1: Share of high digital skills with GDP per capita (current US$, 2023)



Source: World Development Indicators, World Bank

Table 2 presents the distribution of digital skills across demographic characteristics. Educational attainment shows a strong correlation with digital skills. Among those with high digital skills, 42.6 percent have tertiary degree or higher, while this share drops to 7.3 percent among those with less than upper secondary education. Individuals with lower education make up 26.4 percent of the no-digital-skills group, but only 8.7 percent of the basic skilled group.

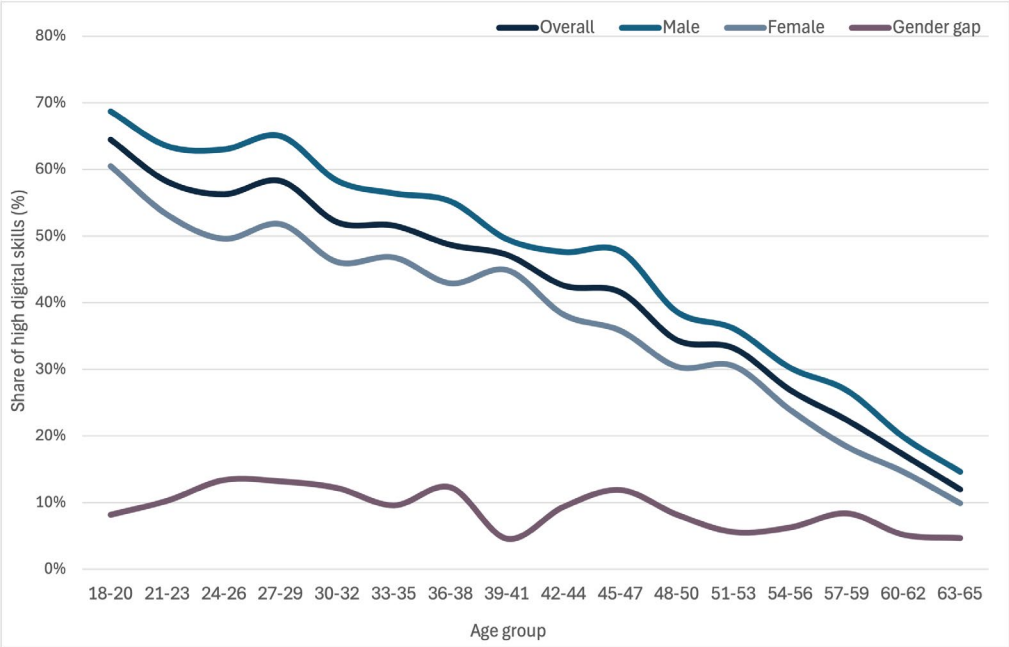
Over half of the respondents are between the ages of 40 and 64 (52 percent) in our sample. Among respondents with no digital skills, this age group also shows the highest share (66.7 percent) while they constitute only 38.3 percent of individuals in the high digital skill group. The prevalence of high digital skills peaks among the 25–39 age group, at 43.4 percent, significantly higher than the average in our sample. The 18–24 age group constitutes 18.4 percent of high digital skills which is higher than the sample average (13 percent).

Table 2: Summary Statistics by variables

	No digital skills (%)	Basic digital skills (%)	High digital skills (%)	Sample(%)
Age				
18–24 years old	7.80	11.07	18.36	13.05
25–39 years old	25.51	33.25	43.38	34.90
40–64 years old	66.69	55.68	38.26	52.05
Education				
Less than (upper) secondary education	26.16	8.69	7.32	14.13
(Upper) Secondary education	62.73	60.22	50.10	56.77
Higher education	11.12	31.08	42.58	29.10
Gender				
Male	45.63	42.62	54.15	48.58
Female	54.37	57.38	45.85	51.42
Urban				
Rural	55.39	35.03	34.73	41.92
Urban	44.61	64.97	65.27	58.08
Sector				
Agriculture, Forestry, Fishing, Mining	8.70	4.33	2.06	4.08
Construction	14.88	9.82	9.48	10.72
Manufacturing	13.23	10.84	10.84	11.35
Transportation, wholesale and retail trade	1.15	3.09	6.17	4.27
Finance, insurance and real estate	20.83	22.73	20.11	20.96
Services	41.21	49.21	51.35	48.61
Occupation				
Elementary workers	52.77	30.60	23.80	31.79
Services / clerical workers	31.08	38.90	35.52	35.49
Managers / professional workers	16.15	30.50	40.68	32.73
Employment				
Self-employed	11.68	8.14	7.18	8.40
Employer	3.72	4.18	4.50	4.25
Employee	79.38	85.96	86.19	84.67
Other	5.22	1.71	2.14	2.68
Experience				
Less than 1 year	15.17	8.40	9.15	10.24
1–3 years	24.09	23.04	29.25	26.48
More than 6 years	60.74	68.57	61.60	63.28
Parental Education				
Less than (upper) secondary education	40.19	22.15	15.11	25.34
(Upper) Secondary education	47.11	56.93	51.74	51.33
Higher education	12.70	20.92	33.15	23.32

Notes: ***No digital skills:*** **This category includes people who cannot copy and move files, send emails, install software or devices and write a computer program.** ***Basic digital skills:*** **This category includes people who can copy and move files and send emails but they cannot install software or devices and write a computer program.** ***High digital skills:*** **This category includes people who can copy and move files, send emails, install software or devices and write a computer program.**

Figure 2: Share of high digital skills by age group



Gender differences are also evident. Men make up 54.2 percent of the high digital skills group, compared to 45.8 percent for women. This contrasts with the no-digital-skills group, where women account for a larger share (54.4 percent). A more pronounced divide exists by urbanity: 65.3 percent of individuals with high digital skills reside in urban areas, while 55.4 percent of those with no digital skills live in rural areas.

Moreover, a more detailed analysis shows a persistent gap between age and gender groups. In particular, while younger cohorts have a higher incidence of high digital skills, the share of individuals having high digital skills experiences a substantial decline with age, reaching only 10 percent in the older adult population. Furthermore, a persistent and significant gender gap is observed in digital skills in Figure 2. This gap, characterized by a lower share of women with high digital skills, remains relatively constant for all age groups.

Sectoral and occupational patterns align with expectations. Workers in services, clerical, and professional occupations dominate the high-skilled group. Managers and professionals make up 40.7 percent of those with high digital skills, compared to only 16.2 percent in the no-digital-skills category. Conversely, elementary workers comprise over half (52.8 percent)

of those without digital skills. Services and clerical occupations represent the highest share of those with basic skills (38.9 percent), which is consistent with job functions requiring only routine digital engagement.

Employment type does not show significant difference among different digital skill groups. Employees constitute the majority across all skill levels but are slightly more represented among high digital skill individuals (86.2 percent). Self-employed individuals have lower representation in the high digital skills group (7.2 percent).

Finally, individuals with more than six years of work experience make up the largest group across all skill categories. Among those with high digital skills, 61.6 percent fall into this category. Parental education appears to be a strong intergenerational correlate: 33.2 percent of those with high digital skills have at least one parent with higher education, compared to only 12.7 percent among those with no digital skills.

5 Results

This section initially presents the findings on the determinants influencing the acquisition of digital skills. Drawing from human capital accumulation theory, we test an array of socio-economic characteristics that exert a significant influence on the formation of digital skills. For instance, individual characteristics including age, gender and schooling, parental factors, and household characteristics are key factors that can differentially impact an individual's propensity to acquire and develop these skills. Subsequently, Section 5.2 presents the results on the wage premium associated with digital skills acquisition within the ECA region.

5.1 Socio-economic determinants of digital skills

To identify the determinants of digital skill acquisition, we estimate an ordered-logit model in which the dependent variable takes three ordered values—0 (no digital skills), 1 (basic skills) and 2 (high skills). Given the nature of our dependent variables, we use the following

ordered logistic regression,

$$digital_{ic} = \beta_0 + \beta_1 X_{ic} + \delta_c + \epsilon_{ic} \tag{2}$$

where $digital_{ic}$ is self-assessed latent digital skills, X_{ic} is the individual and household level characteristics of person i in country c, δ_c is country fixed effects and ϵ_{ic} is a time-varying logit-distributed error term. Table 3 presents the ordered logit estimates in Column (1), Columns (2)-(4) show the marginal effects (MEs). MEs indicate, in percentage-point (p.p) terms, how the probability of belonging to each skill level changes when an explanatory variable rises by one unit. In this case, the results can be understood as the percentage point change in the probability of belonging to each digital skill level.

Pooled sample results show that individual and household-level characteristics have significant impacts on acquisition of digital skills. In particular, education level has the highest marginal effect where having a university degree increases the probability of having high digital skills by 32.4 percentage points. Moreover, secondary education graduates are 12.6 percentage points more likely to have high digital skills compared to people with lower educational attainment.

Household income is positively associated with having high digital skills, indicating that household financial resources amplify those intergenerational effects to a great extent. For instance, individuals are 17.6 percent points less likely to obtain high digital skills if they are from a low-income household. The gap for low-income households could be due to limited access and opportunities to accumulate digital skills. Because device ownership and broadband subscriptions are consumption goods, financial constraints can delay adoption and limit learning opportunities precisely in low-income households. Moreover, factors such as lower quality education and less exposure to digital tools could create the gap for low-income households and generate a digital divide.

Economic literature shows that parental education is an important factor for human capital accumulation of their children (Lochner (2016), Abramitzky et al. (2025)). Looking

Table 3: Marginal effects of ordered logit (Pooled)

	Coefficient		Marginal Effects					
			No Skills		Basic Skills		High Skills	
Age								
25–39 years old	-0.488***	(0.047)	0.078***	(0.007)	0.024***	(0.003)	-0.102***	(0.010)
40 - 64 years old	-1.201***	(0.045)	0.215***	(0.007)	0.031***	(0.003)	-0.246***	(0.009)
Demographics								
Female	-0.319***	(0.028)	0.059***	(0.005)	0.004***	(0.000)	-0.063***	(0.005)
Urban	0.491***	(0.028)	-0.092***	(0.005)	-0.006***	(0.001)	0.098***	(0.006)
Education								
(Upper) Secondary education	0.664***	(0.047)	-0.142***	(0.010)	0.016***	(0.002)	0.126***	(0.008)
Higher education	1.581***	(0.054)	-0.307***	(0.011)	-0.017***	(0.003)	0.324***	(0.010)
Father's Education								
(Upper) Secondary education	-0.051	(0.045)	0.009	(0.008)	0.001	(0.001)	-0.010	(0.009)
Higher education	-0.021	(0.059)	0.004	(0.011)	0.000	(0.001)	-0.004	(0.012)
Mother's Education								
(Upper) Secondary education	0.365***	(0.043)	-0.071***	(0.008)	-0.003***	(0.000)	0.073***	(0.009)
Higher education	0.673***	(0.058)	-0.125***	(0.011)	-0.012***	(0.002)	0.137***	(0.012)
Household Income								
Low Income	-0.893***	(0.032)	0.177***	(0.006)	-0.001	(0.001)	-0.176***	(0.006)
Observations	20,952		20,952		20,952		20,952	

Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. Shows marginal effects of probability of having advanced skills. The dependent variable is a categorical variable where 0 indicates No digital skills, 1 equals Basic skills, 2 equals High skills. Low household income is the bottom 40 percent of the within-country wage distribution. The omitted (benchmark) categories are 15- to 24-year-olds, males, rural residents, persons with less than upper-secondary schooling, and households in the top six national income deciles.

deeper into how intergenerational effects could play out, we find that individuals who lower educated mothers in particular are less likely to possess digital skills. In the pooled ordered-logit estimates, a mother who completed upper-secondary school raises her child's chances of achieving digital skill by 7.3 p.p., and a university-level educated mother lifts it by 13.7 p.p., which is also nearly double the effect size. The corresponding coefficients for fathers are statistically insignificant.

Gender differences, though smaller than educational effects, remain statistically significant. The marginal effect for females indicates a lower probability of acquiring high digital skills, with females having 6.3 p.p. lower probability. This could provide a new input for gender gap in labor market outcomes in Europe, mirroring a regional wage gap of roughly 30 percent and female labor-force participation in the ECA region.[2] Similarly, urban residence

[2] See World Bank data https://genderdata.worldbank.org/en/home.

Table 4: Marginal effects of having high digital skills

	Central Europe	Eastern Europe	Southeast Europe	Baltic States	Western Balkans	South Caucasus	Central Asia
Age							
25–39 years old	-0.099***	-0.233***	-0.022	-0.137***	-0.111***	-0.160***	-0.080***
	(0.018)	(0.038)	(0.027)	(0.029)	(0.019)	(0.028)	(0.018)
40–64 years old	-0.292***	-0.444***	-0.157***	-0.400***	-0.273***	-0.345***	-0.165***
	(0.018)	(0.036)	(0.026)	(0.028)	(0.018)	(0.026)	(0.017)
Demographics							
Female	-0.067***	-0.017	-0.058***	-0.110***	-0.041***	-0.068***	-0.054***
	(0.011)	(0.017)	(0.016)	(0.021)	(0.010)	(0.015)	(0.011)
Urban	0.054***	0.067***	-0.040	-0.075***	0.016	0.103***	0.091***
	(0.011)	(0.019)	(0.021)	(0.023)	(0.011)	(0.016)	(0.012)
Education							
(Upper) Secondary education	0.129***	0.166***	0.196***	0.043	0.168***	-0.028	0.068***
	(0.018)	(0.020)	(0.021)	(0.045)	(0.013)	(0.033)	(0.019)
Higher education	0.299***	0.337***	0.366***	0.205***	0.343***	0.184***	0.339***
	(0.022)	(0.029)	(0.026)	(0.048)	(0.019)	(0.037)	(0.024)
Father's Education							
(Upper) Secondary education	0.038*	0.041	0.018	-0.052	0.046**	0.046	-0.001
	(0.017)	(0.028)	(0.025)	(0.034)	(0.016)	(0.034)	(0.028)
Higher education	0.090***	0.094*	0.075*	-0.018	0.103***	0.130***	-0.010
	(0.026)	(0.040)	(0.035)	(0.040)	(0.027)	(0.037)	(0.029)
Mother's Education							
(Upper) Secondary education	0.061***	0.109***	0.137***	0.130***	0.103***	0.061*	0.058**
	(0.016)	(0.027)	(0.028)	(0.039)	(0.016)	(0.029)	(0.020)
Higher education	0.109***	0.143***	0.215***	0.097*	0.151***	0.055	0.161***
	(0.027)	(0.037)	(0.038)	(0.044)	(0.031)	(0.032)	(0.027)
Household Income							
Low income	-0.175***	-0.077***	-0.104***	-0.177***	-0.096***	-0.180***	-0.099***
	(0.014)	(0.018)	(0.017)	(0.028)	(0.012)	(0.016)	(0.011)
Observations	5,904	1,365	2,325	1,533	4,338	2,114	3,373

Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. Shows the marginal effects of the probability of having advanced skills. The dependent variable is a categorical variable where 0 indicates No digital skills, 1 equals Basic skills, and 2 equals High skills. Low household income is the bottom 40 percent of the within-country wage distribution. The omitted (benchmark) categories are 15- to 24-year-olds, males, rural residents, persons with less than upper-secondary schooling, and households in the top six national income deciles.

generally creates an advantage, urban residents are 9.8 p.p. more likely to have high digital skills and 9.2 p.p. less likely to have low digital skills compared to rural residents.

Moreover, the results show significant heterogeneity across regions. Table 4 shows that education is a significant determinant in all regions for digital skill acquisition. The effect of tertiary education varies between 18.4 p.p. in South Caucasus and around 34-36 p.p. increase in probability of having high digital skills in Central Asia, Eastern Europe and Southeast Europe. Similar to the pooled sample results, individuals from low-income households are significantly less likely to have high digital skills, with the marginal effect varying between 10 p.p. in Central Asia and the Western Balkans and 18 p.p. in the South Caucasus. The effect is steepest in Romania (27.6 p.p.), the Slovak Republic (26.4 p.p.), and Armenia (22.6 p.p.), but insignificant in the Kyrgyz Republic (see Table 9 in the Appendix).

Demographic characteristics show similar patterns with different magnitudes across regions. Being female is associated with a significantly lower probability of having high digital

skills in all regions, with the largest gender gap in the Baltic States (–11 p.p.). Age also plays a substantial role: compared to younger individuals (18–24), those aged 40–64 are 15–44 p.p. less likely to report high digital skills, with the largest age penalty in Eastern Europe and the Baltic States, with 44.4 p.p. and 40 p.p., respectively. Similarly, the urban-rural divide is also significant in all regions, with the highest divide being in the South Caucasus, with 10.3 p.p. greater likelihood of having high digital skills for urban residents compared to the rural population.

More interestingly, the role of parents has significant differences across regions. In general, individuals with mothers with higher education degrees are more likely to acquire digital skills but in some regions fathers' education level also has a significant influence. For instance, in Central Europe, Eastern Europe and the Western Balkans, both parents' educational attainment has a significant impact on their children's digital skills. In the Baltic States and Central Asia, only mothers' education significantly contributes to digital skill development of their children. This relationship is reversed in the South Caucasus where only fathers' educational attainment supports digital skills.

A key assumption for ordered logistic regression models is the parallel slopes assumption, which posits that the effect of the independent variables is consistent across all cumulative categories of the ordinal dependent variable. In particular, the coefficients estimating the relationship between the lowest category versus all higher categories are constrained to be equal to the coefficients estimating the relationship between the subsequent lowest category versus all higher categories, and so forth. Violation of this assumption can lead to biased results. We therefore estimate a logit model and the marginal effects for the probability of having high digital skills, distinguishing this category from all others ("no high digital skills") are presented in Table 5.

Estimations from logit model on determinants of high digital skills show similar impacts to previous model where we assumed ordinal category of digital skills with three categories. The results show that not only the sign of the coefficients but also the magnitude of the coefficients show very similar results. For instance, individual characteristics, including age, gender and

Table 5: Marginal effects of High Skills, by Region

	ECA	Central Europe	Eastern Europe	Southeast Europe	Baltic States	Western Balkans	South Caucasus	Central Asia
Age								
25–39 years old	-0.101***	-0.100***	-0.218***	-0.040	-0.133***	-0.107***	-0.154***	-0.092***
	(0.010)	(0.019)	(0.043)	(0.030)	(0.030)	(0.021)	(0.030)	(0.021)
40-64 years old	-0.257***	-0.287***	-0.472***	-0.154***	-0.378***	-0.279***	-0.355***	-0.194***
	(0.010)	(0.018)	(0.041)	(0.029)	(0.029)	(0.020)	(0.028)	(0.021)
Demographics								
Female	-0.088***	-0.095***	-0.066**	-0.077***	-0.147***	-0.052***	-0.079***	-0.080***
	(0.006)	(0.012)	(0.023)	(0.018)	(0.023)	(0.013)	(0.017)	(0.014)
Urban	0.071***	0.047***	0.052*	-0.069**	-0.090***	0.020	0.101***	0.046**
	(0.006)	(0.012)	(0.025)	(0.023)	(0.024)	(0.013)	(0.018)	(0.014)
Education								
(Upper) Secondary education	0.089***	0.080***	0.088**	0.177***	0.020	0.149***	-0.043	0.140***
	(0.011)	(0.020)	(0.033)	(0.028)	(0.049)	(0.020)	(0.039)	(0.020)
Higher education	0.272***	0.255***	0.282***	0.319***	0.163**	0.309***	0.164***	0.380***
	(0.012)	(0.023)	(0.042)	(0.032)	(0.052)	(0.025)	(0.043)	(0.025)
Father's Education								
(Upper) Secondary education	-0.021*	0.006	-0.013	0.012	-0.050	0.033	0.047	0.010
	(0.010)	(0.018)	(0.037)	(0.029)	(0.037)	(0.019)	(0.039)	(0.037)
Higher education	0.007	0.062*	0.085	0.067	-0.012	0.101**	0.154***	0.022
	(0.013)	(0.028)	(0.051)	(0.038)	(0.043)	(0.031)	(0.042)	(0.039)
Mother's Education								
(Upper) Secondary education	0.082***	0.056**	0.041	0.150***	0.125**	0.086***	0.067*	0.072**
	(0.010)	(0.018)	(0.036)	(0.031)	(0.042)	(0.019)	(0.033)	(0.026)
Higher education	0.142***	0.109***	0.071	0.226***	0.083	0.139***	0.048	0.179***
	(0.014)	(0.029)	(0.046)	(0.041)	(0.048)	(0.034)	(0.036)	(0.032)
Household Income								
Low income	-0.153***	-0.121***	-0.039	-0.124***	-0.137***	-0.086***	-0.168***	-0.084***
	(0.007)	(0.015)	(0.024)	(0.021)	(0.030)	(0.016)	(0.019)	(0.014)
Observations	20,952	5,904	1,365	2,325	1,533	4,338	2,114	3,373

Notes: *** , ** , and * indicate significance at the 1, 5, and 10 percent levels, respectively. Shows marginal effects of probability of having advanced skills. The dependent variable is a categorical variable where 0 indicates No digital skills, Basic skills, 1 equals High skills. Low household income is the bottom 40 percent of the within-country wage distribution. The omitted (benchmark) categories are 15- to 24-year-olds, males, rural residents, persons with less than upper-secondary schooling, and households in the top six national income deciles.

education, are negatively associated with having high digital skills, while age and education level show the highest negative predictor. Individuals with higher education experience large and statistically significant increases in the probability of being in the high digital skills group. The effect is particularly pronounced in Central Asia (38 percentage points), Southeast Europe (31.9 pp), and the Western Balkans (30.9 pp). On the other hand, family background is significantly associated with acquiring high-digital skills. Father's education is generally insignificant or weakly associated with digital skill attainment, whereas mother's education shows more robust effects, particularly in less economically developed regions. For instance, in Southeast Europe, having a mother with higher education increases the probability of high digital skills by 22.6 pp; the effect is 13.9 pp in the Western Balkans and 17.9 pp in Central Asia.

Overall, the results highlight persistent inequalities in digital skill acquisition linked to socioeconomic background, gender, and geography. Policies aiming to close these gaps may need to target not only expansion of formal education, but also structural constraints related to income, gender norms, and regional disparities.

5.2 Wage premium for digital skills

This section estimates the wage premium for digital skills in the ECA region. The Mincerian wage regression specified in Equation 1 is used to understand the relationship between digital skills and wages, as defined in Section 3. Table 7 presents the results for the pooled regression for the ECA region. The results show a positive and significant association between digital skills and wages, with effect sizes increasing by skill level. In particular, high digital skills are associated with a 22.4 to 18.9 percent increase in monthly wages in the region depending on the model specification. When we estimate the impact of digital skills with the very basic model, individuals with basic digital skills earn 13.8 percent higher salaries and individuals with high digital skills have 22.4 percent higher salaries compared to individuals with no digital skills after controlling for individual characteristics including, age, gender, education and residency. The impact of digital skills declines slightly to 11.5 percent for basic digital skills and 18.9 percent for high digital skills after controlling for employment sector, occupation type, employment status, experience, parent's education, firm size and firm ownership.

Wage premium of digital skill varies significantly across the region. Basic digital skills are not significantly associated with a wage premium in many regions and are only significantly associated with higher wages in Central Europe and Eastern Europe. The wage premium associated with basic digital skills is 30.7 percent in the Eastern Europe region compared to individuals with no digital skills. Moreover, high digital skills are significantly associated with higher earnings in all regions except Southeast Europe, the Baltic States and the Western Balkans. The highest wage premium of high digital skills is estimated in Central Asia with a 47.7 percent increase in salaries compared to individuals with no digital skills. The wage premium of high digital skills is 26.7 percent in Eastern Europe and approximately 23.5 and 19.5 percent in the South Caucasus and Central Europe, respectively.

The heterogeneity of the wage premium for digital skills is much higher at the country level.

While basic digital skills are associated with higher earnings in a quarter of the countries, they do not offer a wage premium in majority of countries. On the other hand, wage premium of digital skills is significantly associated with higher earnings in several countries. High digital skills are associated with 134 percent increase in Uzbekistan where our results show the highest wage premium in the ECA region (Table .11). In Moldova, both basic and high digital skills are associated with around 50 percent of increase in earnings. The results show that the wage premium of digital skills varies between 14 and 34 percent in other economies including Bulgaria, Greece, Kazakhstan, Kosovo, Lithuania, Romania, the Slovak Republic, Slovenia and Tajikistan. However, some labor markets do not offer a wage premium for digital skills identified in our model, including Croatia, Estonia, Georgia, Latvia and Germany.

In addition to digital skills, the Mincerian regressions also provide important insights about association between individual and household characteristics and wages. Age is positively associated with wages in most regions, with the strongest effect observed in the South Caucasus (6 percent increase per year of age). In contrast, being female is consistently associated with lower wages across all regions. The wage penalty is particularly pronounced in the South Caucasus and the Baltic States, where women earn approximately 30 percent less than men, underscoring significant gender wage disparities. Combined with the results from Table 4, which show the Baltic States also have the largest gender gap in the probability of possessing high digital skills, these findings may suggest addressing gender inequality—particularly in digital skill acquisition—as a pathway to reducing wage gaps.

Occupational categories reveal that, relative to elementary workers, managerial and professional roles are significantly and positively associated with higher wage returns in some regions. The strongest effect is observed in the Baltic States, where these occupations are linked to nearly a 17 percent wage increase, followed by Western Balkans (12.3 percent). In Central Asia, no statistically significant associations are found across industry or occupational categories, possibly suggesting weaker labor market differentiation in that region. In majority of regions, employment in foreign firms and larger firms are associated with higher

Table 6: Impact of digital skills on monthly wages

	(1)	(2)	(3)	(4)	(5)	(6)
Digital Skills						
Basic skills	0.138***	0.138***	0.130***	0.116***	0.115***	
	(0.032)	(0.033)	(0.033)	(0.034)	(0.034)	
High skills	0.224***	0.225***	0.214***	0.195***	0.189***	
	(0.033)	(0.034)	(0.035)	(0.036)	(0.036)	
Demographics						
Age	0.028***	0.027***	0.027***	0.017**	0.017**	0.018***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.258***	-0.238***	-0.236***	-0.230***	-0.223***	-0.226***
	(0.016)	(0.018)	(0.020)	(0.020)	(0.020)	(0.020)
Urban	0.105***	0.102***	0.103***	0.101***	0.095***	0.098***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)
Education						
(Upper) Secondary	0.092**	0.097***	0.094**	0.067*	0.064*	0.084**
	(0.030)	(0.029)	(0.029)	(0.029)	(0.029)	(0.026)
Higher education	0.328***	0.342***	0.305***	0.261***	0.258***	0.291***
	(0.031)	(0.031)	(0.033)	(0.034)	(0.034)	(0.033)
Employment Sector						
Construction		0.143*	0.131*	0.130	0.126	0.136*
		(0.066)	(0.066)	(0.068)	(0.069)	(0.067)
Manufacturing		0.048	0.035	0.039	0.004	0.007
		(0.065)	(0.064)	(0.067)	(0.070)	(0.068)
Transport, Trade, and Retail		0.118	0.101	0.098	0.088	0.115
		(0.070)	(0.069)	(0.071)	(0.071)	(0.070)
Finance and Real Estate		0.045	0.042	0.042	0.035	0.043
		(0.064)	(0.063)	(0.066)	(0.066)	(0.065)
Services		-0.000	-0.033	-0.034	-0.023	-0.008
		(0.067)	(0.066)	(0.068)	(0.068)	(0.066)
Occupation Type						
Clerical / Service Work			-0.007	-0.008	-0.007	0.006
			(0.022)	(0.022)	(0.022)	(0.023)
Manager / Professional			0.106***	0.098**	0.100***	0.129***
			(0.030)	(0.030)	(0.029)	(0.028)
Experience				0.091***	0.091***	0.092***
				(0.014)	(0.014)	(0.013)
Parental education				0.035**	0.032*	0.041**
				(0.013)	(0.012)	(0.013)
Firm Characteristics						
Private firm					0.054**	0.067**
					(0.021)	(0.021)
Foreign firm					0.171***	0.157***
					(0.046)	(0.048)
Medium size (20-99 employees)					0.061***	0.075***
					(0.018)	(0.018)
Large size (more than 100 employees)					0.091***	0.109***
					(0.021)	(0.020)
Constant	6.035***	6.011***	6.027***	6.012***	5.945***	5.931***
	(0.166)	(0.175)	(0.175)	(0.174)	(0.175)	(0.185)
Observations	8,455	8,450	8,348	8,268	8,268	8,845
R^2	0.936	0.937	0.937	0.937	0.937	0.932

Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. The dependent variable is log monthly wage adjusted by 2021 PPP generated by the International Comparison Program. The omitted (benchmark) categories are no digital skills, males, rural residents, persons with less than upper-secondary schooling, the agriculture industry, elementary workers, and employers.

Table 7: Impact of digital skills on monthly wages

	Central Europe	Eastern Europe	Southeast Europe	Baltic States	Western Balkans	South Caucasus	Central Asia
Basic skills	0.101***	0.307***	0.135	0.057	0.004	0.071	0.280
	(0.030)	(0.076)	(0.145)	(0.056)	(0.061)	(0.097)	(0.160)
High skills	0.195***	0.267**	0.211	0.092	0.086	0.235*	0.477*
	(0.028)	(0.088)	(0.142)	(0.057)	(0.063)	(0.101)	(0.198)
Demographics							
Age	0.023***	0.011	-0.002	0.007	0.022	0.060**	-0.038
	(0.006)	(0.014)	(0.016)	(0.009)	(0.012)	(0.019)	(0.042)
Age^2	-0.000***	-0.000	-0.000	-0.000	-0.000	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Female	-0.237***	-0.279***	-0.227**	-0.306***	-0.135***	-0.281***	-0.080
	(0.018)	(0.040)	(0.070)	(0.033)	(0.037)	(0.074)	(0.183)
Urban	0.069***	0.091	0.033	-0.021	0.117*	0.130	0.288*
	(0.018)	(0.048)	(0.047)	(0.031)	(0.046)	(0.069)	(0.121)
Education							
(Upper) Secondary education	0.112***	-0.087	0.040	0.051	0.146*	-0.131	0.303
	(0.031)	(0.149)	(0.096)	(0.088)	(0.071)	(0.143)	(0.190)
Higher education	0.326***	0.049	0.249**	0.301**	0.214*	0.091	0.543***
	(0.039)	(0.177)	(0.091)	(0.093)	(0.091)	(0.155)	(0.154)
Employment Sector Construction	0.134*	0.155	0.110	0.097	-0.101	0.412*	0.348
	(0.064)	(0.118)	(0.128)	(0.092)	(0.117)	(0.179)	(0.376)
Manufacturing	0.016	-0.004	0.094	0.000	-0.226	-0.226	0.445
	(0.060)	(0.099)	(0.131)	(0.085)	(0.116)	(0.173)	(0.393)
Finance and Real Estate	0.141	0.214	0.023	0.087	-0.155	0.057	-0.047
	(0.075)	(0.121)	(0.165)	(0.097)	(0.133)	(0.195)	(0.328)
Transport, Trade and Retail	0.097	0.067	0.068	0.072	-0.253*	-0.171	0.077
	(0.058)	(0.096)	(0.144)	(0.085)	(0.125)	(0.142)	(0.310)
Services	0.092	-0.022	-0.089	0.074	-0.284*	-0.269*	0.006
	(0.057)	(0.102)	(0.197)	(0.084)	(0.124)	(0.131)	(0.319)
Occupation							
Clerical / Service Work	-0.009	-0.030	0.051	0.027	-0.022	-0.093	-0.007
	(0.023)	(0.072)	(0.121)	(0.046)	(0.040)	(0.117)	(0.110)
Manager / Professional	0.074*	0.112	0.169	0.167***	0.123*	-0.018	0.014
	(0.031)	(0.090)	(0.109)	(0.048)	(0.056)	(0.134)	(0.180)
Firm Characteristics							
Private firms	0.028	0.191***	-0.070	0.160***	0.001	0.116	0.125
	(0.021)	(0.056)	(0.095)	(0.037)	(0.052)	(0.086)	(0.096)
Foreign firms	0.078	0.433***	0.111	0.407***	0.171*	0.411*	0.354
	(0.042)	(0.124)	(0.079)	(0.083)	(0.080)	(0.195)	(0.309)
Medium size (20-99 employees)	0.054**	0.199***	0.030	0.074*	0.003	0.063	0.076
	(0.020)	(0.058)	(0.084)	(0.035)	(0.039)	(0.084)	(0.078)
Large size (over 100 employees)	0.103***	0.211**	0.126*	0.151***	-0.026	0.095	-0.146
	(0.022)	(0.064)	(0.054)	(0.042)	(0.053)	(0.080)	(0.178)
Experience	0.072**	0.048	0.159***	0.119***	0.040*	0.062	0.299***
	(0.022)	(0.038)	(0.044)	(0.025)	(0.019)	(0.061)	(0.090)
Parental education	-0.011	0.029	0.035	0.083***	-0.004	0.065	0.049
	(0.015)	(0.037)	(0.026)	(0.023)	(0.034)	(0.051)	(0.098)
Constant	6.392***	-2.651***	6.732***	6.745***	6.298***	5.154***	5.795***
	(0.142)	(0.288)	(0.377)	(0.216)	(0.296)	(0.454)	(0.706)
Observations	2,982	685	897	969	1,479	426	830
R^2	0.327	0.988	0.322	0.489	0.128	0.439	0.223

Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. The dependent variable is log monthly wage adjusted by 2021 PPP generated by the International Comparison Program. The omitted (benchmark) categories are no digital skills, males, rural residents, persons with less than upper-secondary schooling, the agriculture industry, elementary workers, and employers. It is also worth noting that in August 2022, the Belarusian ruble depreciated by 23 percent against the US dollar, with inflation reaching 17.9 percent. Additionally, nearly half of the observations for Poland were missing wage information, impacting the reliability of the data for these countries. Lastly, Türkiye was recovering from a catastrophic earthquake when the survey took place. Hence, we acknowledge the results may be peculiar compared to other years.

compensation. The foreign firm wage premium is 41 percent in the Baltic States and the South Caucasus compared to public employment, while the large firm premium is significantly associated with higher salaries in Eastern Europe with 43.3 percent.

Work experience, which is both positive and significant, displays a heterogeneous pattern across regions. Work experience shows a consistently positive association, with the steepest returns observed in Central Asia (29.9 percent), Southeast Europe (15.9 percent), and the Baltic States (11.9 percent), reflecting rapid skill acquisition in these catching-up economies. The premium moderates to roughly 7 percent in Central Europe and is small and statistically insignificant in Eastern Europe.

5.3 Heterogeneity Analysis

To explore the differential impact of digital skills on wages, we conduct a heterogeneity analysis examining whether the wage premium associated with digital skills varies across firm size, occupation, and firm type. The analysis helps us to identify whether the returns to digital proficiency are uniformly distributed or concentrated within specific segments of the labor market. By interacting digital skill indicators with firm-level and occupational characteristics in regression models, we identify whether workers in larger firms, certain occupational categories, or specific ownership structures (public, private, or foreign) offer higher wage premiums.

5.3.1 Firm Type

To identify whether the wage premium associated with high digital skills varies by firm type, we interact a high digital skills dummy with categorical indicators for different firm types, public, private, and foreign firms. The regression results presented in Table 8 use public employment as the baseline category. The interaction terms of high digital skills and firm type show that the wage premium for high digital skills does not significantly differ between public and private firms, nor between public and foreign firms. These findings suggest that while

digital skills are generally rewarded in the labor market, the magnitude of the premium does not vary significantly across firm types.

5.3.2 Firm Size

Wage premium of digital skills may also vary if larger firms reward digital skills more than smaller firms. Larger firms often have more advanced digital infrastructure and workflows, making digital skills more integral to job performance and productivity. Moreover, roles in large firms may be more specialized and complex, requiring higher levels of digital proficiency, which in turn results with higher compensation. Table 8 presents the results for the regression whether the wage premium for digital skills differs among small, medium, and large firms. The interaction terms show that the wage premium for high digital skills does not significantly differ between small and medium firms. However, the wage premium is significantly higher in large firms compared to small firms with 11.7 percent higher wages.

5.3.3 Occupation

Digital skills may differ by occupational status as digital skills are often core to job performance in professional and technical occupations. To examine whether the wage premium associated with high digital skills varies across occupational groups, we interact a high digital skills dummy with indicators for three occupation categories: elementary, clerical/service, and professional. However, the wage premium for high digital skills does not significantly differ between elementary and clerical/service and professional occupations. The result highlights that returns to digital skills are broadly consistent across occupational categories.

Table 8: Heterogeneity analysis of digital skills on wages

	(1) Firm type	(2) Firm size	(3) Occupation
High skills	0.115***	0.075**	0.120***
	(0.034)	(0.024)	(0.028)
Occupation			
Clerical / Service Work	-0.000	-0.001	0.020
	(0.023)	(0.023)	(0.029)
Manager / Professional	0.108***	0.108***	0.096
	(0.029)	(0.029)	(0.050)
Firm Characteristics			
Private firms	0.067*	0.055**	0.053*
	(0.033)	(0.021)	(0.021)
Foreign firms	0.071	0.173***	0.173***
	(0.099)	(0.046)	(0.046)
Medium size (20-99 employees)	0.063***	0.062*	0.062***
	(0.018)	(0.028)	(0.018)
Large size (over 100 employees)	0.092***	0.028	0.092***
	(0.020)	(0.039)	(0.021)
High skills × Private firms	-0.023		
	(0.038)		
High skills × Foreign firms	0.161		
	(0.105)		
High skills × Medium size		0.004	
		(0.033)	
High skills × Large size		0.117*	
		(0.049)	
High skills × Clerical / Service Work			-0.038
			(0.032)
High skills × Manager / Professional			0.017
			(0.052)
Constant	5.962***	5.988***	5.972***
	(0.176)	(0.175)	(0.175)
Observations	8,268	8,268	8,268
R^2	0.937	0.937	0.937

Notes: *** , ** , and * indicate significance at the 1, 5, and 10 percent levels, respectively. The dependent variable is log monthly wage adjusted by 2021 PPP generated by the International Comparison Program. The omitted (benchmark) categories are no digital skills, males, rural residents, persons with less than upper-secondary schooling, the agriculture industry, elementary workers.

6 Conclusion and Discussion

Digital skills have been at the forefront of human capital development, providing substantial opportunities for those who are able to leverage them. Digitalization creates a significant impact on the lives of individuals, their employment prospects, and the developmental pathways of nations by effecting transformative changes across multiple sectors. This paper offers one of the first analyses identifying the determinants of digital skills and their impact in the labor market by using internationally comparable data from developing countries. The study provides robust evidence on the critical role of digital skills in shaping labor market outcomes in the ECA region.

Our findings reveal a significant disparity in digital skill acquisition between developing and more developed countries, with the latter exhibiting a more mature landscape of digital proficiency. Within the Europe and Central Asia (ECA) region, the prevalence of individuals lacking digital skills varies substantially, ranging from less than 20 percent in Czechia and Germany to as high as 78 percent in Tajikistan. Furthermore, a clear regional divergence exists, with roughly half the population in Central Europe and the Baltic States possessing high digital skills, a proportion that is halved in Central Asia and the South Caucasus.

The acquisition of digital skills is demonstrably influenced by both individual characteristics (education, gender, and age) and family background (household income, residency, and parental education). The analysis of how socioeconomic factors impact the likelihood of individuals possessing high digital skills is particularly crucial. Such disparities can exacerbate inequalities both across and within countries, especially as economies increasingly transition toward digital service delivery and digital-first models. A lack of essential digital skills among various population segments risks widening existing disparities, potentially deepening the divide between low-income and high-income households (OECD (2016*b*), Bergson-Shilcock & Taylor (2023), OECD (2016*a*)).

Our wage analysis indicates a statistically significant positive correlation between digital

skills and earnings, highlighting digital skills as a key driver of wage premiums. The results also suggest that people with high digital skills earn 19 percent higher wages compared to those with no digital skills. Moreover, the magnitude of this wage premium shows significant heterogeneity across labor markets. In particular, possessing high digital skills is associated with a substantial wage premium of approximately 29-48 percent in Eastern Europe and Central Asia. Even the acquisition of basic digital skills yields considerable gains in Eastern Europe.

This pattern is further reinforced by individual characteristics: higher educational attainment, engagement in managerial or professional occupations, and greater cumulative work experience consistently correlate with increased earnings. Conversely, factors such as gender and rural residency continue to exert a negative influence on wages, offsetting these positive effects. We also find significant wage differentials across industry sectors and employment statuses. Formal wage employment and positions within dynamic private industries (e.g., construction in the South Caucasus, and transport, trade, and retail in Eastern Europe) consistently outperform employment in agriculture and low-productivity service sectors.

In conclusion, our findings underscore the importance of governments prioritizing digital skills development as a cornerstone of contemporary labor market policy in developing countries. This suggests implementing large-scale, accessible digital literacy programs, particularly for rural and low-income communities in developing countries, covering foundational skills. Furthermore, strategies must include granular labor market analyses to inform targeted vocational training and reskilling in dynamic sectors. Finally, integrating digital literacy and computational thinking into national education curricula from early childhood is essential for building a digitally proficient population.

Future research should further explore the causal mechanisms underlying digital skill acquisition and labor market returns in developing countries, as well as the effectiveness of policy interventions aimed at closing digital divides. Such efforts will be vital for ensuring that the benefits of digitalization are equitably distributed across all segments of society.

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Appendix

Table .9: Marginal effects of having high digital skills

	ALB	ARM	AZE	BLR	BIH	BGR	HRV	CZE	EST	GEO	DEU	GRC	HUN	KAZ	KOS	KGZ	LVA	LTU	MDA	MNE	MKD	POL	ROU	RUS	SRB	SVK	SVN	TJK	TUR	UZB
Age																														
25-39 years old	-0.077*	-0.224***	-0.101*	-0.134*	-0.098	-0.061	-0.137*	0.029	-0.094**	-0.167***	-0.029	-0.113*	-0.070	-0.158***	-0.050	-0.070*	-0.230***	-0.080	-0.323***	-0.160**	-0.216***	-0.120*	-0.266***	-0.226***	-0.118*	-0.277***	0.017	-0.035	0.042	-0.162***
	(0.039)	(0.056)	(0.041)	(0.055)	(0.052)	(0.059)	(0.057)	(0.053)	(0.036)	(0.048)	(0.038)	(0.053)	(0.049)	(0.046)	(0.039)	(0.035)	(0.045)	(0.065)	(0.064)	(0.051)	(0.047)	(0.052)	(0.046)	(0.044)	(0.056)	(0.057)	(0.057)	(0.021)	(0.030)	(0.037)
40-64 years old	-0.242***	-0.448***	-0.238***	-0.371***	-0.209***	-0.208***	-0.271***	-0.185***	-0.309***	-0.376***	-0.223***	-0.308***	-0.194***	-0.369***	-0.339***	-0.201***	-0.544***	-0.327***	-0.538***	-0.316***	-0.269***	-0.242***	-0.447***	-0.430***	-0.270***	-0.375***	-0.213***	-0.081***	-0.026	-0.222***
	(0.036)	(0.052)	(0.039)	(0.053)	(0.049)	(0.056)	(0.055)	(0.053)	(0.037)	(0.045)	(0.039)	(0.054)	(0.048)	(0.045)	(0.036)	(0.033)	(0.041)	(0.065)	(0.060)	(0.048)	(0.047)	(0.050)	(0.043)	(0.042)	(0.054)	(0.056)	(0.055)	(0.021)	(0.030)	(0.037)
Demographics																														
Female	-0.016	-0.034	-0.164***	-0.096***	-0.060*	-0.047	-0.126***	-0.076*	-0.101**	-0.001	-0.093**	-0.117***	-0.094**	0.021	-0.073**	-0.077***	-0.042	-0.176***	0.032	-0.019	-0.082***	-0.025	0.002	-0.014	0.008	-0.043	-0.120***	-0.016	-0.048*	-0.097***
	(0.019)	(0.030)	(0.023)	(0.026)	(0.028)	(0.026)	(0.030)	(0.031)	(0.032)	(0.026)	(0.029)	(0.028)	(0.030)	(0.027)	(0.024)	(0.020)	(0.033)	(0.041)	(0.027)	(0.030)	(0.024)	(0.031)	(0.027)	(0.030)	(0.028)	(0.033)	(0.030)	(0.015)	(0.021)	(0.024)
Urban	0.027	0.058	0.072**	0.040	-0.074**	0.083*	0.023	0.084*	-0.069*	0.175***	0.007	0.012	0.016	-0.059*	0.009	0.061**	-0.005	-0.080	0.020	0.090**	-0.029	0.028	0.118***	0.026	0.138***	0.077*	0.095**	0.095***	-0.251	-0.011
	(0.020)	(0.031)	(0.024)	(0.030)	(0.028)	(0.033)	(0.034)	(0.033)	(0.033)	(0.029)	(0.030)	(0.030)	(0.034)	(0.027)	(0.026)	(0.022)	(0.037)	(0.046)	(0.029)	(0.030)	(0.026)	(0.031)	(0.030)	(0.036)	(0.031)	(0.033)	(0.031)	(0.025)	(0.133)	(0.023)
Education																														
(Upper) Secondary education	0.082***	-0.075	-0.021	0.097	0.147***	0.180***	0.106	0.113	0.174*	0.005	0.053	0.275***	0.325***	0.010	0.116***	-0.033	0.059	-0.407***	0.132***	0.195***	0.176***	0.360***	0.184***	-0.140	0.167**	0.212**	0.292***	0.022	0.162***	0.139***
	(0.017)	(0.064)	(0.040)	(0.111)	(0.036)	(0.028)	(0.071)	(0.063)	(0.071)	(0.113)	(0.049)	(0.038)	(0.046)	(0.090)	(0.032)	(0.053)	(0.057)	(0.086)	(0.031)	(0.052)	(0.025)	(0.047)	(0.056)	(0.090)	(0.054)	(0.070)	(0.053)	(0.015)	(0.028)	(0.030)
Higher education	0.308***	0.125	0.166**	0.314**	0.275***	0.406***	0.397***	0.227**	0.375***	0.251*	0.171**	0.536***	0.367***	0.263**	0.349***	0.157**	0.255***	-0.256**	0.270***	0.411***	0.371***	0.493***	0.493***	0.034	0.334***	0.294***	0.443***	0.169***	0.251***	0.515***
	(0.030)	(0.068)	(0.051)	(0.115)	(0.059)	(0.041)	(0.081)	(0.069)	(0.074)	(0.118)	(0.055)	(0.044)	(0.060)	(0.093)	(0.046)	(0.060)	(0.066)	(0.088)	(0.048)	(0.063)	(0.042)	(0.054)	(0.068)	(0.093)	(0.065)	(0.080)	(0.063)	(0.030)	(0.039)	(0.042)
Father's education																														
(Upper) Secondary education	-0.012	0.163**	-0.003	0.113*	0.098*	0.058	0.079	0.065	-0.079	-0.145	0.073	0.034	-0.004	0.104	-0.014	0.057	0.015	-0.188	0.023	-0.033	0.044	0.068	0.115*	0.013	0.025	0.151**	0.073	-0.010	-0.032	-0.098
	(0.026)	(0.057)	(0.041)	(0.046)	(0.043)	(0.058)	(0.050)	(0.076)	(0.041)	(0.116)	(0.057)	(0.043)	(0.041)	(0.067)	(0.030)	(0.044)	(0.047)	(0.105)	(0.035)	(0.055)	(0.038)	(0.049)	(0.046)	(0.052)	(0.045)	(0.055)	(0.044)	(0.028)	(0.033)	(0.087)
Higher education	0.037	0.248***	0.110*	0.239***	-0.043	0.047	0.136	0.106	-0.127*	-0.072	-0.037	0.098	-0.056	0.189*	0.072	0.086	0.029	-0.142	-0.002	0.053	0.136*	0.107	0.099	0.081	0.035	0.236**	0.161*	-0.003	-0.029	-0.062
	(0.052)	(0.057)	(0.051)	(0.062)	(0.075)	(0.076)	(0.076)	(0.089)	(0.051)	(0.122)	(0.097)	(0.067)	(0.068)	(0.075)	(0.050)	(0.052)	(0.065)	(0.112)	(0.055)	(0.074)	(0.068)	(0.082)	(0.078)	(0.059)	(0.072)	(0.088)	(0.069)	(0.029)	(0.058)	(0.091)
Mother's education																														
(Upper) Secondary education	0.050	-0.028	0.061	0.064	0.113**	0.136**	0.146**	0.032	0.191**	0.089	-0.064	0.053	0.198***	0.087	0.067	0.007	0.127*	0.043	0.077*	0.135**	0.116**	0.027	-0.042	0.162**	0.191***	0.098	0.100*	-0.021	0.087	-0.087
	(0.027)	(0.082)	(0.034)	(0.054)	(0.042)	(0.049)	(0.049)	(0.056)	(0.059)	(0.100)	(0.047)	(0.044)	(0.044)	(0.066)	(0.037)	(0.046)	(0.053)	(0.122)	(0.038)	(0.048)	(0.042)	(0.045)	(0.037)	(0.055)	(0.045)	(0.054)	(0.043)	(0.021)	(0.048)	(0.071)
Higher education	0.013	-0.017	0.070	0.085	0.362***	0.251***	0.180*	0.152*	0.242***	0.065	-0.155	0.067	0.132*	0.143	0.120	0.100	0.121	0.035	0.214**	0.187*	0.179*	-0.002	-0.017	0.218***	0.196*	0.254**	0.183**	0.049	0.085	-0.115
	(0.058)	(0.083)	(0.042)	(0.063)	(0.105)	(0.074)	(0.087)	(0.075)	(0.068)	(0.106)	(0.099)	(0.074)	(0.064)	(0.074)	(0.071)	(0.059)	(0.065)	(0.126)	(0.067)	(0.077)	(0.073)	(0.086)	(0.082)	(0.065)	(0.081)	(0.095)	(0.067)	(0.033)	(0.108)	(0.077)
Demographics																														
Low income	-0.083***	-0.203***	-0.152***	-0.016	-0.116***	-0.158***	-0.070	-0.146***	-0.131**	-0.176***	-0.088*	-0.110***	-0.125**	-0.126***	-0.074**	-0.020	-0.206***	-0.131*	-0.130***	-0.090*	-0.117***	0.013	-0.256***	-0.174***	-0.088*	-0.221***	-0.115**	-0.047**	-0.034	-0.173***
	(0.022)	(0.030)	(0.026)	(0.027)	(0.033)	(0.027)	(0.038)	(0.039)	(0.043)	(0.030)	(0.038)	(0.031)	(0.038)	(0.029)	(0.025)	(0.021)	(0.042)	(0.051)	(0.030)	(0.036)	(0.025)	(0.044)	(0.036)	(0.033)	(0.037)	(0.041)	(0.038)	(0.014)	(0.023)	(0.025)
Observations	725	650	792	821	674	607	631	775	570	672	748	751	627	880	798	791	470	493	544	757	670	631	628	749	714	649	608	848	825	854

Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. Shows marginal effects of probability of having advanced skills. The dependent variable is a categorical variable where 0 indicates No digital skills, 1 equals Basic skills, 2 equals High skills. Low household income is the bottom 40 percent of the within-country wage distribution. The omitted (benchmark) categories are 15- to 24-year-olds, males, rural residents, persons with less than upper-secondary schooling, and households in the top six national income deciles.

Table .10: Marginal effects of High Skills, by country

	ALB	ARM	AZE	BLR	BIH	BGR	HRV	CZE	EST	GEO	DEU	GRC	HUN	KAZ	KOS	KGZ	LVA	LTU	MDA	MNE	MKD	POL	ROU	RUS	SRB	SVK	SVN	TJK	TUR	UZB
Age																														
25-39 years old	-0.060	-0.223***	-0.082	-0.133*	-0.133*	-0.058	-0.134*	0.029	-0.094*	-0.183***	-0.029	-0.118*	-0.081	-0.146**	-0.069	-0.096*	-0.239***	-0.045	-0.299***	-0.157**	-0.225***	-0.107*	-0.274***	-0.207***	-0.102	-0.284***	0.022	-0.025	0.030	-0.177
	(0.046)	(0.057)	(0.045)	(0.057)	(0.058)	(0.069)	(0.061)	(0.054)	(0.039)	(0.053)	(0.038)	(0.056)	(0.050)	(0.049)	(0.045)	(0.043)	(0.048)	(0.072)	(0.068)	(0.052)	(0.054)	(0.053)	(0.047)	(0.046)	(0.060)	(0.065)	(0.060)	(0.030)	(0.035)	(.)
40–64 years old	-0.228***	-0.487***	-0.235***	-0.366***	-0.244***	-0.207**	-0.247***	-0.177***	-0.287***	-0.386***	-0.214***	-0.301***	-0.209***	-0.348***	-0.378***	-0.255***	-0.524***	-0.277***	-0.544***	-0.326***	-0.326***	-0.239***	-0.448***	-0.413***	-0.286***	-0.341***	-0.199***	-0.084**	0.048	-0.245
	(0.045)	(0.053)	(0.043)	(0.054)	(0.057)	(0.066)	(0.059)	(0.054)	(0.039)	(0.050)	(0.039)	(0.058)	(0.050)	(0.048)	(0.043)	(0.041)	(0.044)	(0.072)	(0.065)	(0.050)	(0.054)	(0.051)	(0.043)	(0.045)	(0.059)	(0.063)	(0.058)	(0.029)	(0.037)	(.)
Demographics																														
Female	-0.031	-0.065*	-0.190***	-0.113***	-0.099**	-0.085**	-0.173***	-0.100**	-0.125***	0.013	-0.093**	-0.161***	-0.121***	-0.031	-0.033	-0.098***	-0.104**	-0.187***	-0.018	-0.022	-0.122***	-0.054	-0.020	-0.056	-0.010	-0.089*	-0.163***	-0.039	-0.019	-0.110
	(0.027)	(0.032)	(0.026)	(0.030)	(0.034)	(0.033)	(0.035)	(0.032)	(0.033)	(0.032)	(0.030)	(0.032)	(0.033)	(0.031)	(0.029)	(0.025)	(0.038)	(0.043)	(0.033)	(0.032)	(0.029)	(0.033)	(0.031)	(0.033)	(0.033)	(0.036)	(0.034)	(0.020)	(0.027)	(.)
Urban	0.075**	0.043	0.103***	0.072*	-0.102**	0.146***	-0.005	0.090**	-0.065	0.138***	0.002	-0.010	0.012	-0.085**	-0.006	0.026	-0.025	-0.123**	0.027	0.113***	-0.001	0.057	0.109**	-0.005	0.120**	0.071	0.093**	0.058*	-0.287*	-0.036
	(0.028)	(0.033)	(0.027)	(0.035)	(0.034)	(0.044)	(0.039)	(0.034)	(0.034)	(0.036)	(0.030)	(0.034)	(0.037)	(0.031)	(0.032)	(0.027)	(0.041)	(0.047)	(0.036)	(0.033)	(0.034)	(0.034)	(0.033)	(0.041)	(0.037)	(0.037)	(0.034)	(0.029)	(0.140)	(.)
Education																														
(Upper) Secondary education	0.111***	-0.078	-0.028	0.127	0.147**	0.111	0.037	0.089	0.156*	0.031	0.035	0.204***	0.277***	0.131	0.055	0.001	0.091	-0.377***	0.131***	0.218***	0.143**	0.310***	0.180*	-0.134	0.131	0.117	0.294***	0.079***	0.203***	0.173
	(0.031)	(0.064)	(0.050)	(0.167)	(0.053)	(0.073)	(0.101)	(0.066)	(0.078)	(0.137)	(0.049)	(0.061)	(0.049)	(0.121)	(0.044)	(0.069)	(0.071)	(0.083)	(0.039)	(0.064)	(0.046)	(0.051)	(0.071)	(0.097)	(0.075)	(0.092)	(0.073)	(0.018)	(0.036)	(.)
Higher education	0.273***	0.124	0.165**	0.340*	0.329***	0.334***	0.339**	0.207**	0.349***	0.259	0.166**	0.451***	0.330***	0.350**	0.306***	0.150*	0.295***	-0.284***	0.260***	0.402***	0.339***	0.456***	0.489***	0.016	0.276**	0.195	0.444***	0.167***	0.226***	0.556
	(0.041)	(0.068)	(0.061)	(0.169)	(0.075)	(0.084)	(0.107)	(0.072)	(0.080)	(0.143)	(0.054)	(0.065)	(0.062)	(0.123)	(0.057)	(0.076)	(0.078)	(0.086)	(0.058)	(0.073)	(0.059)	(0.055)	(0.083)	(0.100)	(0.086)	(0.102)	(0.080)	(0.030)	(0.045)	(.)
Father's education																														
(Upper) Secondary education	0.012	0.167**	-0.012	0.125	0.053	0.022	-0.075	0.045	-0.065	-0.074	0.060	0.026	-0.001	0.081	-0.015	0.062	0.004	-0.108	-0.018	-0.122	0.045	0.061	0.116*	-0.038	-0.033	0.155*	0.039	-0.001	-0.037	-0.121
	(0.036)	(0.058)	(0.050)	(0.064)	(0.054)	(0.087)	(0.060)	(0.080)	(0.044)	(0.150)	(0.058)	(0.048)	(0.044)	(0.087)	(0.036)	(0.062)	(0.053)	(0.117)	(0.041)	(0.063)	(0.048)	(0.051)	(0.052)	(0.058)	(0.056)	(0.064)	(0.047)	(0.038)	(0.040)	(.)
Higher education	0.040	0.274***	0.115	0.278***	-0.126	0.024	0.001	0.075	-0.127*	0.026	-0.042	0.096	-0.059	0.186*	0.096	0.128	0.015	-0.054	-0.028	-0.037	0.179*	0.091	0.080	0.009	-0.016	0.244*	0.123	0.032	0.035	-0.086
	(0.066)	(0.058)	(0.059)	(0.078)	(0.085)	(0.103)	(0.082)	(0.093)	(0.055)	(0.159)	(0.099)	(0.073)	(0.071)	(0.093)	(0.059)	(0.072)	(0.070)	(0.124)	(0.064)	(0.080)	(0.079)	(0.086)	(0.086)	(0.066)	(0.083)	(0.097)	(0.072)	(0.041)	(0.071)	(.)
Mother's education																														
(Upper) Secondary education	0.026	-0.054	0.085*	0.057	0.056	0.098	0.245***	0.012	0.188**	-0.033	-0.071	0.038	0.186***	0.132	0.017	0.009	0.153*	0.004	0.069	0.237***	0.020	0.018	-0.020	0.177**	0.198***	0.080	0.116*	-0.041	0.115*	-0.131
	(0.035)	(0.085)	(0.039)	(0.081)	(0.049)	(0.081)	(0.061)	(0.057)	(0.063)	(0.135)	(0.048)	(0.049)	(0.045)	(0.083)	(0.042)	(0.068)	(0.065)	(0.125)	(0.046)	(0.058)	(0.048)	(0.047)	(0.043)	(0.068)	(0.056)	(0.061)	(0.047)	(0.031)	(0.056)	(.)
Higher education	0.056	-0.057	0.071	0.057	0.351**	0.201*	0.276**	0.139	0.248***	-0.073	-0.160	0.059	0.123	0.191*	0.050	0.099	0.177*	-0.037	0.231**	0.271**	0.072	-0.005	0.009	0.237**	0.227*	0.270**	0.211**	0.061	0.022	-0.148
	(0.074)	(0.086)	(0.047)	(0.088)	(0.120)	(0.102)	(0.096)	(0.075)	(0.071)	(0.140)	(0.102)	(0.080)	(0.067)	(0.089)	(0.079)	(0.080)	(0.076)	(0.130)	(0.077)	(0.086)	(0.074)	(0.091)	(0.089)	(0.078)	(0.093)	(0.099)	(0.070)	(0.045)	(0.103)	(.)
Household income																														
Low income	-0.086*	-0.208***	-0.125***	0.049	-0.103*	-0.153***	0.010	-0.107**	-0.089*	-0.182***	-0.075	-0.123***	-0.084*	-0.061	-0.066*	-0.004	-0.165***	-0.114*	-0.116**	-0.069	-0.143***	0.049	-0.232***	-0.153***	-0.064	-0.135**	-0.055	-0.044*	-0.088**	-0.150
	(0.034)	(0.032)	(0.031)	(0.032)	(0.046)	(0.039)	(0.045)	(0.039)	(0.044)	(0.039)	(0.038)	(0.037)	(0.041)	(0.034)	(0.031)	(0.026)	(0.050)	(0.054)	(0.038)	(0.040)	(0.034)	(0.045)	(0.042)	(0.039)	(0.046)	(0.049)	(0.042)	(0.021)	(0.030)	(.)
Observations	725	650	792	821	674	607	631	775	570	672	748	751	627	880	798	791	470	493	544	757	670	631	628	749	714	649	608	848	825	854

Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. Shows marginal effects of probability of having advanced skills. The dependent variable is a categorical variable where 0 indicates No digital skills, Basic skills, 1 equals High skills. Low household income is the bottom 40 percent of the within-country wage distribution. The omitted (benchmark) categories are 15- to 24-year-olds, males, rural residents, persons with less than upper-secondary schooling, and households in the top six national income deciles.

Table .11: Impact of digital skills on monthly wages, by country

	ALB	ARM	AZE	BLR	BIH	BGR	HRV	CZE	EST	GEO	DEU	GRC	HUN	KAZ	KOS	KGZ	LVA	LTU	MDA	MNE	MKD	POL	ROU	RUS	SRB	SVK	SVN	TJK	TUR	UZB
Digital skills																														
Basic skills	0.089	0.033	0.015	0.018	0.065	0.188***	0.117	-0.043	0.027	0.069	-0.158	0.089	0.094	0.142	0.170*	0.015	0.032	0.309*	0.549***	0.045	-0.051	0.064	0.181**	0.300	-0.065	0.139	0.039	-0.079	-0.063	0.846*
	(0.441)	(0.121)	(0.121)	(0.081)	(0.069)	(0.054)	(0.069)	(0.123)	(0.115)	(0.164)	(0.133)	(0.051)	(0.088)	(0.105)	(0.083)	(0.110)	(0.075)	(0.123)	(0.137)	(0.039)	(0.055)	(0.082)	(0.056)	(0.362)	(0.067)	(0.073)	(0.087)	(0.143)	(0.113)	(0.413)
High skills	0.364	0.180	0.147	-0.049	-0.022	0.242***	0.018	0.225	0.173	0.358	-0.125	0.147**	0.185*	0.267*	0.224*	-0.163	0.058	0.346**	0.462***	0.062	0.030	0.098	0.290***	0.397	-0.025	0.212**	0.201*	0.281*	-0.089	1.337*
	(0.531)	(0.146)	(0.122)	(0.087)	(0.064)	(0.069)	(0.068)	(0.145)	(0.109)	(0.189)	(0.079)	(0.049)	(0.080)	(0.109)	(0.096)	(0.136)	(0.084)	(0.124)	(0.130)	(0.036)	(0.052)	(0.081)	(0.057)	(0.316)	(0.054)	(0.075)	(0.099)	(0.133)	(0.127)	(0.549)
Demographics age_rand_resp	0.113	0.043	0.060*	0.030*	0.043***	0.023	-0.005	0.039	-0.004	0.028	-0.002	0.021	0.010	0.005	0.015	-0.011	0.021	0.021	-0.016	0.014	0.015	0.041**	0.027*	-0.004	-0.005	0.058***	0.027	0.001	-0.008	-0.122
	(0.087)	(0.037)	(0.026)	(0.013)	(0.012)	(0.013)	(0.016)	(0.032)	(0.016)	(0.029)	(0.015)	(0.011)	(0.018)	(0.030)	(0.016)	(0.032)	(0.018)	(0.014)	(0.030)	(0.011)	(0.015)	(0.014)	(0.013)	(0.026)	(0.014)	(0.015)	(0.019)	(0.031)	(0.037)	(0.142)
Age^2	-0.001	-0.001	-0.001*	-0.000**	-0.001***	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000**	-0.000*	-0.000	0.000	-0.001***	-0.000	0.000	0.000	0.002
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
Female	-0.243	-0.530***	-0.119	-0.288***	-0.178***	-0.209***	-0.142***	-0.288***	-0.300***	-0.016	-0.406***	-0.106***	-0.160**	-0.222*	-0.125	-0.210	-0.279***	-0.286***	-0.220**	-0.048	-0.114**	-0.208***	-0.130**	-0.357**	-0.065	-0.240***	-0.188***	-0.404***	-0.177	0.527
	(0.240)	(0.109)	(0.101)	(0.043)	(0.049)	(0.043)	(0.039)	(0.085)	(0.050)	(0.148)	(0.050)	(0.027)	(0.052)	(0.090)	(0.081)	(0.113)	(0.062)	(0.053)	(0.083)	(0.033)	(0.039)	(0.044)	(0.040)	(0.130)	(0.052)	(0.045)	(0.050)	(0.113)	(0.116)	(0.579)
Urban	0.514	0.067	-0.086	0.131**	-0.025	0.247***	0.017	-0.023	-0.043	0.176	-0.006	-0.044	0.182***	-0.004	0.133*	-0.020	-0.049	0.063	-0.122	0.004	0.095*	-0.027	0.143***	0.188*	0.056	0.108**	0.043	0.351*	-0.614***	0.947**
	(0.288)	(0.118)	(0.096)	(0.043)	(0.047)	(0.064)	(0.040)	(0.094)	(0.045)	(0.129)	(0.037)	(0.027)	(0.051)	(0.083)	(0.058)	(0.098)	(0.064)	(0.059)	(0.095)	(0.032)	(0.043)	(0.045)	(0.041)	(0.078)	(0.046)	(0.041)	(0.047)	(0.155)	(0.177)	(0.334)
Education level																														
(Upper) Secondary education	0.808**	0.087	-0.037	0.655***	0.071	0.078	0.176	0.386**	-0.069	-0.575	0.169**	0.095	0.122*	0.563***	0.182	0.432	0.023	0.445*	-0.158	0.131*	-0.097	0.089	0.216*	-0.285*	0.040	0.503***	0.004	0.163	0.120	-0.243
	(0.254)	(0.140)	(0.161)	(0.142)	(0.077)	(0.118)	(0.101)	(0.131)	(0.115)	(0.389)	(0.062)	(0.059)	(0.059)	(0.168)	(0.113)	(0.218)	(0.144)	(0.183)	(0.145)	(0.065)	(0.163)	(0.066)	(0.084)	(0.142)	(0.141)	(0.069)	(0.109)	(0.218)	(0.127)	(0.399)
Higher education	0.349	0.233	0.224	0.846***	0.186	0.276*	0.374**	0.502**	0.132	-0.216	0.493***	0.119	0.222*	0.771***	0.277*	0.865**	0.227	0.653***	-0.083	0.225**	0.020	0.171	0.427***	0.043	0.187	0.694***	0.322**	0.378	0.412**	0.000
	(0.335)	(0.170)	(0.160)	(0.152)	(0.101)	(0.136)	(0.116)	(0.156)	(0.128)	(0.435)	(0.100)	(0.064)	(0.095)	(0.190)	(0.134)	(0.255)	(0.150)	(0.188)	(0.168)	(0.076)	(0.167)	(0.091)	(0.095)	(0.152)	(0.152)	(0.087)	(0.119)	(0.221)	(0.145)	(.)
Employee Sector																														
Construction	-1.550**	-0.251	0.750***	-0.050	0.070	0.152	0.271*	0.111	0.025	0.622*	0.327	-0.270**	-0.014	-0.253	0.203	-0.308	0.259	0.056	1.183*	-0.432	0.239*	0.266	0.268*	0.149	0.137	0.241	0.334	0.401	0.397*	2.748**
	(0.566)	(0.213)	(0.192)	(0.092)	(0.137)	(0.189)	(0.123)	(0.212)	(0.115)	(0.286)	(0.295)	(0.099)	(0.160)	(0.219)	(0.121)	(0.357)	(0.158)	(0.229)	(0.469)	(0.309)	(0.110)	(0.140)	(0.107)	(0.203)	(0.194)	(0.183)	(0.205)	(0.815)	(0.176)	(0.928)
Manufacturing	-1.266*	-0.272	0.633**	-0.092	0.095	-0.127	0.117	0.161	-0.141	-0.866*	0.174	-0.153	-0.208	-0.069	-0.279*	-0.235	0.135	0.138	0.642*	-0.477	0.241*	0.184	0.149	0.105	-0.084	0.036	0.238	0.235	0.250	2.468*
	(0.514)	(0.198)	(0.194)	(0.091)	(0.145)	(0.178)	(0.114)	(0.196)	(0.099)	(0.380)	(0.307)	(0.104)	(0.178)	(0.216)	(0.108)	(0.367)	(0.143)	(0.218)	(0.310)	(0.313)	(0.102)	(0.145)	(0.111)	(0.240)	(0.184)	(0.171)	(0.189)	(0.716)	(0.159)	(0.966)
Finance and Real Estate	-2.259***	-0.031	0.302	0.182	0.226	0.415*	0.310**	0.085	-0.071	0.216	0.281	-0.214*	-0.076	-0.130	-0.151	-0.777	0.236	0.165	1.250***	-0.457	0.491***	0.295	0.406***	-0.054	-0.307	0.113	0.185	0.295	0.414*	0.757
	(0.627)	(0.227)	(0.335)	(0.114)	(0.169)	(0.205)	(0.117)	(0.500)	(0.109)	(0.327)	(0.299)	(0.089)	(0.191)	(0.184)	(0.154)	(0.428)	(0.168)	(0.237)	(0.321)	(0.315)	(0.119)	(0.151)	(0.112)	(0.286)	(0.221)	(0.187)	(0.197)	(0.702)	(0.207)	(0.833)
Transport, Trade and Retail	-1.072	-0.146	0.304	-0.078	0.031	0.132	0.125	0.183	-0.073	-0.374	0.266	-0.259**	-0.151	-0.165	-0.233	-0.432	0.191	0.147	0.681*	-0.671*	0.229*	0.331*	0.152	0.078	-0.184	0.206	0.344	-0.239	0.208	2.004*
	(0.583)	(0.221)	(0.225)	(0.088)	(0.156)	(0.177)	(0.115)	(0.163)	(0.102)	(0.215)	(0.294)	(0.083)	(0.160)	(0.186)	(0.126)	(0.375)	(0.137)	(0.209)	(0.305)	(0.313)	(0.101)	(0.141)	(0.111)	(0.263)	(0.198)	(0.178)	(0.191)	(0.688)	(0.256)	(0.905)
Services	-1.778***	-0.093	0.273	-0.062	0.095	0.087	0.212	0.137	0.039	-0.460*	0.280	-0.262***	-0.100	-0.216	-0.158	-0.527	0.152	0.075	0.519	-0.634*	0.212*	0.316*	0.210*	-0.238	-0.189	0.126	0.264	0.027	0.198	1.922*
	(0.480)	(0.156)	(0.139)	(0.082)	(0.125)	(0.169)	(0.115)	(0.175)	(0.091)	(0.228)	(0.294)	(0.078)	(0.158)	(0.166)	(0.100)	(0.348)	(0.150)	(0.214)	(0.307)	(0.313)	(0.085)	(0.141)	(0.103)	(0.412)	(0.205)	(0.179)	(0.188)	(0.633)	(0.182)	(0.870)
Occupation																														
Clerical / Service Work	0.046	0.037	0.192	-0.086	0.062	-0.144*	-0.084	-0.071	0.038	-0.258	0.056	-0.045	0.060	-0.205*	-0.077	0.049	0.000	-0.015	-0.027	0.011	-0.117	-0.085	-0.027	0.141	0.083	0.043	-0.072	0.243	0.061	-0.218
	(0.255)	(0.154)	(0.122)	(0.063)	(0.078)	(0.060)	(0.082)	(0.115)	(0.081)	(0.179)	(0.052)	(0.046)	(0.059)	(0.103)	(0.066)	(0.196)	(0.078)	(0.075)	(0.130)	(0.047)	(0.070)	(0.060)	(0.055)	(0.247)	(0.103)	(0.062)	(0.054)	(0.167)	(0.199)	(0.404)
Manager / Professional	0.049	0.060	0.027	-0.006	0.013	-0.062	0.101	-0.150	0.242**	-0.046	0.202**	0.093	0.098	0.086	0.182*	0.180	0.204*	0.045	0.264	0.159**	0.067	0.057	0.127*	0.125	0.329**	0.138**	0.042	0.301*	0.385*	-0.723
	(0.325)	(0.157)	(0.121)	(0.063)	(0.073)	(0.085)	(0.092)	(0.150)	(0.074)	(0.217)	(0.074)	(0.050)	(0.083)	(0.114)	(0.076)	(0.190)	(0.090)	(0.083)	(0.158)	(0.049)	(0.078)	(0.072)	(0.060)	(0.201)	(0.101)	(0.052)	(0.072)	(0.145)	(0.164)	(0.551)
Experience	0.060	0.083	0.217*	0.031	-0.012	-0.004	0.165***	0.292*	0.121**	0.011	0.014	0.035	0.106**	0.159*	0.159*	0.221*	0.101*	0.114**	0.060	-0.023	0.087**	0.001	0.025	0.249**	0.071*	0.001	0.133**	0.097	0.096	0.537
	(0.146)	(0.085)	(0.091)	(0.034)	(0.039)	(0.036)	(0.045)	(0.141)	(0.037)	(0.077)	(0.054)	(0.025)	(0.038)	(0.067)	(0.067)	(0.103)	(0.050)	(0.040)	(0.072)	(0.021)	(0.028)	(0.040)	(0.031)	(0.091)	(0.028)	(0.035)	(0.051)	(0.080)	(0.068)	(0.352)
Parental education	-0.298	-0.112	0.044	0.054	0.012	-0.016	0.045	-0.028	0.091*	0.103	-0.188***	0.014	-0.003	0.128	-0.016	0.146	0.052	0.129**	0.033	0.048	0.036	0.079*	-0.085*	0.009	0.060	0.043	0.044	0.117	0.093	-0.355
	(0.196)	(0.089)	(0.052)	(0.040)	(0.050)	(0.045)	(0.040)	(0.098)	(0.042)	(0.122)	(0.044)	(0.019)	(0.033)	(0.079)	(0.047)	(0.095)	(0.037)	(0.042)	(0.059)	(0.033)	(0.033)	(0.040)	(0.037)	(0.066)	(0.047)	(0.045)	(0.044)	(0.072)	(0.077)	(0.336)
Firm Characteristics																														
Private firms	-0.141	0.343*	0.090	0.197***	-0.178*	0.178***	-0.057	-0.174	0.151*	-0.100	-0.005	-0.096*	0.193**	0.108	0.186	0.437**	0.263**	0.042	0.221*	0.020	-0.050	0.105	-0.031	-0.106	0.142*	0.113	0.048	-0.135	-0.021	0.622*
	(0.256)	(0.163)	(0.124)	(0.057)	(0.077)	(0.052)	(0.057)	(0.099)	(0.061)	(0.123)	(0.059)	(0.037)	(0.062)	(0.106)	(0.105)	(0.146)	(0.079)	(0.054)	(0.107)	(0.038)	(0.080)	(0.064)	(0.046)	(0.190)	(0.064)	(0.059)	(0.054)	(0.280)	(0.147)	(0.309)
Foreign firms	0.504	0.198	0.534***	0.259	0.040	0.193	0.224*	-0.162	0.400***	-0.768*	-0.007	-0.043	0.249**	0.396	0.350*	0.674***	0.572***	-0.061	0.508**	0.044	-0.131	0.119	-0.013	0.034	0.312*	0.122	0.048	0.834*	0.638**	0.149
	(0.284)	(0.448)	(0.129)	(0.208)	(0.263)	(0.103)	(0.089)	(0.180)	(0.117)	(0.321)	(0.087)	(0.102)	(0.079)	(0.208)	(0.136)	(0.185)	(0.116)	(0.145)	(0.154)	(0.214)	(0.088)	(0.066)	(0.091)	(0.159)	(0.145)	(0.070)	(0.081)	(0.404)	(0.201)	(0.696)
Medium size (20-99 employees)	-0.089	0.486**	0.007	0.086	0.068	0.020	-0.034	0.073	0.082	-0.095	0.130**	0.027	0.027	-0.080	0.092	-0.031	0.125	0.019	0.345**	0.000	-0.004	0.029	0.076	-0.013	-0.075	0.044	0.067	0.314*	0.029	0.113
	(0.204)	(0.185)	(0.118)	(0.053)	(0.050)	(0.051)	(0.053)	(0.070)	(0.054)	(0.135)	(0.047)	(0.029)	(0.066)	(0.117)	(0.070)	(0.109)	(0.075)	(0.051)	(0.114)	(0.037)	(0.067)	(0.052)	(0.044)	(0.181)	(0.069)	(0.061)	(0.066)	(0.131)	(0.122)	(0.337)
Large size (over 100 employees)	-0.886*	0.517**	-0.044	0.067	0.128*	0.067	0.037	0.098	0.158*	-0.025	0.106	0.078	0.173*	0.163	0.216	0.149	0.195*	0.147	0.427**	0.057	-0.005	0.040	0.125*	0.092	0.048	0.078	0.112	0.180	0.100	-0.726
	(0.379)	(0.181)	(0.119)	(0.061)	(0.057)	(0.056)	(0.046)	(0.099)	(0.061)	(0.137)	(0.062)	(0.044)	(0.067)	(0.108)	(0.120)	(0.129)	(0.080)	(0.102)	(0.130)	(0.046)	(0.061)	(0.068)	(0.055)	(0.147)	(0.066)	(0.061)	(0.064)	(0.133)	(0.144)	(0.535)
Constant	5.915***	5.487***	4.676***	-3.307***	6.475***	6.366***	6.741***	5.760***	7.060***	6.401***	7.914***	6.873***	6.480***	5.682***	5.879***	5.829***	6.176***	5.903***	5.989***	7.368***	6.399***	6.221***	6.160***	6.634***	6.783***	5.075***	5.962***	4.732***	8.093***	5.722*
	(1.618)	(0.749)	(0.532)	(0.305)	(0.252)	(0.315)	(0.264)	(0.554)	(0.350)	(0.718)	(0.458)	(0.195)	(0.438)	(0.614)	(0.338)	(0.660)	(0.420)	(0.414)	(0.676)	(0.402)	(0.329)	(0.280)	(0.275)	(0.543)	(0.390)	(0.419)	(0.520)	(0.850)	(0.810)	(2.604)
Observations	192	137	128	308	171	307	290	400	388	161	492	347	328	367	173	103	279	302	177	367	358	200	343	401	318	284	338	150	149	210
R^2	0.202	0.379	0.655	0.285	0.401	0.425	0.413	0.184	0.430	0.488	0.404	0.392	0.280	0.255	0.490	0.558	0.441	0.494	0.527	0.314	0.278	0.424	0.478	0.234	0.244	0.441	0.348	0.509	0.359	0.273

Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. The dependent variable is log monthly wage adjusted by ICP 2021.

Table .12: Impact of digital skills on hourly wages

	Central Europe	Eastern Europe	Southeast Europe	Baltic States	Western Balkans	South Caucasus	Central Asia
Basic skills	0.121***	0.224*	0.075	0.045	-0.041	0.048	0.188
	(0.035)	(0.088)	(0.163)	(0.074)	(0.071)	(0.129)	(0.168)
High skills	0.177***	0.260*	0.222	0.096	0.084	0.164	0.478*
	(0.032)	(0.103)	(0.159)	(0.076)	(0.075)	(0.132)	(0.212)
Demographics							
Age	0.020**	0.019	-0.053*	0.016	0.011	-0.008	-0.067
	(0.007)	(0.016)	(0.022)	(0.009)	(0.016)	(0.027)	(0.047)
Age^2	-0.000**	-0.000	0.001*	-0.000*	-0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Female	-0.162***	-0.195***	-0.145	-0.204***	-0.190***	-0.250*	0.115
	(0.020)	(0.053)	(0.080)	(0.042)	(0.047)	(0.105)	(0.184)
Urban	0.032	0.169**	0.069	-0.065	-0.027	-0.009	0.121
	(0.022)	(0.054)	(0.059)	(0.044)	(0.057)	(0.113)	(0.136)
Education							
(Upper) Secondary education	0.067*	-0.055	0.028	0.044	0.133	-0.225	0.178
	(0.034)	(0.147)	(0.170)	(0.089)	(0.093)	(0.275)	(0.300)
Higher education	0.254***	0.075	0.158	0.270**	0.225*	0.212	0.347
	(0.045)	(0.172)	(0.161)	(0.096)	(0.113)	(0.277)	(0.279)
Employment Sector							
Construction	0.118	0.201	0.268	0.034	-0.246	0.557*	0.207
	(0.087)	(0.123)	(0.161)	(0.131)	(0.156)	(0.236)	(0.327)
Manufacturing	0.026	0.064	0.332*	-0.008	-0.268	-0.129	0.101
	(0.081)	(0.116)	(0.163)	(0.131)	(0.152)	(0.273)	(0.357)
Finance and Real Estate	0.149	0.280	0.207	0.162	-0.208	0.032	-0.406
	(0.092)	(0.260)	(0.214)	(0.147)	(0.164)	(0.291)	(0.331)
Transport, Trade and Retail	0.095	0.100	0.264	0.146	-0.319*	-0.228	-0.112
	(0.079)	(0.109)	(0.169)	(0.132)	(0.155)	(0.229)	(0.323)
Services	0.108	0.027	0.103	0.140	-0.289	-0.090	-0.083
	(0.078)	(0.113)	(0.212)	(0.132)	(0.155)	(0.228)	(0.304)
Occupation							
Clerical / Service Work	0.021	-0.018	0.059	-0.061	-0.044	-0.019	0.170
	(0.027)	(0.076)	(0.141)	(0.063)	(0.058)	(0.171)	(0.170)
Manager / Professional	0.108**	0.121	0.231	0.063	0.060	0.091	0.252
	(0.037)	(0.090)	(0.126)	(0.062)	(0.075)	(0.187)	(0.216)
Firm Characteristics							
Private firms	0.045	0.146*	-0.214*	0.134**	-0.184**	-0.065	0.132
	(0.027)	(0.061)	(0.109)	(0.051)	(0.068)	(0.131)	(0.127)
Foreign firms	0.058	0.307*	0.278	0.395***	-0.009	0.530	0.236
	(0.046)	(0.133)	(0.407)	(0.093)	(0.093)	(0.308)	(0.278)
Medium size (20-99 employees)	0.020	0.180**	-0.026	0.098*	-0.033	0.320**	-0.139
	(0.022)	(0.062)	(0.099)	(0.048)	(0.051)	(0.120)	(0.113)
Large size (over 100 employees)	0.076**	0.207**	0.026	0.117*	-0.046	0.199	-0.410*
	(0.028)	(0.072)	(0.080)	(0.052)	(0.066)	(0.125)	(0.193)
Experience	0.039	0.013	0.212***	0.086**	0.011	-0.020	0.116
	(0.026)	(0.043)	(0.058)	(0.028)	(0.031)	(0.089)	(0.104)
Parental education	0.011	0.022	0.107*	0.096**	0.080	-0.121	0.059
	(0.018)	(0.044)	(0.042)	(0.031)	(0.043)	(0.084)	(0.098)
Constant	1.416***	-7.896***	2.288***	1.577***	1.844***	2.255***	2.423**
	(0.163)	(0.351)	(0.473)	(0.252)	(0.386)	(0.660)	(0.891)
Observations	2,982	685	897	969	1,479	426	830
R^2	0.264	0.982	0.260	0.352	0.085	0.455	0.149

Notes: *** , ** , and * indicate significance at the 1, 5, and 10 percent levels, respectively. The dependent variable is log hourly wage adjusted by PPP. Log hourly wage is constructed by dividing the monthly wage by weekly working hours multiplied by 4. The omitted (benchmark) categories are no digital skills, males, rural residents, persons with less than upper-secondary schooling, the agriculture industry, elementary workers, and employers.

Table .13: Firm Type on monthly wages

	Central Europe	Eastern Europe	Southeast Europe	Baltic States	Western Balkans	South Caucasus	Central Asia
High skills	0.112***	0.000	0.081	-0.026	0.165*	0.092	0.321
	(0.030)	(0.062)	(0.057)	(0.051)	(0.070)	(0.102)	(0.179)
Demographics							
Age	0.023***	0.014	-0.000	0.009	0.021	0.060**	-0.033
	(0.006)	(0.015)	(0.015)	(0.009)	(0.012)	(0.018)	(0.041)
Age^2	-0.000***	-0.000	-0.000	-0.000	-0.000	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Female	-0.235***	-0.286***	-0.219***	-0.306***	-0.134***	-0.273***	-0.073
	(0.018)	(0.042)	(0.064)	(0.033)	(0.037)	(0.073)	(0.185)
Urban	0.075***	0.105*	0.038	-0.024	0.118*	0.118	0.309*
	(0.018)	(0.049)	(0.044)	(0.031)	(0.046)	(0.067)	(0.126)
Education							
(Upper) Secondary education	0.127***	-0.004	0.047	0.051	0.150*	-0.113	0.349
	(0.030)	(0.150)	(0.092)	(0.084)	(0.067)	(0.147)	(0.180)
Higher education	0.341***	0.151	0.267**	0.308***	0.213*	0.135	0.651***
	(0.038)	(0.178)	(0.084)	(0.089)	(0.085)	(0.162)	(0.163)
Employment Sector Construction	0.134*	0.150	0.125	0.097	-0.092	0.410*	0.397
	(0.065)	(0.121)	(0.128)	(0.089)	(0.114)	(0.163)	(0.418)
Manufacturing	0.017	-0.014	0.094	-0.003	-0.215	-0.247	0.448
	(0.060)	(0.105)	(0.133)	(0.082)	(0.113)	(0.173)	(0.421)
Finance and Real Estate	0.143	0.241	0.028	0.080	-0.139	0.004	-0.031
	(0.075)	(0.124)	(0.166)	(0.095)	(0.129)	(0.191)	(0.359)
Transport, Trade and Retail	0.097	0.060	0.084	0.071	-0.230	-0.198	0.093
	(0.058)	(0.101)	(0.141)	(0.082)	(0.121)	(0.139)	(0.334)
Services	0.090	-0.045	-0.073	0.068	-0.269*	-0.292*	0.005
	(0.058)	(0.109)	(0.190)	(0.082)	(0.120)	(0.129)	(0.340)
Occupation							
Clerical / Service Work	-0.003	-0.018	0.065	0.035	-0.032	-0.099	-0.005
	(0.023)	(0.075)	(0.136)	(0.044)	(0.040)	(0.113)	(0.113)
Manager / Professional	0.081*	0.140	0.182	0.171***	0.117*	-0.035	0.050
	(0.032)	(0.095)	(0.120)	(0.046)	(0.054)	(0.128)	(0.176)
Firm Characteristics							
Private firms	0.027	0.164*	-0.097	0.101*	0.064	0.006	0.168
	(0.033)	(0.068)	(0.145)	(0.050)	(0.068)	(0.101)	(0.135)
Foreign firms	0.004	0.309	0.122	0.153	0.064	-0.088	0.289
	(0.096)	(0.159)	(0.080)	(0.133)	(0.093)	(0.133)	(0.423)
High skills × Private firms	0.002	0.035	0.055	0.091	-0.152*	0.244	-0.093
	(0.035)	(0.090)	(0.110)	(0.061)	(0.077)	(0.136)	(0.233)
High skills × Foreign firms	0.108	0.156	0.052	0.375*	0.196	0.716**	0.539
	(0.106)	(0.199)	(0.187)	(0.170)	(0.151)	(0.267)	(0.578)
Medium size (20-99 employees)	0.056**	0.190**	0.032	0.075*	-0.002	0.082	0.067
	(0.020)	(0.059)	(0.084)	(0.035)	(0.039)	(0.085)	(0.076)
Large size (over 100 employees)	0.105***	0.199**	0.134**	0.158***	-0.024	0.118	-0.151
	(0.022)	(0.065)	(0.052)	(0.042)	(0.053)	(0.083)	(0.181)
Experience	0.075***	0.053	0.166***	0.119***	0.038*	0.076	0.297***
	(0.022)	(0.040)	(0.050)	(0.025)	(0.019)	(0.059)	(0.089)
Parental education	-0.009	0.041	0.035	0.078***	-0.003	0.054	0.064
	(0.015)	(0.038)	(0.025)	(0.023)	(0.035)	(0.050)	(0.100)
Constant	6.425***	-2.514***	6.752***	6.810***	6.282***	5.226***	5.740***
	(0.145)	(0.302)	(0.397)	(0.210)	(0.296)	(0.432)	(0.710)
Observations	2,982	685	897	969	1,479	426	830
R^2	0.325	0.988	0.319	0.494	0.133	0.448	0.218

Notes: *** , ** , and * indicate significance at the 1, 5, and 10 percent levels, respectively. The dependent variable is log monthly wage adjusted by ICP 2021. The omitted (benchmark) categories are no digital skills, males, rural residents, persons with less than upper-secondary schooling, the agriculture industry, elementary workers.

Table .14: Firm Size on monthly wages

	Central Europe	Eastern Europe	Southeast Europe	Baltic States	Western Balkans	South Caucasus	Central Asia
High skills	0.084**	0.194*	0.022	0.010	0.017	0.095	0.411**
	(0.030)	(0.082)	(0.055)	(0.049)	(0.072)	(0.166)	(0.129)
Demographics							
Age	0.024***	0.014	-0.001	0.006	0.021	0.061**	-0.035
	(0.006)	(0.014)	(0.015)	(0.009)	(0.012)	(0.019)	(0.041)
Age^2	-0.000***	-0.000	-0.000	-0.000	-0.000	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Female	-0.232***	-0.283***	-0.221***	-0.308***	-0.135***	-0.283***	-0.069
	(0.018)	(0.041)	(0.064)	(0.033)	(0.037)	(0.076)	(0.185)
Urban	0.073***	0.099*	0.026	-0.018	0.117*	0.123	0.311*
	(0.018)	(0.048)	(0.048)	(0.031)	(0.046)	(0.067)	(0.127)
Education							
(Upper) Secondary education	0.128***	0.013	0.058	0.051	0.148*	-0.129	0.353*
	(0.030)	(0.145)	(0.087)	(0.087)	(0.067)	(0.139)	(0.179)
Higher education	0.340***	0.164	0.272**	0.300**	0.220*	0.101	0.659***
	(0.038)	(0.174)	(0.083)	(0.091)	(0.085)	(0.153)	(0.166)
Employment Sector Construction	0.140*	0.147	0.149	0.107	-0.105	0.401*	0.411
	(0.065)	(0.123)	(0.131)	(0.091)	(0.117)	(0.169)	(0.390)
Manufacturing	0.023	-0.020	0.111	0.004	-0.220	-0.231	0.451
	(0.061)	(0.103)	(0.135)	(0.084)	(0.117)	(0.169)	(0.401)
Finance and Real Estate	0.149*	0.235	0.046	0.087	-0.154	0.031	-0.020
	(0.075)	(0.120)	(0.161)	(0.096)	(0.133)	(0.192)	(0.333)
Transport, Trade and Retail	0.106	0.059	0.106	0.071	-0.253*	-0.179	0.072
	(0.059)	(0.099)	(0.139)	(0.084)	(0.125)	(0.138)	(0.313)
Services	0.097	-0.039	-0.049	0.076	-0.284*	-0.267*	0.008
	(0.058)	(0.107)	(0.181)	(0.083)	(0.123)	(0.128)	(0.324)
Occupation							
Clerical / Service Work	-0.006	-0.016	0.064	0.034	-0.022	-0.085	0.012
	(0.023)	(0.073)	(0.134)	(0.044)	(0.040)	(0.120)	(0.110)
Manager / Professional	0.079*	0.148	0.185	0.172***	0.120*	-0.009	0.033
	(0.032)	(0.096)	(0.124)	(0.047)	(0.054)	(0.134)	(0.178)
Firm Characteristics							
Private firms	0.029	0.176**	-0.066	0.160***	0.002	0.132	0.139
	(0.021)	(0.056)	(0.090)	(0.037)	(0.052)	(0.090)	(0.093)
Foreign firms	0.081	0.461***	0.208**	0.409***	0.171*	0.421*	0.401
	(0.041)	(0.124)	(0.079)	(0.083)	(0.081)	(0.195)	(0.310)
Medium size (20-99 employees)	0.060*	0.296***	-0.101	0.047	-0.024	0.021	0.195*
	(0.029)	(0.076)	(0.164)	(0.051)	(0.058)	(0.102)	(0.086)
Large size (over 100 employees)	0.031	0.253**	0.105	0.073	-0.089	-0.007	-0.199
	(0.040)	(0.085)	(0.063)	(0.068)	(0.078)	(0.091)	(0.270)
High skills × Medium size	-0.003	-0.314**	0.249	0.040	0.067	0.112	-0.328*
	(0.037)	(0.101)	(0.169)	(0.063)	(0.081)	(0.193)	(0.156)
High skills × Large size	0.116*	-0.163	0.069	0.112	0.152	0.216	0.115
	(0.047)	(0.127)	(0.083)	(0.077)	(0.096)	(0.182)	(0.397)
Experience	0.075***	0.049	0.161***	0.121***	0.040*	0.071	0.302***
	(0.022)	(0.039)	(0.048)	(0.025)	(0.019)	(0.062)	(0.088)
Parental education	-0.010	0.044	0.037	0.085***	-0.004	0.062	0.067
	(0.015)	(0.038)	(0.026)	(0.023)	(0.035)	(0.051)	(0.105)
Constant	6.431***	-2.600***	6.786***	6.804***	6.339***	5.187***	5.725***
	(0.144)	(0.301)	(0.395)	(0.207)	(0.288)	(0.453)	(0.700)
Observations	2,982	685	897	969	1,479	426	830
R^2	0.327	0.988	0.324	0.490	0.130	0.441	0.222

Notes: *** , ** , and * indicate significance at the 1, 5, and 10 percent levels, respectively. The dependent variable is log monthly wage adjusted by ICP 2021. The omitted (benchmark) categories are no digital skills, males, rural residents, persons with less than upper-secondary schooling, the agriculture industry, elementary workers.

Table .15: Occupation on monthly wages

	Central Europe	Eastern Europe	Southeast Europe	Baltic States	Western Balkans	South Caucasus	Central Asia
High skills	0.161***	0.027	0.303	0.050	0.006	0.070	0.533*
	(0.029)	(0.081)	(0.156)	(0.059)	(0.051)	(0.280)	(0.228)
Demographics							
Age	0.024***	0.018	0.002	0.007	0.019	0.062***	-0.034
	(0.006)	(0.015)	(0.015)	(0.009)	(0.012)	(0.019)	(0.042)
Age^2	-0.000***	-0.000	-0.000	-0.000	-0.000	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Female	-0.233***	-0.284***	-0.224***	-0.308***	-0.132***	-0.295***	-0.067
	(0.018)	(0.041)	(0.064)	(0.033)	(0.036)	(0.076)	(0.195)
Urban	0.075***	0.106*	0.041	-0.020	0.118**	0.129	0.308*
	(0.018)	(0.049)	(0.044)	(0.031)	(0.046)	(0.066)	(0.127)
Education							
(Upper) Secondary education	0.127***	-0.009	0.033	0.053	0.150*	-0.161	0.322
	(0.030)	(0.149)	(0.094)	(0.087)	(0.068)	(0.141)	(0.171)
Higher education	0.343***	0.137	0.262**	0.306***	0.220**	0.066	0.633***
	(0.038)	(0.177)	(0.084)	(0.092)	(0.085)	(0.161)	(0.177)
Employment Sector Construction	0.127*	0.152	0.138	0.098	-0.095	0.407*	0.347
	(0.064)	(0.123)	(0.127)	(0.090)	(0.114)	(0.173)	(0.385)
Manufacturing	0.006	-0.018	0.139	-0.001	-0.221	-0.241	0.454
	(0.060)	(0.103)	(0.131)	(0.083)	(0.113)	(0.177)	(0.410)
Finance and Real Estate	0.133	0.216	0.056	0.086	-0.148	0.043	-0.027
	(0.074)	(0.116)	(0.157)	(0.096)	(0.130)	(0.197)	(0.343)
Transport, Trade and Retail	0.086	0.056	0.091	0.071	-0.246*	-0.191	0.088
	(0.058)	(0.100)	(0.140)	(0.083)	(0.122)	(0.145)	(0.324)
Services	0.081	-0.048	-0.061	0.074	-0.280*	-0.271*	0.006
	(0.057)	(0.108)	(0.183)	(0.082)	(0.120)	(0.130)	(0.333)
Occupation							
Clerical / Service Work	0.055	-0.072	0.170	0.034	-0.019	-0.174	0.073
	(0.030)	(0.084)	(0.198)	(0.058)	(0.046)	(0.100)	(0.130)
Manager / Professional	0.064	0.206*	0.324	0.179**	0.028	-0.008	0.089
	(0.062)	(0.090)	(0.191)	(0.065)	(0.087)	(0.122)	(0.248)
High skills × Clerical / Service Work	-0.100**	0.165	-0.235	-0.001	0.020	0.250	-0.326
	(0.036)	(0.107)	(0.163)	(0.071)	(0.071)	(0.296)	(0.261)
High skills × Manager / Professional	0.009	-0.145	-0.292	-0.009	0.203	0.097	-0.245
	(0.059)	(0.102)	(0.170)	(0.076)	(0.107)	(0.295)	(0.311)
Firm Characteristics							
Private firms	0.025	0.162**	-0.059	0.160***	-0.007	0.123	0.132
	(0.022)	(0.055)	(0.089)	(0.037)	(0.053)	(0.089)	(0.094)
Foreign firms	0.079	0.416***	0.118	0.407***	0.162*	0.404*	0.398
	(0.042)	(0.122)	(0.078)	(0.084)	(0.080)	(0.199)	(0.317)
Medium size (20-99 employees)	0.057**	0.190**	0.032	0.073*	-0.004	0.072	0.074
	(0.020)	(0.058)	(0.082)	(0.035)	(0.039)	(0.084)	(0.076)
Large size (over 100 employees)	0.105***	0.183**	0.134**	0.151***	-0.028	0.098	-0.136
	(0.022)	(0.064)	(0.051)	(0.042)	(0.053)	(0.080)	(0.184)
Experience	0.074***	0.049	0.160***	0.120***	0.044*	0.065	0.296***
	(0.022)	(0.040)	(0.048)	(0.025)	(0.019)	(0.059)	(0.088)
Parental education	-0.011	0.043	0.035	0.084***	-0.004	0.073	0.062
	(0.015)	(0.038)	(0.025)	(0.023)	(0.035)	(0.050)	(0.099)
Constant	6.407***	-2.587***	6.629***	6.782***	6.372***	5.173***	5.734***
	(0.144)	(0.286)	(0.349)	(0.213)	(0.288)	(0.452)	(0.711)
Observations	2,982	685	897	969	1,479	426	830
R^2	0.327	0.988	0.324	0.488	0.132	0.441	0.218

Notes: *** , ** , and * indicate significance at the 1, 5, and 10 percent levels, respectively. The dependent variable is log monthly wage adjusted by ICP 2021. The omitted (benchmark) categories are no digital skills, males, rural residents, persons with less than upper-secondary schooling, the agriculture industry, elementary workers.