



Adam Płatkowski  
Department of Economics, Gdańsk
University of Technology, Poland

Digitalisation and Regional Income Inequality. Evidence from European NUTS 2 Regions

Cyfryzacja a regionalne nierówności dochodowe.
Analiza dla regionów europejskich NUTS 2

Keywords:

digitalisation, income inequality,
regional inequality, digital inclusion,
NUTS 2

JEL classification codes:

D31, D63, O18, O33, R13

Article history:

submitted: August 7, 2025
revised: October 30, 2025
accepted: December 9, 2025

Słowa kluczowe:

cyfryzacja, nierówności dochodowe,
nierówności regionalne, włączenie
cyfrowe, NUTS 2

Kody klasyfikacji JEL:

D31, D63, O18, O33, R13

Historia artykułu:

nadestany: 7 sierpnia 2025 r.
poprawiony: 30 października 2025 r.
zaakceptowany: 9 grudnia 2025 r.

Abstract

This paper investigates how digitalisation affected regional income inequality across European NUTS 2 regions during the period 2006–2021. Digitalisation is analysed in relation to selected regional factors, including labour market characteristics and the level of employee education, which potentially – although indirectly – determine equal earning opportunities, or conversely, enhance income inequality. To examine these relationships, panel fixed-effects and instrumental-variable regression models are employed. Empirical results demonstrate a non-linear relationship between digitalisation and income inequality, with initial increases in digitalisation associated with rising inequality due to skill-biased effects, although the relationship reverses with more advanced digitalisation. It is also found that the effect of digitalisation on income inequality is relatively stronger in regions with a higher share of tertiary-educated individuals and a more active labour force.

Streszczenie

W artykule podjęto zagadnienie wpływu cyfryzacji na regionalne nierówności dochodowe w regionach europejskich NUTS 2 w latach 2006–2021. W badaniu przeanalizowano zjawisko cyfryzacji w kontekście wybranych charakterystyk regionalnych, takich jak aktywność zawodowa oraz poziom wykształcenia, które mogą pośrednio sprzyjać wyrównywaniu szans dochodowych bądź prowadzić do pogłębiania się nierówności. Aby uchwycić te zależności, zastosowano modele regresji panelowej z efektami stałymi oraz modele wykorzystujące zmienne instrumentalne. Uzyskane wyniki wskazują na nieliniową relację między cyfryzacją a nierównościami dochodowymi – początkowy wzrost poziomu cyfryzacji wiąże się z narastaniem nierówności dochodowych na skutek efektów premiujących osoby o wysokich kwalifikacjach, jednak przy wyższych poziomach cyfryzacji zależność ta ulega odwróceniu. Zaobserwowano również, że wpływ cyfryzacji na nierówności dochodowe jest relatywnie silniejszy w regionach charakteryzujących się większym udziałem osób z wyższym wykształceniem oraz bardziej aktywną siłą roboczą.

Introduction

The process of digitalisation in Europe, which has been ongoing since the 1990s and has expanded opportunities and access to information, has so far not changed the overall picture of income inequality [Richiardi et al., 2025]. While in some European regions digital technology has led to a drop in income inequality, other regions have experienced further income gap growth [Antonietti et al., 2025]. These processes, however, are not exclusively related to internet access or the use of computers, but are driven largely by the structural characteristics of societies, including institutional [Acemoglu, Robinson, 2012], educational [van Maarseveen, 2021] and those linked to the degree of urbanisation [Baum-Snow, Pavan, 2012]. These factors determine whether or not digital tools improve the economic conditions and create more equal opportunities. With its diverse regional landscape, Europe represents a particularly interesting case for demonstrating how digitalisation affects income inequality in different regional contexts. Despite the existing research on both digital divides and regional income inequality, relatively little is still known about how specific regional factors influence the relationship between digitalisation and income inequalities, with only a few studies having tackled this issue to date. Antonietti et al. [2025] show that institutional quality shapes the digitalisation impact on income inequality. Consoli et al. [2023] demonstrate the importance of digital skills in reducing income inequality across European regions. Peng and Dan [2023] document similar patterns in China, where certain factors can dampen the effects of inequality. Existing studies create a solid foundation for further research. Yet, broader structural elements, such as education levels, urbanisation patterns, and labour market conditions, have not received enough empirical attention. These intra-regional differences cannot be captured at the national level, where huge regional disparities within countries (such as between northern and southern Italy, or western and eastern Poland) are often of utmost importance when evaluating local trends [Consoli et al., 2023; Antonietti et al., 2025].

This research examines how digitalisation shaped income inequality across European NUTS 2 regions during the period 2006–2021, contributing to our understanding of how digitalisation affects income inequality and how the impact of digitalisation is determined by various regional features, such as the level of education or labour market characteristics. The study is based on the assumption, derived from the existing literature, that digitalisation operates through two competing mechanisms. On the one hand, it may reduce inequality by promoting inclusion and creating new opportunities, particularly in less developed regions [Gao et al., 2018; Liu et al., 2024; Zhang et al., 2025]. On the other hand, it can also boost inequality through skill-biased effects, especially in more advanced and urbanised regions [Baum-Snow, Pavan, 2012; Akerman et al., 2015; Capello et al., 2024]. The analysis centres on two key regional characteristics: the share of tertiary education attainment and labour force participation. These two variables represent potential moderators of how digitalisation influences regional income disparities, and so the study approach builds on contributive research showing that strong labour market performance correlates with lower inequality [Perugini, Martino, 2008].

Moreover, this paper aims to deepen our understanding of how regional characteristics interact with digitalisation and shape income inequality, thereby offering insights to policymakers seeking to ensure a more equitable and responsible digital transformation. This study proposes further policy-relevant insights for promoting equitable growth in a growingly digitalised Europe, building on the findings of Consoli et al. [2023] and Antonietti et al. [2025], thereby advancing the understanding of inequality determinants in digitally transforming economies and offering concrete insights for policymakers looking to promote social cohesion across diverse regional contexts.

The paper proceeds as follows. First, it presents a literature review on income inequality and digitalisation, including regional studies. Next, it describes the dataset and explains how the key variables were developed and selected. The methodological strategy is then explained, including the panel regression framework and instrumental-variable strategy. The methodological section is followed by an illustration and discussion

of the empirical results, with the discussion interpreting these findings relative to prior research and considering further policy implications. The paper concludes with remarks concerning future research directions and limitations.

Literature review

To analyse and assess the impact of digitalisation on regional income inequality, it is necessary to refer to both general studies on the impact of new technology on the labour market and regional studies demonstrating the impact of specific digitalisation policies on the economic consequences within regions. Recent research increasingly focuses on the impact of new technology, including automation, computerisation and digitalisation, on wage differences across labour markets and occupational groups. In their works, **Acemoglu and Restrepo [2018, 2022]** demonstrate that technological transformation shifts labour productivity, although benefit distribution is uneven, mainly in favour of highly-skilled workers with more cognitive jobs. Since the technological transformation tends to favour better-educated workers, urban areas gain an advantage in this respect due to residents generally having better access to education and spending more time in school [**van Maarseveen, 2021**]. People in urban areas are more likely to develop analytical and social skills that earn higher wages, while financial centres create network effects that strengthen these benefits [**Poon et al., 2015**]. Urban job markets provide a better match between workers and job positions, and offer a higher return on experience [**Baum-Snow, Pavan, 2012**]. Digitalisation may thus increase the inequality among regions, especially as the increasing number of digital service jobs favours highly-skilled workers and widens the wage gap [**Akerman et al., 2015; Capello et al., 2024**]. However, these urban premiums may distort important regional differences in how digitalisation affects inequality. While regions with extractive institutions often experience skill-biased effects that deepen the existing inequality [**Acemoglu, Robinson, 2012; Antonietti et al., 2025**], less developed regions face entirely different circumstances. **Forman et al. [2012]** found that the internet impacted wages in only a small share of countries, mostly highly developed ones. At the same time, this relationship may also depend on broader global trends, as globalisation based on digital inclusion negatively affects the bargaining power and employment opportunities of less educated workers [**Autor et al., 2013**].

In contrast, digital access in less developed regions (China, Mexico) can reduce barriers to economic activity and labour-market participation by improving access to information, education, and essential services [**Gao et al., 2018; Mora-Rivera, García-Mora, 2021**]. Less-developed regions face structural obstacles that limit their ability to turn digitalisation into equal economic opportunities. Lower population density, weaker educational systems, and limited workforce participation all contribute to these differences, along with other region-specific factors. Yet, these same areas could benefit substantially from digitalisation efforts, although the outcome can vary considerably depending on local conditions [**Iammarino et al., 2019**]. For instance, studies from China demonstrate the positive effects of digital inclusion in rural areas [**Gao et al., 2018; Zhang et al., 2025**], with other research indicating that the strongest benefits occur where governments invest heavily in digital infrastructure and education programmes [**Liu et al., 2024**]. **Braesemann et al. [2020]** found similar patterns in the U.S., where rural workers are able to compete effectively with their urban counterparts in online skilled labour markets. Rural communities also experience greater poverty reduction from digital inclusion than urban areas [**Mora-Rivera, García-Mora, 2021**]. Overall, studies conducted across different geopolitical regions reach a similar conclusion – digitalisation tends to support the most educated individuals, but under the appropriate conditions and policy frameworks, it can also help equalise opportunities for disadvantaged groups.

The complexity of the potential effects of digitalisation has pushed research on regional income inequality towards more complex analyses aiming to help understand changes in income inequality by considering conditional interactions that depend on local characteristics. Various researchers have applied decomposition methods to separate the inequality sources between and within regions [**Novotný, 2007; Doran, Jordan,**

2016], as well as adopted spatial models to capture geographic spillovers in inequality patterns [Breau, 2015; Ezcurra et al., 2007]. A network analysis was used to show how financial centres concentrate high-paying jobs and increase wage gaps [Poon et al., 2015]. More recently, semiparametric and structural models examined wage dynamics and worker mobility between urban and rural areas, showing the advantages of highly-developed regions [Baum-Snow, Pavan, 2012].

The diffusion of digital technology across European regions interacts with deeply-rooted institutional and historical characteristics, shaping uneven digital development and thus distributional outcomes. Regions with effective and impartial administrations are better positioned to convert investments into regional advantages [Charron et al., 2014; Crescenzi et al., 2016]. The administrative culture shaped by a region's history can significantly influence the quality of governance at the regional level, and thus significantly impact the pace of digital development [Tabellini, 2010]. Moreover, decentralisation and regional governance, both crucial for digital adoption, may have differing effects on income inequality depending on the quality of institutions and the degree of fiscal autonomy in the region [Kyriacou et al., 2015]. Improvements in government quality in less-developed regions may enhance the employment benefits of digital transformation [Rodríguez-Pose, Ketterer, 2020]. In a broader European context, digitalisation may reinforce the need for regionally tailored policies that align technological diffusion with institutional strengthening and administrative reforms [Iammarino et al., 2019], thereby helping to prevent digital divides from transforming into new forms of spatial inequality.

Although the existing literature provides substantial evidence on whether and how digitalisation and income inequality are interrelated, such evidence at the regional level remains limited. This paper addresses the gap by providing novel evidence for European NUTS 2 regions. In doing so, it complements existing cross-national comparisons concerning digitalisation as a source of various global inequalities [Lessmann, Seidel, 2017], addressing this phenomenon across European regions.

Data and sample

The analysis presented in this paper draws on a panel dataset comprising 810 observations for 96 NUTS 2 regions across 14 European countries between 2006 and 2021. The research sample includes regions from Austria, Belgium (selected regions), Switzerland, Czech Republic, Denmark, Estonia, Spain, Finland, France (selected regions), Italy, Luxembourg, Romania, Slovakia and Sweden. For most regions, between 12 and 15 observations were collected, depending on data availability. The final dataset is somewhat unbalanced, with gaps related to the lack of regional inequality data in the LIS Database and the lack of information on regional digitalisation indicators in Eurostat. However, the dataset includes highly urbanised, economically advanced regions, such as Vienna (AT13), Brussels (BE10) and Île-de-France (FR10), alongside less developed areas, including southern Italian regions (ITF4, ITF6) and parts of Romania (such as RO31, RO42). This variety is crucial with regard to the research question on how digital inclusion affects income inequality differently across various regional settings.

Table 1. Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Gini (eq. total income)	810	0.325	0.043	0.163	0.455
Gini (eq. factor income)	810	0.485	0.049	0.314	0.691
GE 1 (eq. total income)	810	0.19	0.057	0.042	0.578
GE 1 (eq. factor income)	810	0.443	0.105	0.21	1.583
Atkinson 0.5 (eq. total income)	810	0.092	0.025	0.021	0.198
Atkinson 0.5 (eq. factor income)	810	0.261	0.054	0.132	0.506
Internet use (once a week, %)	810	0.679	0.183	0.211	0.984

cont. Table 1

Variable	Obs.	Mean	Std. Dev.	Min	Max
Internet access (% of households)	810	0.726	0.172	0.231	1
GDP per capita (EUR PPP)	810	28098.6	11499.6	7600	79000
Unemployment (in %)	810	0.102	0.071	0.019	0.361
Population density (p. per km ²)	810	508.2	1357.8	3.3	7526.7
Tertiary education (in %)	810	0.266	0.108	0.073	0.561
Labour force participation (in %)	810	0.473	0.047	0.315	0.589
High-tech employment (in %)	767	0.034	0.02	0.007	0.115
ICT units in the region	694	4516.4	8718	18	102766

Source: Author's own elaboration based on data from Eurostat and the LIS Database. Inequality measures are based on equivalised household total income and factor income, with top- and bottom-coding applied.

According to Table 1, the research sample includes regions at different stages of development (ranging from 69 to 7.9 thousand EUR PPP), with varying levels of unemployment (from less than 2% to over 36%) and varying population densities.

The research sample spans both highly urbanised, high-income regions and less-developed areas, although it omits certain regions where LIS coverage at the required regional level is unavailable, or no proxies of digitalisation are available in Eurostat. Thus, the in-sample summary statistics are compared to the overall population of European NUTS 2 regions with regard to general economic indicators. Table 2 presents the results of this comparison.

Table 2. Comparison of in-sample and out-of-sample summary statistics

	In sample			Out of sample		
	Obs.	Mean	St. dev.	Obs.	Mean	St. dev.
GDP per capita (EUR PPP)	810	28098.6	11499.6	3736	25046.5	11263.0
Unemployment (in %)	810	0.102	0.071	4246	0.081	0.056
Population density (p. per km ²)	810	508.2	1357.8	4338	444.8	1154.5
Tertiary education (in %)	810	0.266	0.108	4289	0.268	0.107
Labour force participation (in %)	810	0.473	0.047	4289	0.464	0.060

Source: Author's own elaboration based on Eurostat data.

The comparison indicates that regions included in the research sample are broadly similar to the population of European NUTS 2 regions, although the sample has slightly higher average levels of income and labour market activity. Key variables of interest, namely tertiary attainment and labour force participation, exhibit similar values between the two groups (differences of less than 1 percentage point). Thus, it can be claimed that the sample remains representative across most structural indicators, though it may slightly over-represent more urbanised and economically developed regions.

In this study, regional income inequality is measured through multiple complementary indicators in order to ensure the robustness of the results. The primary measure is the Gini coefficient of total and factor household income. Total income includes all sources of household income, while factor income includes only labour and capital income (without public transfers and pensions), reflecting pre-distributional inequality. Given the nature of redistributive policies, factor income inequality exceeds total income inequality. In addition, the GE (1) (Generalised Entropy) index and the Atkinson index (with alpha equal to 0.5) are calculated to potentially demonstrate sensitivity to different parts of the income distribution. The focus on factor income allows for the assessment of the market-driven dimension of inequality, aligning with the aim to investigate structural, rather than policy-mediated, dynamics. All inequality measures are derived from household-level microdata available through the Luxembourg Income Study (LIS), which generally enables harmonised cross-country comparison by applying a consistent methodology for income definitions, equivalence scales, and household

composition. Simultaneously, the Luxembourg Income Study is based on microdata from national income surveys. Differences in survey design, sampling methodologies, and responses may vary in considerable ways across countries, and thus the representativeness and comparativeness of the data may be affected. Previous studies documented the underrepresentation of top income and wealth in household surveys, even when harmonised at the international level [Hlasny, 2020; Brzeziński et al., 2020]. In this study, equivalised income is computed using the square root scale, with all data top-coded and bottom-coded following Neugschwender [2020] in order to minimise the influence of outliers.

The key independent variable – digitalisation – captures digital inclusion by measuring the percentage of the population using the internet at least once per week, based on Eurostat's regional ICT survey. Usage frequency provides the most accurate proxy for digitalisation compared to conventional access measures. As van Deursen and van Dijk [2014] demonstrate, the digital divide has evolved from a first-level divide concerning physical access to a second-level divide focused on actual usage patterns, with weekly usage therefore reflecting sustained engagement rather than sporadic access, and better capturing the consistent digital participation necessary for deriving economic benefits from digital technology. For robustness checks, internet access rates are employed as an instrument for internet usage in the instrumental variable specifications, following established approaches in the literature [Consoli et al., 2023].

To ensure that the relationship between digitalisation and income inequality reflects causal mechanisms rather than just accidental correlation, several key variables identified in prior literature are included as controls in the analysis (see Table 3). The selected control variables encompass regional economic characteristics, including educational attainment levels, labour force participation, demographic composition, and certain spatial characteristics. These factors may simultaneously influence both digital technology adoption and local inequality patterns. All independent and control variables were derived from Eurostat and were log-transformed to ensure that their distribution in the sample is as close as possible to the normal distribution (non-log-transformed variable histograms and density plots are provided in the Appendix).

Table 3. List of control variables

Control variable	Justification for choice
GDP per capita (EUR PPP)	Reflects the overall level of economic development. Wealthier regions may have higher digital access but also differing baseline inequality patterns. Used also by Antonietti et al. [2025]; Consoli et al. [2023] and Crescenzi and Rodríguez-Pose [2012].
Unemployment rate (in %)	Captures labour market slack, which directly affects income distribution by influencing bargaining power and job availability. Higher unemployment may increase inequality. Used also by Antonietti et al. [2025] and Consoli et al. [2023].
Tertiary education (in %)	Acts as a proxy for human capital. Higher education levels are associated with greater employability and wage potential, influencing both inequality and digital adoption. Used also by Antonietti et al. [2025]; Consoli et al. [2023].
Labour force participation (in %)	Indicates structural labour supply and economic inclusion. A higher participation rate suggests broader income-generating potential across the population. Although this variable is not widely used, Kuhn and Mansour [2014] demonstrated strong evidence of the effects of digitalisation on the labour market and labour force participation.
Population density (p. per km ²)	Captures the spatial structure of the region. Acts as an effect modifier and proxy for urbanisation, linked to agglomeration economies and digital returns. Used as a control variable by Peng and Dan [2023] and Antonietti et al. [2025].

Source: Author's own elaboration.

Research methodology

To assess the relationship between digital inclusion and regional income inequalities in European NUTS 2 regions, two-way fixed effects (FE) panel regression models are adopted. The fixed effects approach accounts for evaluating heterogeneity across regions and for time-specific shocks. The baseline model is specified as:

$$Ineq_{it} = \alpha_0 + \beta_1 IU_{it} + (\beta_2 IU_{it})^2 + \beta_{3..n} X_{it} + \theta_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where $Ineq_{it}$ corresponds to the inequality measure in the region, X_{it} corresponds to a vector of control variables, θ_i stands for regional fixed effects, and λ_t stands for time fixed effects. The FE model was selected over random effects based on theoretical assumptions concerning unobserved heterogeneity and a Hausman test confirming significant differences between estimators ($p < 0.001$). Standard errors are clustered at the regional level to account for serial correlation and heteroskedasticity.

To capture heterogeneity in the effects of digitalisation across the region, particularly between densely and sparsely populated areas, the baseline model is extended to include interaction terms:

$$Ineq_{it} = \alpha_0 + \beta_1 IU_{it} + \beta_2 IU_{it} \times Attribute_{it} + \beta_{3..n} X_{it} + \theta_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where $Attribute_{it}$ denotes the moderating variable, including tertiary education and/or labour force participation. This formulation enables the marginal effect of internet use to vary by regional characteristics, allowing theoretical expectations from the literature regarding the dual nature of digital technologies to be explored, with mainly inclusionary effects in regions with higher tertiary attainment and labour force participation, and skill-biased effects in other areas.

Endogeneity issues may also raise concerns. Reverse causality could occur if the region with higher inequality demonstrates unnatural digital participation based on affordability, with more wealthier groups driving the average usage. Moreover, digital infrastructure may evolve in response to income distribution changes, particularly when policymakers promote digital access as a strategy for reducing inequality. Omitted variable bias is also possible if unobserved factors such as governance quality, social capital, or innovation systems influence both inequality and digital inclusion. To address these concerns and move closer to identifying causal relationships, a two-stage fixed effects instrumental-variable (FE-IV) model is additionally estimated. Regional household internet access is used as an instrument for weekly internet usage. Internet access is a strong predictor of actual internet use and is likely independent of other factors affecting inequality, particularly after controlling for regional and year fixed effects. This approach follows recent work in this field [Consoli et al., 2023]. The first-stage equation is specified as follows:

$$IU_{it} = \pi_0 + \pi_1 IV_{it} + (\pi_2 IV_{it} \times Attribute_{it}) + \pi_{3..n} X_{it} + \eta_{it} \quad (3)$$

The second-stage equation is specified as follows:

$$Ineq_{it} = \alpha_0 + \widehat{\beta_1 IU_{it}} + (\widehat{\beta_2 IU_{it}} \times \widehat{Attribute_{it}}) + \beta_{3..n} X_{it} + \theta_i + \lambda_t + \varepsilon_{it} \quad (4)$$

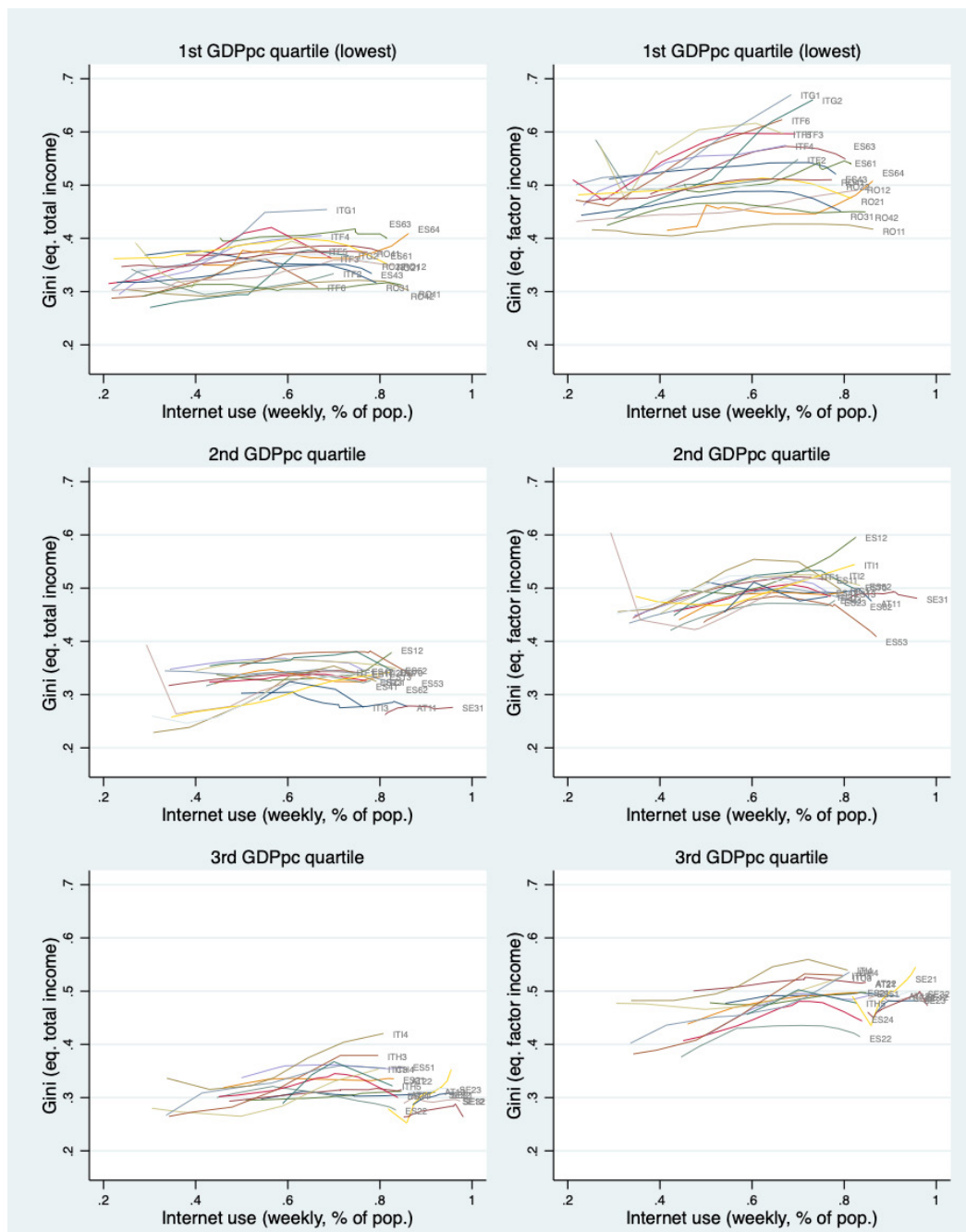
where IV_{it} denotes the instrument variable. To ensure the validity of the interaction specification within the IV framework, an interaction between the instrument and the moderator variable is included in the first stage. The robustness of the IV strategy is assessed through standard diagnostics, including first-stage F-statistics for weak instruments and Hansen's J-test for overidentification where applicable. This approach strengthens the causal interpretation of the digital inclusion effect.

The selection of instrumental variables was made in two ways. In the first approach, the percentage of households with access to the internet serves as an instrument. This choice is justified on the basis that internet access influences internet use but is unlikely to affect inequality directly once regional and temporal fixed effects are included – a common assumption in the prior literature, see e.g. Consoli et al. [2023]. In the second approach, the share of high-tech employment and the number of ICT units per region were adopted as regression instruments. The above choice is also justified empirically and theoretically, as regions with more developed digital infrastructure should also see a higher percentage of people using the internet, while at the same time, there is no direct link between these variables and the level of income inequality.

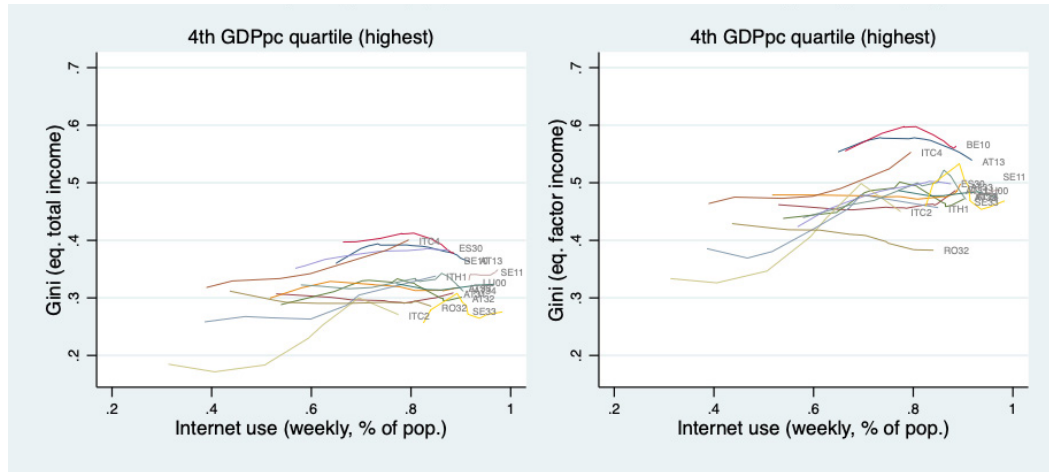
Empirical research

To illustrate the empirical relationship between digitalisation and income inequalities, regional patterns across European NUTS 2 regions from 2006 to 2021 are examined. Figure 1 presents best-fit lines for individual regions, showing the relationship between the Gini coefficient of total income and two digitalisation measures – the percentage of frequent internet users in the population and the percentage of households with internet access.

Figure 1. Digitalisation and income inequalities in European NUTS 2 regions (2006–2021)



cont. Figure 1



Source: Author's own elaboration based on Eurostat and the LIS Database. GDP per capita quartiles calculated according to GDP per capita between 2018 and 2020.

While regional trajectories vary considerably, a relatively regular pattern emerges in both panels, with many regions exhibiting a non-linear, inverted U-shaped relationship. This suggests that income inequality initially rises with digital adoption and subsequently declines, which is broadly consistent with theoretical expectations regarding competing mechanisms: skill-biased technological change may increase inequality during the early stages of digitalisation, whereas inclusion effects may reduce inequality at more advanced stages. Early digital adoption may create skill-biased effects favouring higher-skilled residents [Akerman et al., 2015; Capello et al., 2024], while broader internet coverage then enhances economic opportunities across the population [Gao et al., 2018; Zhang et al., 2025].

Direct influence

Regression results for the baseline model, presented in Table 4, indicate a statistically significant negative coefficient for the squared term of internet use (IU squared) across multiple specifications, particularly for total income inequality measures (Gini, GE1, and Atkinson). Although the linear effect of internet use itself is insignificant in most cases, the negative and statistically significant coefficient on the squared internet-use term points to a non-linear relationship. This suggests that the effect of digitalisation on income inequality becomes more pronounced and inequality-reducing as internet use increases.

Table 4. Panel fixed-effects regression results for 96 NUTS 2 regions

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Gini (total)	Gini (factor)	GE1 (total)	GE1 (factor)	Atkinson 0.5 (total)	Atkinson 0.5 (factor)
Internet Use (IU)	-0.009 (0.03)	-0.003 (0.03)	-0.033 (0.05)	-0.017 (0.08)	-0.014 (0.02)	0.008 (0.03)
Internet Use ² (IU ²)	-0.030** (0.01)	-0.018 (0.02)	-0.050** (0.03)	-0.051 (0.04)	-0.022** (0.01)	-0.013 (0.02)
Unemployment (UEMP)	0.016** (0.01)	0.022*** (0.01)	0.009 (0.01)	0.013 (0.02)	0.008* (0.00)	0.018** (0.01)
GDP per capita (GDP)	-0.025 (0.02)	-0.091*** (0.03)	-0.055 (0.04)	-0.232*** (0.08)	-0.016 (0.01)	-0.080*** (0.03)
Tertiary education (TEDU)	-0.018* (0.01)	-0.025* (0.01)	-0.024 (0.02)	-0.042 (0.03)	-0.012* (0.01)	-0.017 (0.01)
Labour force part. (LABF)	0.101** (0.05)	0.062 (0.06)	0.137* (0.08)	0.175 (0.16)	0.065** (0.03)	0.050 (0.06)

cont. Table 4

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Gini (total)	Gini (factor)	GE1 (total)	GE1 (factor)	Atkinson 0.5 (total)	Atkinson 0.5 (factor)
Population density (DENS)	0.030	-0.099*	0.091	-0.144	0.020	-0.121*
	(0.04)	(0.06)	(0.06)	(0.13)	(0.03)	(0.06)
Regional fixed effects	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
Constant	0.519	1.933***	0.394	3.562***	0.207	1.702***
	(0.35)	(0.50)	(0.52)	(1.25)	(0.21)	(0.53)
Observations	810.000	810.000	810.000	810.000	810.000	810.000
Regions (number)	96.000	96.000	96.000	96.000	96.000	96.000
R2 within	0.214	0.333	0.122	0.201	0.188	0.376
R2 between	0.206	0.002	0.198	0.010	0.195	0.001

Notes: Inequality measures based on equivalised household total income and factor income, with top- and bottom-coding applied. SE are reported in parentheses; * for $p < 0.1$; ** for $p < 0.05$; *** for $p < 0.01$.

Source: Author's own elaboration based on data from Eurostat and the LIS Database.

The above findings demonstrate the relationship between digitalisation and regional inequality. Until a certain threshold, digital adoption may produce ambiguous effects on inequality. With deeper engagement, including both coverage and intensity of ICT infrastructure, digitalisation may decrease income inequality, both in regard to total and factor household income. In sparsely populated or less developed regions, this pattern likely reflects the gradual overcoming of structural barriers such as inadequate infrastructure, skill gaps, and economic isolation, allowing digital technology to eventually foster more equal access to economic opportunities. These dynamics mirror findings from rural China [Gao et al., 2018; Zhang et al., 2025] and cross-regional evidence on broadband-induced employment effects [Mora-Rivera, García-Mora, 2021].

The R2 values across models reveal important insights regarding the structural nature of inequality in European regions. A clear pattern emerges: for all inequality measures, models explain substantially more variance between regions in total income inequality than in factor income inequality. Factor income models consistently show R2 values close to zero, reflecting fundamental differences between these inequality types, which is justified by the theoretical background. Factor income inequality captures pre-distributional disparities from labour market outcomes and capital returns, before redistribution occurs. This inequality generally becomes higher in magnitude and more region-specific over time, driven by microeconomic factors such as employment structures, wage dispersion, and capital concentration. Such disparities prove to be less systematic, making them harder to explain through regional averages and characteristics. By contrast, income inequalities measured using total income reflect institutional and policy-driven mechanisms, including redistribution policies, which tend to remain relatively stable across regions. Regional predictors such as GDP per capita, education levels, and digital inclusion therefore explain a larger share of the variation in total income inequality across regions. This distinction reinforces the importance of separating market-generated inequalities from those mediated by government policies. The higher R2 within values across all models indicates that most inequality variation over time occurs within regions rather than between them, underscoring the dynamic character of inequality as regions respond to evolving factors such as internet adoption, labour force participation and educational attainment.

The role of regional characteristics

Table 5 provides robust and consistent evidence of an interaction effect between internet use and tertiary education (IU $\times$ TEDU). The estimated interaction term is negative and statistically significant at the 1% level across all model specifications, which suggests that the inequality-reducing potential of digital inclusion is significantly enhanced in regions with higher levels of tertiary education attainment.

The strong moderating role of education is consistent with the concept of complementarity between the ability to use new technology and human capital [Consoli et al., 2023]. In regions with a higher proportion of highly educated residents, digital access is more likely to translate into effective use – supporting higher employability, entrepreneurial capacity, and adaptation to knowledge-intensive labour markets. This is in line with the broader literature on skill-biased technological change [Acemoglu, Restrepo, 2018, 2022], which highlights how digital returns are mediated through the skill profile of the workforce. In this context, digitalisation not only reduces income disparities but may also foster long-term structural convergence by boosting productivity and innovation in lagging regions. At the same time, in regions with lower levels of education, the benefits of digital technology may be concentrated among a relatively small share of the population, thereby limiting the distributive effect and potentially reinforcing existing inequality. These findings reinforce the argument that digital access must be accompanied by capacity-building measures in order to effectively promote equality.

Table 5. Panel fixed-effects regression results for 96 NUTS 2 regions

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Gini (total)	Gini (factor)	GE1 (total)	GE1 (factor)	Atkinson 0.5 (total)	Atkinson 0.5 (factor)
Internet Use (IU)	−0.144*** (0.04)	−0.128*** (0.05)	−0.193*** (0.06)	−0.256** (0.11)	−0.086*** (0.02)	−0.096** (0.04)
Interaction (IU-TEDU)	−0.086*** (0.02)	−0.073*** (0.02)	−0.114*** (0.03)	−0.151*** (0.05)	−0.050*** (0.01)	−0.059*** (0.02)
Unemployment (UEMP)	0.024*** (0.01)	0.029*** (0.01)	0.019* (0.01)	0.027 (0.02)	0.013*** (0.00)	0.024*** (0.01)
GDP per capita (GDP)	−0.039 (0.02)	−0.102*** (0.03)	−0.075* (0.04)	−0.256*** (0.09)	−0.025* (0.01)	−0.088*** (0.03)
Tertiary education (TEDU)	−0.066*** (0.01)	−0.066*** (0.02)	−0.087*** (0.02)	−0.127*** (0.04)	−0.040*** (0.01)	−0.050*** (0.02)
Labour force part. (LABF)	0.080* (0.05)	0.043 (0.06)	0.112 (0.07)	0.138 (0.16)	0.054* (0.03)	0.035 (0.06)
Population density (DENS)	0.048 (0.04)	−0.079 (0.06)	0.109* (0.07)	−0.111 (0.14)	0.028 (0.03)	−0.104 (0.07)
Regional fixed effects	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
Constant	0.492 (0.37)	1.875*** (0.51)	0.411 (0.54)	3.508*** (1.29)	0.211 (0.23)	1.647*** (0.54)
Observations	810.000	810.000	810.000	810.000	810.000	810.000
Regions (number)	96.000	96.000	96.000	96.000	96.000	96.000
R2 within	0.267	0.358	0.153	0.218	0.230	0.393
R2 between	0.274	0.000	0.225	0.005	0.263	0.000

Notes: Inequality measures based on equivalised household total income and factor income, with top- and bottom-coding applied. SE are reported in parentheses; * for $p < 0.1$; ** for $p < 0.05$; *** for $p < 0.01$.

Source: Author's own elaboration based on data from Eurostat and the LIS Database.

Table 6 provides further evidence by incorporating the interaction between internet use and labour force participation (IU × LABF). Here once again, the interaction terms are negative and statistically significant, indicating that regions with higher levels of labour market engagement benefit more from digital inclusion in terms of reducing income inequality.

Table 6. Panel fixed-effects regression results for 96 NUTS 2 regions

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Gini (total)	Gini (factor)	GE1 (total)	GE1 (factor)	Atkinson 0.5 (total)	Atkinson 0.5 (factor)
Internet Use (IU)	−0.109** (0.04)	−0.089* (0.05)	−0.181** (0.07)	−0.225* (0.13)	−0.076*** (0.03)	−0.062 (0.05)
Interaction (IU-LABF)	−0.167*** (0.05)	−0.131** (0.05)	−0.259*** (0.08)	−0.330** (0.15)	−0.110*** (0.03)	−0.103* (0.06)
Unemployment (UEMP)	0.018** (0.01)	0.024*** (0.01)	0.013 (0.01)	0.018 (0.02)	0.010** (0.00)	0.020*** (0.01)
GDP per capita (GDP)	−0.006 (0.02)	−0.076** (0.03)	−0.027 (0.04)	−0.194** (0.09)	−0.004 (0.01)	−0.067** (0.03)
Tertiary education (TEDU)	−0.013 (0.01)	−0.021 (0.01)	−0.015 (0.02)	−0.032 (0.03)	−0.008 (0.01)	−0.014 (0.01)
Labour force part. (LABF)	−0.008 (0.06)	−0.024 (0.07)	−0.030 (0.10)	−0.040 (0.21)	−0.006 (0.04)	−0.017 (0.07)
Population density (DENS)	0.048 (0.05)	−0.082 (0.06)	0.116* (0.07)	−0.104 (0.14)	0.031 (0.03)	−0.107 (0.06)
Regional fixed effects	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
Constant	0.186 (0.39)	1.646*** (0.52)	−0.103 (0.59)	2.869** (1.38)	−0.003 (0.25)	1.471*** (0.55)
Observations	810.000	810.000	810.000	810.000	810.000	810.000
Regions (number)	96.000	96.000	96.000	96.000	96.000	96.000
R2 within	0.226	0.338	0.132	0.207	0.199	0.380
R2 between	0.207	0.001	0.204	0.009	0.196	0.000

Notes: Inequality measures based on equivalised household total income and factor income, with top- and bottom-coding applied. SE are reported in parentheses; * for $p < 0.1$; ** for $p < 0.05$; *** for $p < 0.01$.

Source: Author's own elaboration based on data from Eurostat and the LIS Database.

The results suggest that the economic activation of the population serves as a crucial transmission mechanism through which digital inclusion influences inequality. In regions where individuals are more likely to participate in the labour market, internet use becomes an important tool for job search, access to remote work opportunities, and upgrading skills through digital learning platforms. This reflects the increasing role of internet-enabled labour platforms, as highlighted by [Kuhn and Mansour \[2014\]](#) and [Braesemann et al. \[2020\]](#), in expanding employment options beyond traditional geographic constraints. In regions with lower labour force participation, the mitigating potential of internet use is likely to be constrained. These findings underscore the importance of considering broader institutional and demographic conditions when evaluating the effects of digitalisation on inequality.

Robustness check

Furthermore, to address potential endogeneity concerns where regional inequality might influence internet usage rather than the reverse, fixed-effects instrumental-variable (FE-IV) models are estimated using broadband internet access as an instrument for weekly internet use. Tables 7 and 8 present these results with interaction terms for tertiary education (TEDU) and labour-force participation (LABF), respectively. The IV results generally reinforce the main conclusions from baseline regressions. Internet use remains a negative and statistically significant predictor across all six inequality measures, confirming that higher digital engagement associates with lower total and factor income inequalities. The consistency after instrumenting strengthens the causal interpretation – digitalisation appears to directly reduce inequality rather than merely reflecting

broad developmental trends. The interaction terms prove particularly robust, remaining negative and highly significant across all models.

In Table 7, the interaction between internet use and tertiary education is significant at the 1% or 5% level across specifications, confirming that digitalisation has stronger inequality-reducing effects in regions with higher levels of educational attainment. This is consistent with theoretical expectations, since residents in these areas are better equipped to translate internet use into economic opportunities, in line with the skill-biased effect theory and supporting earlier findings [Consoli et al., 2023; Acemoglu, Restrepo, 2022].

Table 7. Instrumental-variable fixed-effects regression results for 96 NUTS 2 regions

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Gini (total)	Gini (factor)	GE1 (total)	GE1 (factor)	Atkinson 0.5 (total)	Atkinson 0.5 (factor)
Internet Use (IU)	-0.147*** (0.04)	-0.123** (0.05)	-0.169*** (0.06)	-0.196* (0.11)	-0.084*** (0.02)	-0.089* (0.05)
Interaction (UI x TEDU)	-0.082*** (0.02)	-0.063*** (0.02)	-0.100*** (0.03)	-0.115** (0.05)	-0.047*** (0.01)	-0.048** (0.02)
Tertiary education (TEDU)	-0.067*** (0.01)	-0.064*** (0.02)	-0.081*** (0.02)	-0.111*** (0.04)	-0.039*** (0.01)	-0.048*** (0.02)
Other control vars.	YES	YES	YES	YES	YES	YES
Regional fixed effects	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
Constant	0.552 (0.37)	1.962*** (0.52)	0.467 (0.53)	3.660*** (1.28)	0.247 (0.22)	1.742*** (0.55)
Observations	810.000	810.000	810.000	810.000	810.000	810.000
Regions (number)	96.000	96.000	96.000	96.000	96.000	96.000
R2 within	0.266	0.356	0.152	0.217	0.229	0.391
R2 between	0.269	0.001	0.222	0.006	0.251	0.000

Notes: Inequality measures based on equalised household total income and factor income, with top- and bottom-coding applied. SE are reported in parentheses; * for $p < 0.1$; ** for $p < 0.05$; *** for $p < 0.01$.

Source: Author's own elaboration based on data from Eurostat and the LIS Database.

Table 8 illustrates even stronger results for the internet use $\times$ labour force participation interaction, with larger coefficient magnitudes suggesting that active labour market engagement amplifies the distributive benefits of digitalisation. In regions with higher economic activity, internet access appears to facilitate employment opportunities, access to training, and flexible work arrangements. These mechanisms have been identified in rural labour market studies [Braesemann et al., 2020; Kuhn, Mansour, 2014].

Table 8. Instrumental-variable fixed-effects regression results for 96 NUTS 2 regions

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Gini (total)	Gini (factor)	GE1 (total)	GE1 (factor)	Atkinson 0.5 (total)	Atkinson 0.5 (factor)
Internet Use (IU)	-0.126*** (0.04)	-0.110** (0.05)	-0.186*** (0.07)	-0.229* (0.14)	-0.084*** (0.03)	-0.084 (0.05)
Interaction (UI x LABF)	-0.190*** (0.05)	-0.150*** (0.05)	-0.280*** (0.08)	-0.341** (0.15)	-0.122*** (0.03)	-0.121** (0.06)
Labour force part. (LABF)	-0.023 (0.07)	-0.037 (0.07)	-0.045 (0.10)	-0.048 (0.22)	-0.014 (0.04)	-0.028 (0.08)
Other control vars.	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES

cont. Table 8

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Gini (total)	Gini (factor)	GE1 (total)	GE1 (factor)	Atkinson 0.5 (total)	Atkinson 0.5 (factor)
Time fixed effects	YES	YES	YES	YES	YES	YES
Constant	0.108	1.608***	-0.224	2.809**	-0.047	1.454***
	(0.40)	(0.53)	(0.61)	(1.41)	(0.25)	(0.56)
Observations	810.000	810.000	810.000	810.000	810.000	810.000
Regions (number)	96.000	96.000	96.000	96.000	96.000	96.000
R2 within	0.226	0.338	0.131	0.207	0.199	0.380
R2 between	0.206	0.001	0.202	0.009	0.196	0.000

Notes: Inequality measures based on equivalised household total income and factor income, with top- and bottom-coding applied. SE are reported in parentheses; * for $p < 0.1$; ** for $p < 0.05$; *** for $p < 0.01$.

Source: Author's own elaboration based on data from Eurostat and the LIS Database.

While overall trends remain stable, slight differences in internet use coefficient magnitudes are observed between the IV and non-IV models. Some specifications show slightly reduced coefficients, suggesting that earlier models may have captured correlated but not strictly causal effects. However, the interaction terms remain highly robust, affirming the central hypothesis that the effects of digitalisation depend fundamentally on regional characteristics, particularly education and labour market structures.

Table 9. Instrumental-variable fixed-effects regression results for 96 NUTS 2 regions, the high-tech share of employment, and the number of ICT units as instruments

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Gini (total)	Gini (factor)	GE1 (total)	GE1 (factor)	Atkinson 0.5 (total)	Atkinson 0.5 (factor)
Internet Use (IU)	-0.389**	-0.201	-0.591**	-0.484	-0.226**	-0.046
	(0.17)	(0.19)	(0.26)	(0.41)	(0.10)	(0.19)
Interaction (UI x EDUC)	-0.232***	-0.174***	-0.327***	-0.360***	-0.134***	-0.108**
	(0.05)	(0.05)	(0.09)	(0.13)	(0.03)	(0.05)
Tertiary education (TEDU)	-0.122***	-0.080*	-0.174***	-0.167*	-0.071***	-0.037
	(0.03)	(0.04)	(0.06)	(0.09)	(0.02)	(0.04)
Other control vars.	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES
Country fixed effects	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
Constant	-0.154	1.226	-0.153	2.774	-0.185	0.782
	(0.94)	(0.77)	(1.39)	(2.02)	(0.54)	(0.79)
Observations	653.000	653.000	653.000	653.000	653.000	653.000
Regions (number)	86.000	86.000	86.000	86.000	86.000	86.000
R2 within	0.096	0.219	0.046	0.148	0.105	0.277
R2 between	0.219	0.025	0.210	0.010	0.205	0.008

Notes: Inequality measures based on equivalised household total income and factor income, with top- and bottom-coding applied. SE are reported in parentheses; * for $p < 0.1$; ** for $p < 0.05$; *** for $p < 0.01$.

Source: Author's own elaboration based on data from Eurostat and the LIS Database.

The choice of instrumental variable for the IV regression affects the reliability of the results. Therefore, to overcome potential doubts linked to the choice of instrument, additional IV regressions were conducted using an alternative selection of instruments. The earlier models instrumented internet use with indicators of household internet access and their interactions with structural variables. New instruments were chosen to provide characteristics of the regional ICT sector, namely the employment in high-technology industries and the num-

ber of ICT sector units operating in a given region. It can be argued that these alternative instruments capture the technological capacity and intensity of the ICT sector across regions, which may influence the development of digital infrastructure and internet use, while remaining sufficiently distant from the mechanisms that shape income inequality. This allows for assessing the stability and reliability of the results by verifying whether the estimated coefficients remain consistent when alternative sources of exogenous variation in the endogenous variable are employed. From an econometric perspective, this serves as a further robustness test against the potential weakness or misspecification of the original instruments.

The results presented in Table 9 align with the previous results, confirming the correlation of higher internet use with lower income inequality. The interaction between internet use and tertiary attainment is consistently negative and highly significant, suggesting that regions with both greater internet use and higher levels of education tend to experience lower inequality. Once again, these findings remain stable after accounting for other control variables and including region and time fixed effects. Consequently, the results demonstrate that, regardless of whether instruments are chosen from the consumers' perspective (household internet access) or in relation to the ICT sector, in both cases the results confirm the existence of the examined correlation.

Discussion

The findings of this paper reveal the impact of digitalisation on income inequality, and how this impact varies significantly across European NUTS 2 regions depending on their spatial and socioeconomic characteristics. Rather than a uniform relationship, context-dependent effects are observed, which may help to explain seemingly contradictory findings in the existing literature. In sparsely populated and less urbanised regions, digitalisation substantially reduces income inequality. This pattern is consistent with an “inclusion effect”, whereby internet use helps overcome geographic isolation by facilitating access to information, education, and economic opportunities previously out of reach. These results mirror findings from developing countries – studies in China [Gao et al., 2018; Zhang et al., 2025] and Mexico [Mora-Rivera, García-Mora, 2021] demonstrate similar positive effects of digitalisation in rural areas. This paper extends these insights to high-income European contexts, demonstrating that inclusion mechanisms may operate similarly in developed economies. These results support the hypothesis that digital technology creates a skill-biased effect and that economic returns disproportionately benefit better-educated individuals. However, in regions with higher levels of education, this effect is more equally distributed over the population. The same effects can be spotted regarding labour market participation. Thus, rather than creating new opportunities for disadvantaged groups, digital technology may reinforce existing disparities, consistent with Consoli et al. [2023], who document an unequal distribution of digital benefits across European income groups and regions.

The complementary role of human capital therefore emerges clearly through our interaction effects with tertiary education and labour force participation. Regions with higher levels of educational attainment and greater labour force participation experience stronger inequality-reducing effects from digitalisation, highlighting that internet access alone is insufficient to promote inclusive development without the capacity for productive use. These findings complement recent work by Antonietti et al. [2025], who examine how institutional quality moderates the inequality effects of digitalisation. While they focus on institutional heterogeneity, the results in this paper emphasise the important heterogeneity regarding tertiary education and labour force participation as other crucial determinants of distributional outcomes. That said, both studies converge on a key insight: digitalisation does not automatically reduce inequality; rather, its effects depend heavily on contextual conditions, including institutional and social factors.

Conclusions

The empirical results presented in this paper reveal that the impact of digitalisation on income inequality across European regions follows non-linear patterns, dependent on regional characteristics. First, it provides further systematic empirical evidence of how regional characteristics shape the inequality effects of digitalisation across regions. Second, it attempts to examine the conditional effects of digitalisation that vary across different regional contexts, focusing more on labour market factors. With the above-presented results, this research aligns and confirms the conclusions brought earlier by [Consoli et al. \[2023\]](#) and [Antonietti et al. \[2025\]](#), demonstrating moderating effects of skills and institutions on digital transformation outcomes. The paper illustrates the convex relationship between digital inclusion and inequality, where inequality-reducing effects intensify with greater digital engagement. Tertiary education and labour force participation serve as crucial moderators, as regions with a higher level of educational attainment and active labour markets experience substantially greater inequality reductions. Instrumental-variable estimates confirm these causal relationships while addressing endogeneity concerns. These findings align with recent conclusions from the literature, helping to understand how location and institutions work together to shape the relationship between digitalisation and inequality.

The results generally support the important notion that the inequality effects of digitalisation are not pre-determined, but rather depend on the strength and timing of accompanying policies. Human-capital accumulation and labour market activation emerge as the key proxies through which digitalisation can be transformed into an equalising force, rather than a polarising one. On the one hand, where education and participation levels are already high, digitalisation may deepen inclusive growth. On the other hand, in lagging regions, premature digitalisation in the absence of prior investment in foundational and digital skills risks perpetuating existing inequalities. This sequencing argument implies that policy interventions should first lock in human capital foundations – through general tertiary and vocational education, digital literacy, and life-long learning – before intensifying digital activation programmes such as online labour platforms or remote-work incentives. Digital inclusion programmes should therefore not only expand connectivity but be accompanied by regionally specific capacities for skill development and labour absorption. As evidenced in this paper, regional differences play a huge role in shaping the overall impact of the implementation of new technologies. Consequently, policy interventions should reflect these differences through deliberate choices regarding resource allocation and institutional priorities. [Piketty \[2024\]](#) claimed that inequality patterns depend fundamentally on governance decisions and policy design, as none of the countries are “inegalitarian or egalitarian by nature”. Effective digital policies need to account for distinct regional challenges and characteristics, since uniform approaches may inadvertently reproduce the very inequalities they are meant to address.

At the same time, this study has a number of limitations that may be developed in further research. The first limitation is linked to the scope of the research sample, which includes only 96 European NUTS 2 regions due to lack of information concerning income inequality measures and digitalisation proxies. Despite the relatively large digitalisation sample, the exclusion of German, French and numerous Eastern European regions, among others, weakens the universality of the conclusions, in particular since the sample overrepresents certain better-developed regions. Furthermore, some of the variation between European regions may also result from methodological issues related to data on income inequalities – the lack of a uniform database and methodology for measuring regional inequality hinders cross-regional comparability. Moreover, this study overlooks the impact of new technology on the situation of specific individuals at the micro level, instead aggregating data at the regional level. Further similar studies on digitalisation based on microdata will allow for a broader discussion on the impact of technological changes on individuals.

Declaration of generative AI and AI-assisted technology in the writing process

During the preparation of this work, the author used *Deepl.com* and *Grammarly.com* to assist with language editing and improve readability. The author subsequently reviewed and edited the content as needed and takes full responsibility for the content of the publication.

References

- Acemoglu D., Restrepo P. [2018], The race between man and machine: implications of technology for growth, factor shares, and employment, *American Economic Review*, 108 (6): 1488–1542, <https://doi.org/10.1257/aer.20160696>.
- Acemoglu D., Restrepo P. [2022], Tasks, automation, and the rise in U.S. wage inequality, *Econometrica*, 90 (5): 1973–2016, <https://doi.org/10.3982/ECTA19815>.
- Acemoglu D., Robinson J. A. [2012], *Why nations fail: the origins of power, prosperity, and poverty*, Crown Publishers, New York.
- Akerman A., Gaarder I., Mogstad M. [2015], The skill complementarity of broadband internet, *The Quarterly Journal of Economics*, 130 (4): 1781–1824, <https://doi.org/10.1093/qje/qjv028>.
- Antonietti R., Burlina C., Rodríguez-Pose A. [2025], Digital technology and regional income inequality: are better institutions the solution?, *Papers in Regional Science*, (104) 2: 100079, <https://doi.org/10.1016/j.pirs.2025.100079>.
- Autor D. H., Dorn D., Hanson G. H. [2013], The China syndrome: local labor market effects of import competition in the United States, *American Economic Review*, 103 (6): 2121–2168, <https://doi.org/10.1257/aer.103.6.2121>.
- Baum-Snow N., Pavan R. [2012], Understanding the city size wage gap, *The Review of Economic Studies*, 79 (1): 88–127, <https://doi.org/10.1093/restud/rdr022>.
- Beer J. de, Gaag N. van der, Erf R. van der [2014], *New classification of urban and rural NUTS 2 regions in Europe*, NIDI Working Paper No. 2014/3, <https://www.nidi.nl/shared/content/output/papers/nidi-wp-2014-03.pdf> (accessed on 12.06.2026).
- Braesemann F., Lehdonvirta V., Kässi O. [2020], ICTs and the urban-rural divide: can online labour platforms bridge the gap?, *Information, Communication & Society*, 25 (1): 34–54, <https://doi.org/10.1080/1369118X.2020.1761857>.
- Breau S. [2015], Rising inequality in Canada: a regional perspective, *Applied Geography*, 61: 58–69, <https://doi.org/10.1016/j.apgeog.2014.11.010>.
- Brzeziński M., Sałach K., Wroński M. [2020], Wealth inequality in Central and Eastern Europe: evidence from household survey and rich lists' data combined, *Economics of Transition and Institutional Change*, 28 (4): 637–660, <https://doi.org/10.1111/ecot.12257>.
- Capello R., Lenzi C., Panzera E. [2024], The nexus between the digital service economy and intraregional wage inequalities, *Economic Geography*, 100 (3): 246–273, <https://doi.org/10.1080/00130095.2024.2343693>.
- Charron N., Dijkstra L., Lapuente V. [2014], Regional governance matters: quality of government within European Union member states, *Regional Studies*, 48 (1): 68–90, <https://doi.org/10.1080/00343404.2013.770141>.
- Consoli D., Castellacci F., Santoalha A. [2023], E-skills and income inequality within European regions, *Industry and Innovation*, 30 (7): 919–946, <https://doi.org/10.1080/13662716.2023.2230222>.
- Crescenzi R., Di Cataldo M., Rodríguez-Pose A. [2016], Government quality and the economic returns of transport infrastructure investment in European regions, *Journal of Regional Science*, 56 (4): 555–582, <https://doi.org/10.1111/jors.12264>.
- Crescenzi R., Rodríguez-Pose A. [2012], Infrastructure and regional growth in the European Union, *Papers in Regional Science*, 91 (3): 487–513, <https://doi.org/10.1111/j.1435-5957.2012.00439.x>.
- Deursen A. J. van, Dijk J. A. van [2014], The digital divide shifts to differences in usage, *New Media & Society*, 16 (3): 507–526, <https://doi.org/10.1177/1461444813487959>.
- Doran J., Jordan D. [2016], Decomposing US regional income inequality from 1969 to 2009, *Applied Economics Letters*, 23 (11): 781–784, <https://doi.org/10.1080/13504851.2015.1109030>.
- Ezcurra R., Pascual P., Rapún, M. [2007], The spatial distribution of income inequality in the European Union, *Environment and Planning A*, 39 (4): 869–890, <https://doi.org/10.1068/a3893>.
- Forman C., Goldfarb A., Greenstein S. [2012], The internet and local wages: a puzzle, *American Economic Review*, 102 (1): 556–575, <https://doi.org/10.1257/aer.102.1.556>.
- Gao Y., Zang L., Sun J. [2018], Does computer penetration increase farmers' income? An empirical study from China, *Telecommunications Policy*, 42 (5): 345–360, <https://doi.org/10.1016/j.telpol.2018.03.002>.
- Hlasny V. [2020], Nonresponse bias in inequality measurement: cross-country analysis using Luxembourg income study surveys, *Social Science Quarterly*, 101 (2): 712–731, <https://doi.org/10.1111/ssqu.12762>.

- Iammarino S., Rodríguez-Pose A., Storper M. [2019], Regional inequality in Europe: evidence, theory and policy implications, *Journal of Economic Geography*, 19(2): 273–298, <https://doi.org/10.1093/jeg/lby021>.
- Kuhn P., Mansour H. [2014], Is internet job search still ineffective?, *The Economic Journal*, 124(581): 1213–1233, <https://doi.org/10.1111/eoj.12119>.
- Kyriacou A. P., Muínelo-Gallo L., Roca-Sagalés O. [2015], Fiscal decentralization and regional disparities: the importance of good governance, *Papers in Regional Science*, 94(1): 89–108, <https://doi.org/10.1111/pirs.12061>.
- Lessmann C., Seidel A. [2017], Regional inequality, convergence, and its determinants – a view from outer space, *European Economic Review*, 92: 110–132, <https://doi.org/10.1016/j.euroecorev.2016.11.009>.
- Liu H., Wang X., Wang Z., Cheng Y. [2024], Does digitalization mitigate regional inequalities? Evidence from China, *Geography and Sustainability*, 5(1): 52–63, <https://doi.org/10.1016/j.geosus.2023.09.007>.
- Maarseveen R. van [2021], The urban–rural education gap: do cities indeed make us smarter?, *Journal of Economic Geography*, 21(5): 683–714, <https://doi.org/10.1093/jeg/lbaa033>.
- Mora-Rivera J., García-Mora F. [2021], Internet access and poverty reduction: evidence from rural and urban Mexico, *Telecommunications Policy*, 45(2): 102076, <https://doi.org/10.1016/j.telpol.2020.102076>.
- Neugschwender J. [2020], *Top and bottom coding at LIS*, LIS Technical Working Paper Series No. 9, <https://www.lisdatacenter.org/wps/techwps/9.pdf> (accessed on 12.06.2026).
- Novotný J. [2007], On the measurement of regional inequality: does spatial dimension of income inequality matter?, *The Annals of Regional Science*, 41(3): 563–580, <https://doi.org/10.1007/s00168-007-0113-y>.
- Peng Z., Dan T. [2023], Digital dividend or digital divide? Digital economy and urban–rural income inequality in China, *Telecommunications Policy*, 47(9): 102616, <https://doi.org/10.1016/j.telpol.2023.102616>.
- Perugini C., Martino G. [2008], Income inequality within European regions: determinants and effects on growth, *Review of Income and Wealth*, 54(3): 373–406, <https://doi.org/10.1111/j.1475-4991.2008.00280.x>.
- Piketty T. [2024], *Nature, culture, and inequality: a comparative and historical perspective*, Other Press, LLC, New York.
- Poon J. P., Tan G. K., Yin W. [2015], Wage inequality between financial hubs and periphery, *Applied Geography*, 61: 47–57, <https://doi.org/10.1016/j.apgeog.2014.12.023>.
- Richiardi M. G., Westhoff L., Astarita C., Ernst E., Fenwick C., Khabirpour N., Pelizzari L. [2025], The impact of a decade of digital transformation on employment, wages, and inequality in the EU: a “conveyor belt” hypothesis, *Socio-Economic Review*, 23(3): 1225–1251, <https://doi.org/10.1093/ser/mwaf011>.
- Rodríguez-Pose A., Ketterer T. [2020], Institutional change and the development of lagging regions in Europe, *Regional Studies*, 54(7): 974–986, <https://doi.org/10.1080/00343404.2019.1608356>.
- Tabellini G. [2010], Culture and institutions: economic development in the regions of Europe, *Journal of the European Economic Association*, 8(4): 677–716, <https://doi.org/10.1111/j.1542-4774.2010.tb00537.x>.
- Zhang Y., Hainan L., Feng F., Wu X. [2025], Digital economy, education, human capital and urban – rural income disparity, *Finance Research Letters*, 71: 106464, <https://doi.org/10.1016/j.frl.2024.106464>.

Appendix

Pairwise correlations between inequality and digitalisation measures are presented below.

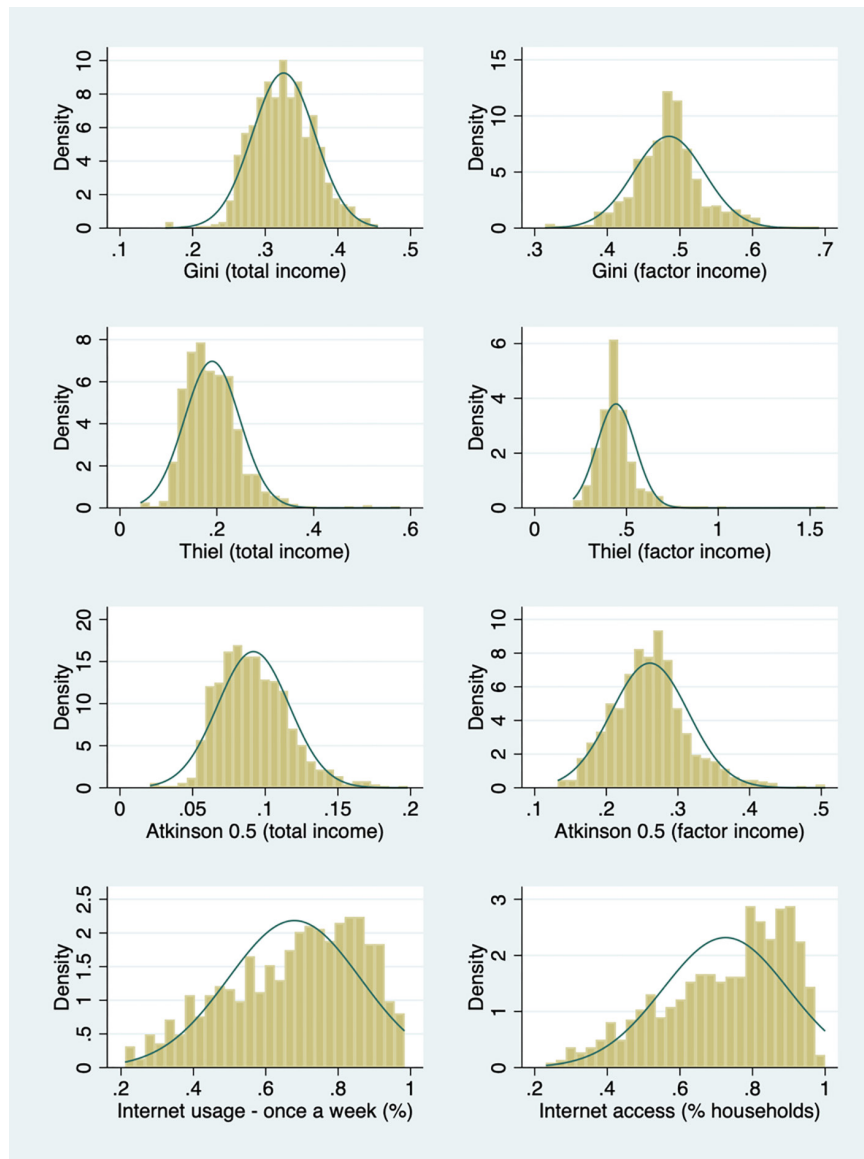
Table 1A. Pairwise correlations matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Gini (total)	1.000							
(2) Gini (factor)	0.675	1.000						
(3) GE1 (total)	0.923	0.681	1.000					
(4) GE1 (factor)	0.551	0.917	0.691	1.000				
(5) Atk.O5 (total)	0.978	0.684	0.966	0.618	1.000			
(6) Atk.O5 (factor)	0.371	0.888	0.448	0.902	0.420	1.000		
(7) Internet use	–0.070	0.108	–0.012	0.160	–0.054	0.215	1.000	
(8) Internet access	–0.031	0.140	0.022	0.189	–0.009	0.235	0.952	1.000

Notes: Inequality measures based on equalised household total income and factor income, with top- and bottom-coding applied.

Source: Author's own elaboration based on data from Eurostat and the LIS Database.

Figure 2. Histograms for variables used in the study



Source: Author's own elaboration based on Eurostat and the LIS Database.