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Digital technology and regional income inequality: Are better institutions the solution?

Roberto Antonietti [a], Chiara Burlina [a,*], Andres Rodríguez-Pose [b]

[a] "Marco Fanno" Department of Economics and Management, University of Padova, Via del Santo 33, Padova 35123, Italy
[b] Cañada Blanch Centre & Department of Geography and Environment, London School of Economics and Political Science, Houghton Street, London WC2A 2AE, UK

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ABSTRACT

In this paper, we examine the effect of regional digital technology (including computing, communication equipment, software, and databases) on income distribution at the regional level. We aim to fill a gap in existing research by exploring the moderating role of formal and informal institutions —such as bonding and bridging social capital— in shaping how digital technology affects income inequality across European NUTS2 regions from 2006 to 2016. The results indicate that regions with greater access to digital technology are prone to higher levels of income inequality. However, this negative link is mitigated by strong formal and informal institutions, particularly through improved government effectiveness and bridging social capital. The findings are robust to potential endogeneity concerns, as demonstrated by the instrumental variable approach adopted.

1. Introduction

Since the inception of Industry 4.0, there has been renewed interest in understanding how investments in (and the adoption of) digital technologies (DTs) affect income inequality (e.g., Acemoglu and Restrepo, 2020; Berg et al., 2018; Klenert et al., 2022; Last, 2017; Liao et al., 2022). The prevailing theory suggests that the adoption of DTs leads companies to adjust their hiring strategies, prioritising highly skilled workers with non-routine capabilities. This shift ultimately benefits those with higher education levels or technical proficiency, while marginalising individuals with medium or low skills (Fuchs, 2009; van Dijk, 2005; Niebel, 2018; Wang et al., 2021; Mitrovic, 2020; Nicoletti et al., 2020).

However, recent literature indicates that the relationship between DT adoption and inequality is far more complex (Autor, 2022). Rather than a straightforward correlation between higher skills and higher wages, technology tends to automate routine, middle-skill jobs. This pushes the labour market towards two extremes: high-skill, well-paid jobs and low-skill, low-paid ones. Consequently, middle-income occupations are eroded, exacerbating wage inequality and creating a "hollowing out" effect. Wage polarisation and greater inequality across the income distribution are the results.

However, others argue that the effects of the adoption of DTs are not always bad. Montobbio et al. (2023) suggest that technology creates new employment opportunities, particularly in high-skill, non-routine jobs, but that these developments do not necessarily lead to increased inequality. They stress the importance of labour market institutions, education policies, and training programmes in mediating the effects of technology. Without institutions and policies to enable workers to upskill or reskill, task polarisation in advanced economies may further widen income inequalities as workers displaced by automation struggle to find new opportunities in a rapidly evolving labour market.

Addressing the digital divide, therefore, requires a multi-faceted approach, including tailored policy interventions, targeted education and training, and technology design that accounts for the needs of diverse users (Vassilakopoulou and Hustad, 2023). Unfortunately, much of the evidence on the role of institutions and policies in this context has been limited to country or macro-level studies. This paper seeks to fill this gap by examining the relationship at the regional level in Europe.

Specifically, we consider two types of institutions: formal and informal. Formal institutions primarily relate to regional government quality, while informal institutions concern social capital, divided into Robert Putnam's (2000) concepts of bridging and bonding social capital. To our knowledge, no prior research has studied the role of institutions as a moderating factor in the relationship between DTs and income inequality. We address this by examining whether increased availability

* Corresponding author.
E-mail addresses: roberto.antonietti@unipd.it (R. Antonietti), chiara.burlina@unipd.it (C. Burlina), A.Rodriguez-Pose@lse.ac.uk (A. Rodríguez-Pose).

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of DTs[1] in a region correlates with higher interpersonal income inequality and, crucially, whether formal and informal institutions moderate the impact of DTs on regional income inequality.

Our analysis spans 140 European NUTS2 regions from 2006 to 2016, incorporating data from a range of sources, including EU-KLEMS, Eurostat's Statistics on Income and Living Conditions (SILC) survey, the Luxembourg Income Study (LIS), the *European Value Survey (EVS)*, the Quality of Government (QoG) dataset, and Eurostat's regional statistics. Using a panel fixed-effects estimator, we assess the influence of real DT investments per employee on inequality, proxied by the Gini index, while controlling for other regional characteristics such as investments in research and development (R&D), human capital, and population density. We further examine the interaction between DTs and institutions and address potential reverse causality through an instrumental variable (IV) approach.

The findings reveal that regions with higher DT endowments experience increased income inequality. However, in regions with stronger formal and informal institutions, the negative impact of DTs is mitigated, and in some cases, higher DT endowments can contribute to a more equitable income distribution. This moderating effect is particularly significant for informal institutions, especially bridging social capital. The results underscore the vital role of institutions in smoothing the digital transition in European regions and highlight the need for policies that promote both DT investment and social capital development.

The remainder of the paper is organised as follows: Section 2 examines the theoretical relationship between DTs and formal and informal institutions; Section 3 outlines the data and methodology; Section 4 presents the key findings; and Section 5 concludes with policy recommendations to support DT adoption in the European context.

2. Digital technology, inequality, and institutions

2.1. Digital technology and income inequality

In Europe, there is a growing interest —not exempt from concern— over the rise in income inequality. Inchauste and Karver (2018) observe that while income inequality has declined across the European Union (EU) over the last two decades, it has steadily increased within individual EU countries, particularly after the 2007 financial crisis. This trend is largely attributed to the polarisation of labour income, with high-income individuals concentrating wealth at the top, while low-income individuals fall further behind. This phenomenon is especially pronounced in Southern and Central European countries and is often linked to higher unemployment rates and the proliferation of low-quality jobs.

Since the 1990s, a growing body of scholarly research has pointed to information and communication technology (ICT) and digital technology (DT) as two key drivers behind the rise in inequality. These technologies tend to favour those with high skills or those involved in routine tasks, while displacing lower-skilled jobs and routine activities (Acemoglu, 1998, 2002; Autor et al., 2003; Krusell et al., 2000). Bauer et al. (2023) provide three main explanations for this. First, DT affects the productivity of labour and capital, impacting their demand and compensation. The digital capital-skill complementarity theory suggests an increasing demand for capital and high-skilled labour, alongside a declining demand for low-skilled labour, thereby exacerbating income disparities. Second, the enhanced division of labour enabled by ICT allows firms to fragment their value chains and outsource activities abroad. As globalisation and international trade expand, the economic returns for entrepreneurs, managers, and highly skilled workers in technologically advanced economies rise, potentially at the expense of medium and low-skilled workers. Finally, digital innovation fosters a process of creative destruction, where high-quality, well-paid jobs created by multinationals, digital platforms, or high-tech start-ups progressively replace lower-quality, lower-paid positions.

Empirical studies testing these hypotheses generally focus on firms or national/cross-country levels. Prior research identifies several key factors driving income inequality. They include labour supply variables (e.g., human capital endowment and distribution), population and migration dynamics, and national institutional frameworks that include labour market regulations, social welfare, education access, and credit system development (Li and Zou, 1998; Barro, 2000). More recently, Richmond and Triplett (2018) examined the ICT-inequality nexus across 109 countries from 2001 to 2014, finding that broadband subscriptions are the only ICT measure positively correlated with inequality, contributing to a significant rise in the Gini index. Their study also shows that this effect is moderated by the quality of institutions: in less stable countries, broadband access tends to be concentrated among high-income households, enabling them to generate non-market forms of income. Xiao et al. (2024) explore how technological innovation can both alleviate and exacerbate income inequality in 59 countries between 1995 and 2020. They find that, while innovations like communication equipment and software initially reduce inequality by enhancing productivity and accessibility, they often lead to long-term disparities, favouring high-skilled workers and asset owners. Moreover, biased technological change, particularly through automation and skill-biased advancements, influences the income gap.

Research on the determinants of income inequality at the regional level, by contrast, remains sparse and fundamentally concentrates on the United States context. Studies in this area highlight the significance of distinct and unequal factor endowments in shaping income distribution dynamics. Topel (1994) demonstrate that the employment of women and immigrants in US counties negatively impacts men's wages, while technological advancements tend to benefit high-skilled workers. Partridge et al. (1996) find that escalating inequality in US states is primarily driven by international immigration, urbanisation, and the rise of female-led households, while formal institutions such as unionisation rates show no significant influence.

Research on the EU and its regions is even scarcer. Among the few studies focusing on European regions, Perugini and Martino (2008) identify three main factors influencing income inequality: economic development, technology, and formal institutions. Analysing data from the Luxembourg Income Survey for 1995 and 2000, they find that technology and innovation are consistently associated with higher levels of income inequality, while certain institutions —particularly the implementation of a centralised wage bargaining system— facilitate a more even distribution of income across regions. More recent analyses by Barbero and Rodríguez-Crespo (2022) —who examine access to internet and broadband across households in 229 European regions between 2007 and 2018— reveal that higher ICT diffusion is connected with increases in GDP per capita and a reduced poverty risk. Other research further indicates that the distribution of DT services across the EU is highly uneven and may contribute to growing income disparities within countries (Evangelista et al., 2014; Capello et al., 2023, 2024). On the same vein, Brunetti et al. (2020) examine the distribution of low-skill jobs and routine task specialization across Italian provinces. Their findings suggest that provinces with a higher concentration of routine-intensive occupations are more vulnerable to the adverse effects of digital technologies, such as automation and digitization. These technologies lead to job displacement and wage stagnation, particularly within low-skill employment sectors.

Moreover, DT-related indicators include several categories based on ICT adoption and use, which complicate the analysis of the digital divide across regions. Measuring digital inequality is challenging due to ICT's multidimensional nature, which is constantly evolving and includes various aspects of how people use technology for work, education, and

[1] In particular, we analyse the effects of three broader DT categories: (i) computing equipment, (ii) communication equipment, and (iii) computers, software, and databases.

social interactions (Cruz-Jesus et al., 2012). Limiting the literature on ICT to categories such as computing equipment, communication devices, and software and databases — the primary focus of this paper — reveals that only two recent studies have examined their role in shaping income inequality. The first, by Özcan Alp and Baycan (2024), explores the digital divide between regions in Turkey, focusing on how disparities in technology adoption impact economic and social development. Using a principal component analysis (PCA), the authors develop an index to measure regional digital inequalities based on ICTs, gender inequality, and R&D investment variations. Their findings show that the digital divide is more pronounced at the city level than at the broader regional scale, emphasising the need for targeted policies to improve digital inclusion and promote balanced regional development. The second study, by Consoli et al. (2023), investigates how the workforce's digital skills relate to income inequality across European regions from 2003 to 2013. Their results show that the effect of digital skills on income inequality varies across income groups. Increased digitalisation exacerbates inequalities among lower income individuals, but mitigates them for those in higher income brackets. This highlights that the benefits of digital skills are unevenly distributed, with digital progress potentially deepening the economic divide, especially among the less affluent.

Given this background, we propose our first research hypothesis:

Hypothesis 1. *A greater provision of digital technologies in a region is connected with higher income inequality*.

2.2. The role of institutions for inequality

Income distribution is influenced by more than just digital technology. Some of the studies presented earlier also highlight the availability of high-quality institutions as an additional factor affecting income disparity both between and within countries. For instance, Perugini and Martino (2008) find that robust and inclusive labour markets, along with centralised wage bargaining systems and social protection benefits, attenuate income inequality in European regions. This conclusion is further supported by Barbero and Rodríguez-Crespo (2022), who demonstrate that stronger institutions are associated with higher GDP per capita and a lower risk of poverty across European regions between 2007 and 2018.

At the national level, Richmond and Triplett (2018) observe that internet use and broadband penetration tend to exacerbate income disparities in politically unstable contexts or when government effectiveness is low. They also note that the impact of mobile phone use on income inequality depends on the strength of the rule of law, particularly regarding property rights and contract enforcement.

In transition economies, Dell'Anno and Solomon (2014) identify a positive relationship between ICT investment and income inequality, which is moderated by education and institutional quality. In contrast, Taniguchi and Yamada (2022) do not find a significant role for collective bargaining in influencing ICT-skill complementarity in OECD countries.

Institutions can also indirectly affect income inequality through other variables, such as productivity growth (Antonietti and Burlina, 2023; Rodríguez-Pose and Ganau, 2022), investment efficiency (Rodríguez-Pose and Garcilazo, 2015; Rodríguez-Pose and Ketterer, 2020), entrepreneurship (Nistotskaya et al., 2015), and innovation (Rodríguez-Pose and Di Cataldo, 2015), which in turn may correlate with income dispersion. While most of these studies focus on the quality of formal institutions, few explore the role of informal institutions or social capital.

We argue that social capital plays a crucial role in reducing the income-distorting effects of digital capital by facilitating job reallocation or preventing job displacement. This is particularly true for bridging social capital, which consists of weak and inclusive ties between diverse groups (Putnam, 2000). Such social capital can serve as an informal channel for reintegrating displaced workers into the labour market, even in unrelated sectors (Antonietti et al., 2023), or by nurturing the creation of related and unrelated activities within a region (Antonietti and Boschma, 2021). Bonding social capital —characterised by strong, exclusive links among homogenous groups— may also matter. Strong within-group ties can shield displaced workers from the negative economic shocks associated with skill-biased technological change or help them find employment in similar or related sectors.

In summary, both forms of social capital can mitigate the income inequality induced by technological change (Farivar and Richardson, 2021), complementing formal institutions like contract enforcement, wage-bargaining systems, and redistributive tax policies.

Based on this discussion, we formulate our second research hypothesis:

Hypothesis 2. *Formal and informal institutions moderate the (expected) positive relationship between a region's DT endowment and income inequality*.

3. Data description and methodology

To examine the relationship between DTs, institutions, and income inequality, we develop a unique dataset at the regional level, drawing from four key sources: (i) the *Statistics on Income and Living Conditions (SILC)* and *Luxembourg Income Study (LIS)* surveys, which provide data on the dependent variable, income inequality; (ii) *EU-KLEMS* and the *Annual Regional Database (ARDECO)* from the European Commission's Directorate-General for Regional and Urban Policy, from which we obtain information on regional DT endowments; (iii) the *European Value Survey (EVS)*, which we use to compute social capital indicators; and (iv) the *Quality of Government (QoG) Institute* at the University of Gothenburg and the World Bank's *World Governance Indicators*, which provide data on formal institutions across European regions.

Additional control variables were sourced from *Eurostat's Regional Statistics*. The full dataset covers 140 NUTS-2 regions for the period 2006–2016. However, the number of regions drops to 113 when formal institutions are considered, and to 102 when both formal and informal institutions are included in the analysis.

3.1. Dependent variable

The dependent variable is the Gini index, which serves as a proxy for income disparities within regions. The Gini index measures the extent to which the distribution of equivalised disposable income after social transfers deviates from perfect equality. For most regions in our sample, data are sourced from the SILC survey, with the exception of Germany, where information is derived from the LIS database (Ravallion, 2015). The Gini index ranges from 0 (perfect equality) to 1 (complete inequality). Although other indices, such as the relative poverty index or the share of individuals in the top 20 % or 5 % of income distribution, are used in inequality studies (Guellec and Paunov, 2017), the Gini index remains prevalent in studies related to internet diffusion (e.g., Zhang, 2013; Howard et al., 2010), DT-driven investments (e.g., Mohd Daud et al., 2021; Baiardi and Morana, 2018), and ICT access (e.g., Fuchs, 2009; Richmond and Triplett, 2018).

3.2. Digital technology

Our chosen measure for DT is defined by investments per employee, encompassing gross fixed capital formation (GFCF) in three sectors: computing equipment (IT), communication equipment (CT), and computer software and databases (CSD). This approach captures both the hardware and software aspects of DT. Taking into consideration both hardware and software is important as far as hardware is crucial for closing the digital divide, as investments in infrastructure enhance regional economic performance and reduce disparities; at the same time, software transforms access into outcomes, facilitating education, capabilities, and productivity (Autor, 2015). Their integration is critical, as hardware provides accessibility, and software ensures utility, complementing human labour and fostering opportunities for skill development (Acemoglu and Restrepo, 2018). Data are expressed in constant 2010 market prices and sourced from the *EU-KLEMS* database (2019 release), which offers annual, sector-specific data at the country level. We adjust these values using regional weights from 2001 to estimate DT at the regional level, calculated as follows:

$$DT_{r,t} = w_{r,2001} * (GFCF_{IT\,c,t} + GFCF_{CT\,c,t} + GFCF_{CSD\,c,t}),$$

where c represents the country, r denotes the region, and t is the year. The weights ($w_{r,2001}$) are calculated using the following formula:

$$w_{r,2001} = \frac{GFCG_{r,2001}}{GFCG_{c,2001}}$$

where $GFCF_r$ is the stock of capital assets in 2001 at the NUTS-2 level. This indicator is extracted from the ARDECO database. It implicitly assigns equal importance to the three components of DT, without accounting for the fact that the three specific elements considered might contribute differently to the formation of the stock of capital assets. Since, to the best of our knowledge, data on CT, IT, and CSD for European NUTS-2 regions are not available, we proceed to compute three alternative regional weights, based on employment data extracted from the EU Labour Force Survey (LFS).

Inspired by Castellacci et al. (2020) and the capital-skill complementarity hypothesis (Griliches, 1969; Goldin and Katz, 1998), we develop three alternative weights, assuming that DT investments are higher in regions where digital skills are more prevalent and intense.

1. Weight 1 (w_1): Based on the share of employees classified as professionals (ISCO08 category 2) and technician and associate professionals (ISCO08 category 3), who exhibit the highest digital skills as developers, practitioners, and users (Castellacci et al., 2020).
2. Weight 2 (w_2): Incorporates employees in categories 2 and 3, alongside clerical support workers (ISCO08 category 4) and skilled agricultural, forestry, and fishery workers (ISCO08 category 6), representing users of digital skills.
3. Weight 3 (w_3): Reflects e-skill task intensity in each region, calculated by matching all ISCO occupations with 69 e-skills items from ESCO, the European Commission's O*NET-like database on tasks and skills. A regional e-skill intensity indicator is then generated by weighting the e-skill intensity index by ISCO employment shares.

With these employment-based weights, we compute three alternative measures of DT:

$$DT1_{r,t} = w_{1r,2001} * (GFCF_{IT\,c,t} + GFCF_{CT\,c,t} + GFCF_{CSD\,c,t}),$$

$$DT2_{r,t} = w_{2r,2001} * (GFCF_{IT\,c,t} + GFCF_{CT\,c,t} + GFCF_{CSD\,c,t}),$$

$$DT3_{r,t} = w_{3r,2001} * (GFCF_{IT\,c,t} + GFCF_{CT\,c,t} + GFCF_{CSD\,c,t}).$$

To obtain a more reliable measure of the regional fixed capital stock, we first compute $GFCG_{r,2001}$ using the perpetual inventory method as follows, starting from year 1980 until 2001:

$$GFCG_{r,t} = (1 - \partial) * GFCG_{r,t-1} + I\_GFCG_{r,t}$$

where ∂ is a depreciation rate set at 0.15 in line with previous literature (Antonietti and Montresor, 2021; Montresor and Vezzani, 2015) and I_GFGC is the annual investment in fixed capital assets operated in each available NUTS-2 European region. Our weights refer to 2001, as we believe that a five-year lag with respect to the other variables can prevent possible endogeneity issues. Finally, we divide our $DT_{r,t}$ by the number of employees in region r and year 2001 to avoid possible endogeneity with respect to the capital variables.

Fig. 1 illustrates the geographical distribution of DT investments in 2006 (a) and the average annual growth rates for 2006–2016 (b). European regions exhibit significant heterogeneity in the adoption of and investments in digital technologies, a trend highlighted also by Giannini and Martini (2024). Specifically, regions with higher DT investments are predominantly in Northern Europe, specifically in Sweden and Denmark, as well as in Romania and Hungary in Eastern Europe (Fig. 1 (a)). This pattern aligns with substantial investments by the European Commission in digitalisation and connectivity in Romania and Hungary (Evangelista et al., 2014), while Sweden and Denmark are recognised as two of the most innovative countries globally (Binz and Truffer, 2017). The DT investment landscape remains relatively stable over time, as shown in Fig. 1(b) for 2016, although there is a notable recovery in DT investment in regions such as Rhône-Alpes, Auvergne, and Bourgogne in France, as well as in nearly all regions of the Netherlands and the most industrialised regions of Spain (Lucendo-Monedero et al., 2023; Anghel et al., 2024; Acemoglu et al., 2023; Khlystova and Kalyuzhnova, 2023).

3.3. Institutions

The second factor shaping the relationship between inequality and digital technologies (DT) relates to institutions. We distinguish between formal and informal institutions. Formal institutions consist of

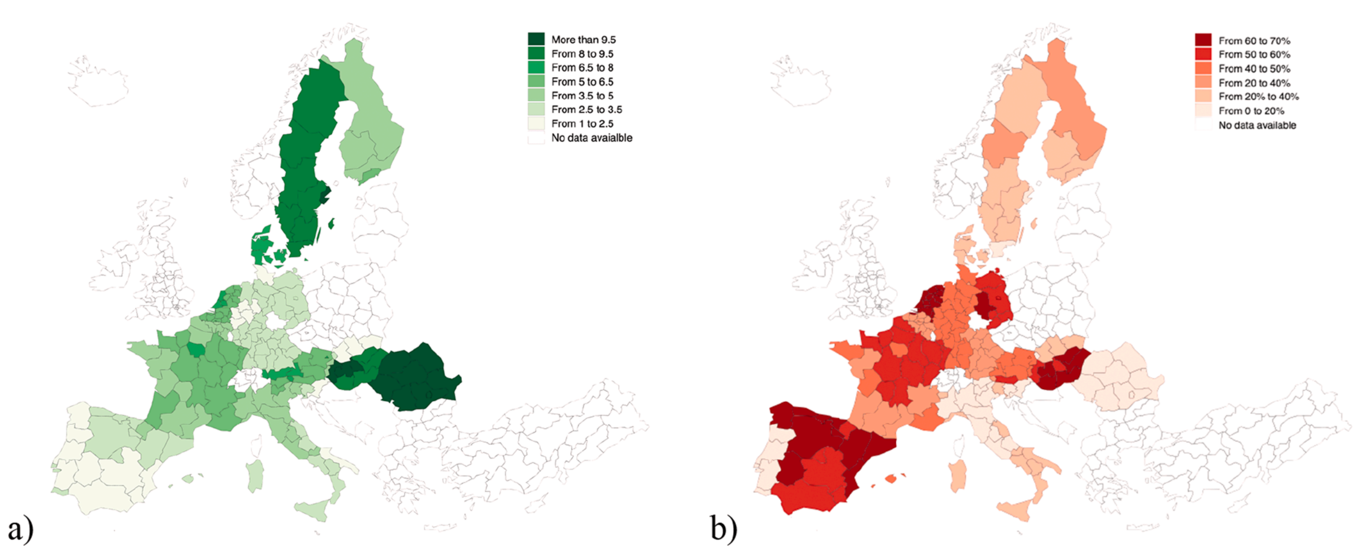

Fig. 1. Per capita investments in DT in 2006 (a) and 2006–2016 average annual growth rates (b). Note: Authors' elaboration based on EU-KLEMS data.

recognisable and transferable rules and the quality of the regional governments and administrations, while informal institutions are represented here by bonding and bridging social capital.

To measure formal institutions, we rely on the *Worldwide Governance Indicators (WGI)* developed by the World Bank (Kaufmann and Kraay, 2023). This composite indicator is based on five pillars: voice and accountability, political stability and absence of violence/terrorism, government effectiveness, regulatory quality, rule of law, and control of corruption. Among these, we specifically focus on government effectiveness since it is a widely recognised measure for monitoring social growth and effectively captures the quality of public and civil services (Dubey et al., 2023; Wandaogo, 2022). To measure government effectiveness at the regional level, we use the approach of Rodriguez-Pose and Garcilazo (2015), who combine and interpolate data from the Quality of Government Institute, University of Gothenburg (Charron et al., 2014), available for European regions only for specific years, with the World Bank's Worldwide Governance Indicators (WGI), which are available for more years but at the national level.

For informal institutions, we use social capital indicators, that are widely employed in research on income inequality (e.g., Muringani et al., 2021; Hoyman et al., 2016). To construct our measures of bonding and bridging social capital, we use data from the *European Value Survey (EVS)*, which provides individual-level data on participation in various types of organisations. We calculate the share of social capital at the regional level following the methodology outlined in Muringani et al. (2021), which is detailed in the Appendix.

3.4. Control variables

Our analysis includes several control variables. First, we calculate the annual number of patent applications (in log) to the European Patent Office per capita (*ln*PATENT). Patent application data are sourced from *OECD REGPAT*, where we assign patents to NUTS-2 regions based on the location of applicants.

We also incorporate the level (in log) of human capital (*ln*HC), defined as the share of the resident population with tertiary education (ISCED levels 3–8), as well as the log-transformed levels of population (*ln*POP) and population density (*ln*POPDEN), calculated as the number of people per square kilometre. Education is often linked to the digital divide in academic literature, as individuals with higher educational attainment tend to be more proficient in using DTs (Lythreatis et al., 2021). Population density accounts for potential agglomeration effects (Combes et al., 2011; Lavoratori and Castellani, 2021). Both the HC and POPDEN variables are sourced from *Eurostat's Regional Statistics* database.

Based on the literature reviewed in Section 2, we also include the log-transformed share of the female labour force (*ln*FEMALE) and the log-transformed shares of gross regional value added (GVA) from manufacturing and service activities, respectively (*ln*GVAMAN and *ln*GVASERV). The share of female employment reflects gender balance in a region's labour market, and we expect it to be positively associated with a more equitable income distribution, corresponding to a negative correlation with the Gini index. The other two variables capture a region's macroeconomic structure and development level. We expect regions with a higher share of value added from the secondary (manufacturing) and tertiary (services) sectors to be less prone to rent-seeking behaviours, which are more common in regions dominated by agriculture, extraction, or mining activities. These regions are also expected to exhibit a more equal income distribution.

Detailed summary statistics, descriptions, and sources for each variable are presented in the Appendix (Table A1), while Table A2 shows the pairwise correlations among the regressors.

3.5. Methodology

To test our hypotheses, we estimate the following equation:

$$\ln Gini_{r,t} = \beta_1 \ln DT_{r,t} + \beta_2 \quad Inst_{r,t} + \beta_3 \quad (\quad \ln DTs_{r,t} * Inst_{r,t}) + \quad \mathbf{X}\prime_{r,t}\beta_4 + \theta_t + \mu_r + \varepsilon_{r,t} \tag{1}$$

where, the dependent variable is the logarithm of the Gini coefficient in region r in year t, and the independent variables include the logarithm of digital technology capital per employee and the quality of institutions, measured through either government effectiveness or bonding versus bridging social capital. We also introduce their interaction term and a vector $\mathbf{X}_{r,t}$ of control variables, such as the logarithms of population density, human capital endowment, patent applications per capita, share of female labour force, and shares of gross value-added originating from manufacturing and from services. The terms θ_t and μ_r denote, respectively, year-specific and region-specific unobserved fixed effects, while $\varepsilon_{r,t}$ represents the stochastic error term.

To address unobserved, time-invariant omitted variables, our initial estimation is based on a panel fixed-effects model. To adjust for potential cross-sectional dependence, which may arise from regional spillovers, we use the Driscoll and Kraay (1998) method. This kernel-based approach accounts for cross-sectional and temporal lags in the error terms, providing consistent and efficient estimates even in the presence of spatial autocorrelation. By applying this adjustment, we improve the reliability of our econometric models.

An important issue concerns endogeneity, especially in the form of possible reverse causality from income inequality to digital technology endowment. We address the potential simultaneity between the Gini index and DT employing an instrumental variable approach based on the two-step efficient generalised method of moments (GMM). We use real per capita investments in vocational training activities as an external instrument. These data, sourced from the EU-KLEMS database at the country level, are allocated among NUTS-2 European regions using a population weight for the year 2001.[2] This instrument respects the two core assumptions of the IV approach: it is correlated with *ln*DT but uncorrelated with the error term in the model. Our exclusion restriction is that while training investments may not directly influence income inequality, they can indirectly have an impact on it by first affecting the rate of adoption and use of DT within firms. Following Mushtaq et al. (2021) and Gopalan et al. (2022), we argue that firms investing in employee training are more likely to adopt digital technologies. Thus, the need for DT adoption drives the provision of worker training. Although there is no direct research linking training investments to regional income inequality, we suggest that any effects on income distribution are mediated through enhanced worker proficiency with DTs.

We also check for the exogeneity of *ln*DT using the Durbin-Wu-Hausman test, and we evaluate our instruments by running a reduced-form regression of Eq. (1), using our instrument *ln*TRAINING as a regressor. Table A3 in the Appendix presents the results, where the estimated coefficient of our training variable is consistently non-significant.

We do not consider the potential endogeneity of social capital variables in this analysis. Social capital, rooted in networks of relationships, trust, and norms of reciprocity, predates the widespread adoption of digital technology. Historically, social capital has been built through family ties, community interactions, social organisations, and institutions (Duranton et al., 2009; Knack and Keefer, 1997; Putnam,

[2] To distribute training investments at the regional level, we employ a weighting method distinct from w_{2001} to prevent any potential overlap between the endogenous variable, *ln*DT, and the instrument. This approach ensures the independence of our instrumental variable from the primary variable of interest, maintaining the integrity of the instrumental variable method by avoiding endogeneity issues between *ln*DT and the chosen instrument for training investments. This consideration is necessary for the validity of our instrumental variable strategy, allowing us to accurately assess the impact of digital technology on income inequality while accounting for the moderating role of institutions.

1993, 2000; Guiso et al., 2008), long before the digital era. This suggests that the origins and drivers of social capital are largely independent of digital technology, indicating exogeneity.

Moreover, social capital is shaped by cultural, historical, and institutional contexts (e.g., norms, traditions, and civic engagement), which are deeply rooted in non-digital aspects of society. In addition, digital capital is unevenly distributed across socioeconomic groups, while social capital can exist even in populations with limited digital access. For example, immigrant or marginalised communities may have strong social capital despite lacking digital resources, further supporting the notion that social capital operates independently of digital capital. The accumulation of trust, norms, and social networks is slow and less responsive to technological changes, making social capital more embedded in long-term social dynamics.

Based on these considerations, in the IV regressions we use *ln*TRAINING as an instrument for *ln*DT, and *ln*TRAINING*GOVEFF, lnTRAINING*BRIDGING, and *ln*TRAINING*BONDING as instruments for, respectively, *ln*DT*GOVEFF, *ln*TDT*BRIDGING, and *ln*DT*BONDING.

4. Results

Table 1 presents the findings from our analysis of digital technologies (DTs) and formal institutions. In Column 1, the coefficient of *ln*DT is positively significant at the 1 % level, as expected. This significance holds across all specifications, even after incorporating institutions and other control variables. The positive coefficient in Column 1 indicates that a 10 % increase in digital capital endowment is associated with an approximate 1.3 % increase in income inequality within the same region. When formal institutions (government effectiveness) are introduced in Column 2, the coefficient for *ln*DT remains positive and significant, while the coefficient for government effectiveness becomes negative and significant at the 5 % level. This suggests that higher government effectiveness can reduce income inequality in European regions.

The relationship remains consistent when digital technology interacts with government effectiveness, as shown in Columns 3 and 4. Regional income inequality decreases when higher digital technology endowment is combined with stronger formal institutions (Beaunoyer et al., 2020). This implies that high-quality formal institutions can mitigate the adverse effects of digital technology on income distribution, potentially by providing more opportunities for less-educated individuals or redistributing income to poorer segments of the population. Additionally, regions with higher female employment, more frequent patent applications, and more value added from manufacturing and service sectors tend to have lower income inequality.

Table 2 examines the role of informal institutions, specifically bridging and bonding social capital. In Column 1, the coefficient for *ln*DT is no longer statistically significant, indicating that investments in digital technology alone, when controlling for social capital, do not have a clear relationship with income inequality at the regional level. However, in Columns 2 and 3, when combined with greater bridging social capital, the interaction term between *ln*DT and bridging social capital becomes negative and strongly significant, suggesting that bridging social capital helps mitigate the inequality-inducing effects of digital technology. Similarly, in Columns 4–6, bonding social capital shows a negative and significant impact, reinforcing the importance of informal institutions in counteracting the adverse effects of digital technology on income inequality.

The results from Tables 1 and 2 provide partial support for our hypotheses. While digital technology alone is correlated with higher income inequality in the EU, the presence of strong formal and informal institutions moderates this effect. Our second hypothesis is fully supported: both formal and informal institutions play a crucial role in promoting equitable income distribution and mitigating the potentially negative effects of digital capital.

Tables 1 and 2 distinguish between two types of institutions, treating them as separate entities. Table 3, however, integrates both formal and informal institutions to examine their collective impact on income inequality. Due to the high correlation between bridging and bonding social capital (approximately 0.8, see Table A2 in the Appendix), we evaluate them independently within the analysis.

The findings in Table 3 indicate that, when considered together in the same model, both formal and informal institutions exhibit a significant and negative association with the Gini coefficient. This suggests that improved government effectiveness and/or a greater provision of bonding and bridging social capital are linked to reduced income disparities, even after accounting for the regional availability of DT. A comparison of the standardized coefficients reveals that those for bonding and bridging social capital consistently surpass the coefficient for government effectiveness. This implies that informal institutions play a more substantial role than formal institutions in mitigating income inequality. However, the effect sizes are modest: a one standard deviation increase in bridging or bonding social capital leads to a decrease in the Gini index by approximately 0.04 %, whereas a one standard deviation enhancement in government effectiveness is associated with a 0.001 % reduction in the Gini index.

Fig. 2 shows the marginal effects of *ln*DT on *ln*Gini, corresponding to increasing levels of GOVEFF (2a), BRIDGING (2b), and BONDING (2c), respectively.

Tables A4, A5, and A6 in the Appendix show the results of the panel fixed effects regressions where *ln*DT is replaced by *ln*DT1, *ln*DT2, and *ln*DT3. For reasons of space, we only report the estimated coefficients of the main regressors. The results remain similar to those presented in Tables 2 and 3: regardless of the measure of regional digital technology adopted, formal, but especially informal institutions help digital technologies reduce income inequalities within European regions.

4.1. Endogeneity

Our analysis may be subject to reverse causality bias, arising if higher income inequality influences the accumulation of digital capital in a region. For instance, the adoption of DT might depend on the local availability of high-skilled workers, who typically earn higher incomes

Table 1
Digital technology and income inequality: the role of formal institutions.

	(1)	(2)	(3)
Dep. Var.: *ln*GINI	FE	FE	FE
lnDT	0.013***	0.012***	0.014***
	[0.002]	[0.002]	[0.001]
GOVEFF	−0.001**	−0.008**	−0.009***
	[0.000]	[0.003]	[0.003]
lnDT x GOVEFF		−0.001***	−0.002***
		[0.000]	[0.000]
*ln*POP			0.003***
			[0.000]
*ln*POPDEN			−0.126
			[0.129]
*ln*HC			0.017
			[0.017]
*ln*FEMALE			−0.346***
			[0.090]
*ln*PATENT			−0.001***
			[0.000]
*ln*GVAMAN			−0.115**
			[0.051]
*ln*GVASERV			−0.255**
			[0.111]
Year FE	Yes	Yes	Yes
Nr. obs.	1232	1232	1232
Nr. regions	112	112	112
R^2 within	0.103	0.104	0.122

Note: Driscoll-Kraay standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 2
Digital technology and income inequality: the role of informal institutions.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.: *ln*Gini	FE	FE	FE	FE	FE	FE
lnDT	−0.025	−0.030	−0.010	−0.016	−0.029	0.002
	[0.029]	[0.028]	[0.032]	[0.029]	[0.029]	[0.032]
BRIDGING	0.001	−0.196***	−0.236***			
	[0.012]	[0.041]	[0.046]			
lnDT x BRIDGING		−0.040***	−0.045***			
		[0.007]	[0.009]			
BONDING				−0.027**	−0.104***	−0.062***
				[0.013]	[0.027]	[0.016]
lnDT x BONDING					−0.022***	−0.014***
					[0.005]	[0.004]
*ln*POP			0.011***			0.011***
			[0.002]			[0.003]
*ln*POPDEN			−0.099			−0.087
			[0.120]			[0.126]
*ln*HC			0.025			0.018
			[0.015]			[0.016]
*ln*FEMALE			−0.203***			−0.170**
			[0.087]			[0.085]
*ln*PATENT			−0.0005*			−0.0004
			[0.0003]			[0.0003]
*ln*GVAMAN			−0.120**			−0.123**
			[0.058]			[0.056]
*ln*GVASERV			−0.314*			−0.300*
			[0.162]			[0.153]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nr. obs.	1243	1243	1243	1243	1243	1243
Nr. regions	113	113	113	113	113	113
R^2 within	0.086	0.093	0.116	0.091	0.099	0.122

Note: Driscoll-Kraay standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3
Digital technology and income inequality: comparing formal and informal institutions.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.: *ln*Gini	FE	FE	FE	FE	FE	FE
lnDT	−0.005	−0.001	0.004	0.008	−0.001	−0.000
	[0.027]	[0.033]	[0.028]	[0.033]	[0.031]	[0.030]
GOVEFF	−0.0014**	−0.013***	−0.0016*	−0.0016***	0.0008	0.0006
	[0.0005]	[0.003]	[0.0008]	[0.0004]	[0.0008]	[0.0009]
BRIDGING	−0.036***	−0.047***			−0.179***	
	[0.012]	[0.011]			[0.046]	
BONDING			−0.038***	−0.047***		−0.105***
			[0.013]	[0.013]		[0.029]
lnDT x GOVEFF		−0.0027***		−0.0033***		
		[0.0005]		[0.0006]		
lnDT x BRIDGING					−0.0029***	
					[0.0009]	
lnDT x BONDING						−0.0019***
						[0.0006]
*ln*POP		0.005***		0.007***	0.005***	0.007***
		[0.001]		[0.002]	[0.002]	[0.002]
*ln*POPDEN		−0.063		−0.070	−0.097	−0.106
		[0.147]		[0.145]	[0.143]	[0.142]
*ln*HK		0.012		0.005	0.013	0.012
		[0.018]		[0.020]	[0.017]	[0.018]
*ln*FEMALE		−0.273***		−0.239***	−0.196*	−0.163*
		[0.082]		[0.084]	[0.103]	[0.100]
*ln*PATENT		−0.0013**		−0.0011**	−0.0011***	−0.0008**
		[0.0005]		[0.0004]	[0.0003]	[0.0003]
*ln*GVAMAN		−0.147***		−0.154***	−0.138**	−0.139**
		[0.049]		[0.047]	[0.054]	[0.053]
*ln*GVASERV		−0.422***		−0.430***	−0.399**	−0.400***
		[0.139]		[0.132]	[0.157]	[0.149]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nr. obs.	1122	1122	1122	1122	1122	1122
Nr. regions	102	102	102	102	102	102
R^2 within	0.084	0.103	0.091	0.113	0.101	0.110

Note: Driscoll-Kraay standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

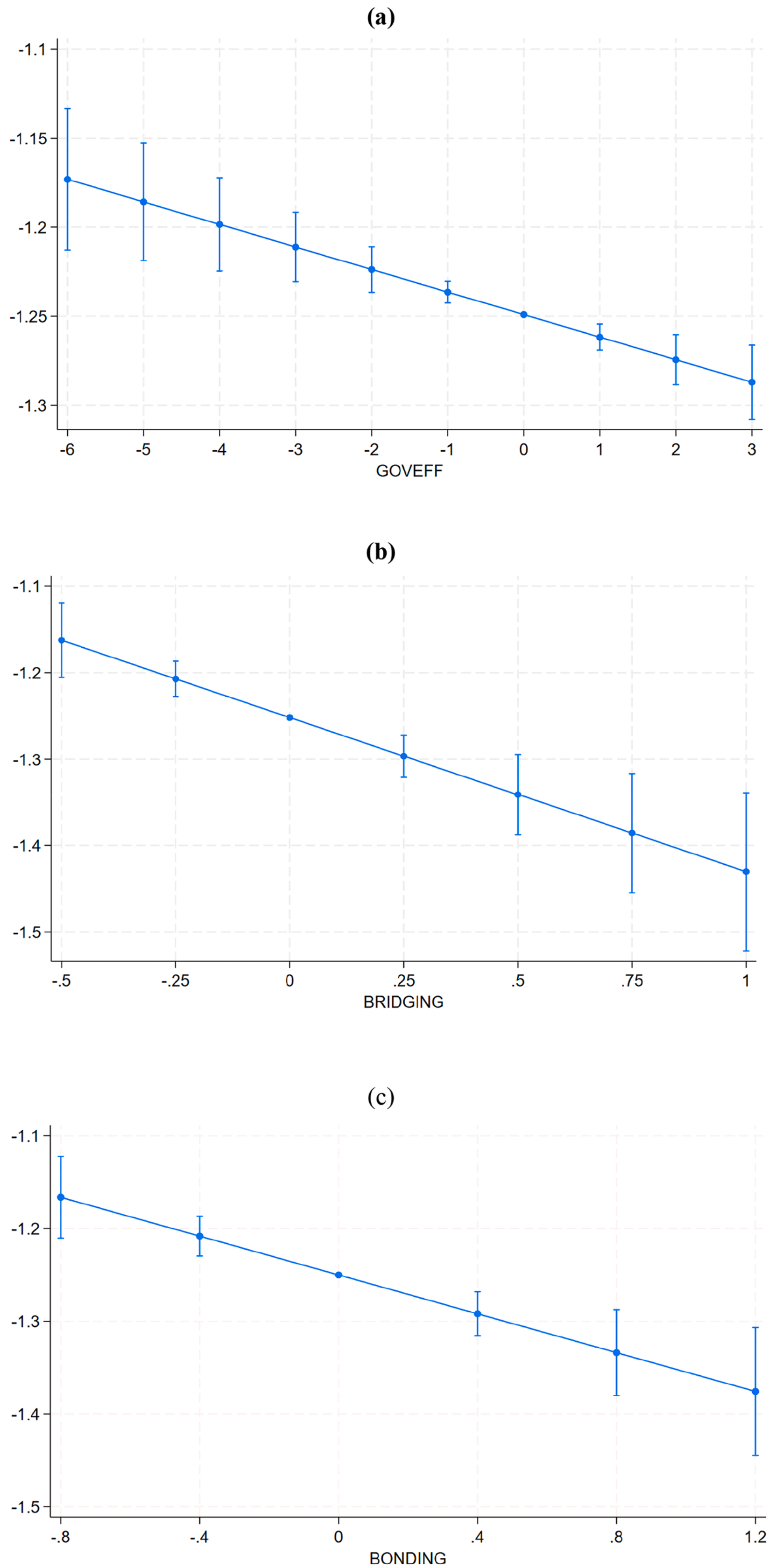

Fig. 2. Marginal effects.

than their low-skilled counterparts. To address this issue, we employ the instrumental variable (IV) approach outlined in Section 3.5.

As an external instrument, we use the logarithm of investments in training per capita (*ln*TRAINING), extracted from the EU-KLEMS database and distributed across EU regions using a population weight for the year 2001 To enhance the robustness of our estimates against potential heteroskedasticity, we apply an IV-GMM estimator with standard errors clustered at the NUTS-2 regional level. The findings are presented in Table 4, while Table A7 in the Appendix shows the first-stage regression results. In all the columns, the results consistently validate previous panel fixed-effect findings: both formal (GE) and informal (BRIDGING and BONDING) institutions contribute to mitigating income inequality in European regions, particularly when paired with a substantial stock of digital capital per employee.

The validity of our instruments is confirmed by the Sanderson-Windmeijer under-identification test, with chi-squared statistics robustly rejecting the null hypothesis that the potentially endogenous variable, *ln*DT, is unidentified. The strength of the instruments is further evidenced by the Kleibergen-Paap F statistics, surpassing the widely accepted benchmark of 10. Finally, the Durbin, Wu, and Hausman test upholds the exogeneity of *ln*DT in two out of three cases, i.e., when informal institutions are accounted for (Columns 2 and 3).

Table 4
Digital technology, income inequality, and institutions: IV-GMM regressions.

	(1)	(2)	(3)
Dep. Var.: *ln*Gini	IV-GMM	IV-GMM	IV-GMM
lnDT	0.010**	0.165	0.186
	[0.004]	[0.134]	[0.149]
GOVEFF	−0.003***		
	[0.001]		
lnDT x GOVEFF	−0.014***		
	[0.005]		
BRIDGING		−0.279***	
		[0.076]	
lnDT x BRIDGING		−0.051**	
		[0.014]	
BONDING			−0.114***
			[0.035]
lnDT x BONDING			−0.018*
			[0.010]
*ln*POP	0.004**	0.014***	0.016***
	[0.002]	[0.003]	[0.003]
*ln*POPDEN	−0.061	0.010	0.007
	[0.103]	[0.131]	[0.134]
*ln*HK	0.010	0.046	0.045
	[0.022]	[0.028]	[0.027]
lnFEMALE	−0.271**	−0.324**	−0.307**
	[0.120]	[0.145]	[0.150]
*ln*PATENT	−0.001	−0.000	0.000
	[0.001]	[0.014]	[0.001]
*ln*GVA_MAN	−0.110**	−0.112**	−0.118**
	[0.044]	[0.045]	[0.055]
*ln*GVA_SERV	−0.235**	−0.316**	−0.328**
	[0.093]	[0.143]	[0.140]
Year FE	Yes	Yes	Yes
Nr. obs.	1232	1243	1243
Nr. regions	112	113	113
Centered R^2	0.117	0.058	0.055
First stage			
Cragg-Donald F	89.98	11.24	10.14
Kleiberger-Paap F	16.30	12.96	11.59
Underid. Test	30.18***	25.78***	23.45***
Endogeneity test	9.919***	2.952	4.472

Note: NUTS-2 region clustered standard errors in parentheses. Instruments set Columns 1: *ln*TRAINING, *ln*TRAINING*GOVEFF. Instruments set Columns 2: *ln*TRAINING, *ln*TRAINING*BRIDGING. Instruments set Columns 3: *ln*TRAINING, *ln*TRAINING*BONDING. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5. Conclusions

This paper has explored the relationship between digital technologies (DTs), institutions, and income inequality at the regional level in the EU. Its main aim has been to shed light on the complex interactions between DTs, which are often expected to trigger greater inequalities, and the varying contexts shaped by differences in the quality of formal and informal institutions. Our investigation stands out from previous research by examining how government efficiency and social capital can moderate the potential impact of digital endowments on income inequality. We do this by estimating not only the direct impact of DTs on social polarisation, but also the mitigating (or enhancing) role that formal and informal institutions play in shaping income inequality across EU regions. This dual focus introduces a fresh perspective into the debate, underlining the importance of institutions and social dynamics in determining the socioeconomic outcomes of technological adoption.

Our contributions are twofold. First, from a theoretical perspective, we add a new dimension to the ongoing discourse on the societal impact of DTs by showing how this impact varies according to the quality of local institutional ecosystems. The key message is that beyond the mere adoption of DTs, the nature of local institutions —both formal and informal— is critical for shaping the distributional consequences of technological progress. This insight addresses a gap in existing knowledge by highlighting the buffering capabilities of strong institutions against technology-induced polarisation. The findings align with previous literature showing the vital role of social capital in driving innovation and mediating the societal outcomes of policy interventions. This connection emphasizes the interplay between social capital, institutional strength, and technological progress in fostering equitable development (Murphy et al., 2016).

Second, our findings offer an alternative perspective for researchers and policymakers, demonstrating that digital progress does not necessarily exacerbate income disparities if institutional conditions are supportive or can be improved. By propping up their formal and informal institutions, regions can harness DTs not only for innovation and economic growth but also for social cohesion and equality (Dosso, 2020). The evidence presented here advocates for comprehensive regional policies that promote both technological innovation and institutional development, suggesting a synergistic approach to reducing inequality and promoting inclusive growth.

Despite its contributions, this study has certain limitations. The reliance on specific data sources and the inherent challenges of fully capturing the multifaceted nature of social capital constrain our conclusions to some extent, as they are shaped by the available empirical evidence. Specifically, the use of regional-level data on digital technologies (DT), computed as a weighted measure to address the limitations of national-level data, occasionally impacts the consistency of our results across certain model specifications. Furthermore, while the application of instrumental variable techniques helps mitigate endogeneity concerns, it also adds complexity to the interpretation of causality, particularly with respect to the indirect effects mediated by social capital. These methodological considerations underscore opportunities for future research to refine and build upon our findings

Notwithstanding these limitations, our research advances the current understanding of how DTs intersect with social and institutional frameworks to shape income inequality. By illustrating the protective and positive role of institutions in the context of digital transformation, our work enriches both academic discourse and policy discussions. It opens new avenues for research into the social dimensions of technological change and offers a nuanced blueprint for policies aimed at achieving equitable outcomes in the digital age.

CRediT authorship contribution statement

Roberto Antonietti: Methodology, Formal analysis, Conceptualization, Writing – review & editing, Writing – original draft. **Chiara**

Burlina: Conceptualization, Formal analysis, Writing – review & editing, Writing – original draft, Data curation. **Andres Rodriguez-Pose:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix: A1. Social capital in European regions

In this section, we outline the methodology used to calculate the indicators for bridging and bonding social capital. These metrics are derived following the approach used by Muringani et al. (2021), with data from the European Value Survey (EVS), and are based on the original framework proposed by Beugelsdijk and Smulders (2009) and Cortinovis et al. (2017). The primary objective is to measure the proportion of the population in each region actively participating in various types of organisations, as active participation provides a more accurate representation of bonding and bridging social capital than mere membership, as highlighted in previous research (Putnam, 2000).

We differentiate between bonding and bridging social capital by categorising organisations into "Olson" and "Putnam" groups, respectively. Olson-type groups, characterised by rent-seeking behaviour, include political parties, local political action groups, labour or trade unions, and professional associations, representing bonding social capital networks. In contrast, Putnam-type groups are more inclusive and offer benefits to non-members. These include religious or church organisations, welfare groups, youth work, cultural activities, sports and recreation clubs, women's groups, development and human rights organisations, environmental and animal rights groups, and peace and health organisations, which form the bridging social capital networks.

Using the EVS data, we proceed as follows: we first identify individuals who voluntarily answered 'yes' to whether they belong to one or more of the aforementioned organisations. We then calculate their proportion relative to the total number of respondents in each region. Next, we compute the average score per region for the two categories of associations, Olson-type versus Putnam-type. Finally, we standardise these proportions to have a mean of 0 and a variance of 1.

Table A1
Variable description and summary statistics

VARIABLES	Source	Description	N	Mean	Std. Dev.	Min.	Max.
Gini Index	EU-SILC and LIS	Gini index	1353	0.294	0.034	0.217	0.419
DT	EU-KLEMS & ARDECO	Regional investments in ICT per capita (in thousand €)	1540	7.933	138.8	.001	4610
Bridging SC	EVS	Bridging social capital	1430	0.0406	0.306	−0.885	1.843
Bonding SC	EVS	Bonding social capital	1430	0.0233	0.371	−1.073	2.289
GOVEFF	Kaufmann and Kraay (2020) and World Bank	Worldwide Governance Indicators	1419	−0.0109	1.117	−7.042	9.138
POP	EUROSTAT	Resident population	1540	2,483,594	2,592,146	577.95	1.81e+07
POPDEN	EUROSTAT	Population per km^2	1540	345.8	835.3	3.300	7455
HK	EUROSTAT	Share of population with tertiary education	1540	0.251	0.090	0.086	0.516
FEMALE	EUROSTAT	Share of female employment	1520	0.454	0.031	0.317	0.519
PATENT	OECD REGPAT	Patent applications per capita	1540	837.5	12,030.4	0.000	363,519
GVAMAN	EUROSTAT	Share of gross value added from manufacturing	1540	0.283	0.086	0.088	0.626
GVASERV	EUROSTAT	Share of gross value added from services	1540	0.685	0.097	0.361	0.876

Table A2
Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11
1. *ln*DT	1										
2. GOVEFF	0.052	1									
3. BRIDGING	0.057	0.099	1								
4. BONDING	0.064	0.045	0.814	1							
5. *ln*POP	−0.286	0.024	−0.143	−0.162	1						
6. *ln*POPDEN	−0.131	0.057	0.203	0.142	0.302	1					
7. *ln*HK	0.160	−0.117	0.115	0.113	0.054	0.193	1				
8. *ln*FEMALE	0.286	0.083	0.106	0.089	−0.078	0.057	0.526	1			
9. *ln*PATENT	0.009	0.041	0.113	0.095	−0.020	0.111	0.103	0.162	1		
10. *ln*GVAMAN	0.158	−0.131	−0.117	−0.089	−0.182	−0.421	−0.121	−0.009	−0.001	1	
11. *ln*GVASERV	−0.161	0.117	0.120	0.099	0.237	0.455	0.216	0.099	0.114	−0.923	1

Table A3
Testing the exogeneity of the instrument

	(1)	(2)	(3)
Dep. Var.: *ln*Gini	FE	FE	FE
lnTRAINING	0.039	0.043	0.047
	[0.047]	[0.029]	[0.029]
GOVEFF	−0.002		
	[0.001]		
BRIDGING		−0.019	
		[0.013]	
BONDING			−0.036***
			[0.011]
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1265	1243	1243
R^2 within	0.060	0.110	0.117

Note: Driscoll-Kraay standard errors in parentheses. Controls include *ln*POP, *ln*POPDEN, *ln*HK, *ln*FEMALE, *ln*PATENT, *ln*GVAMAN, and *ln*GVASERV. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A4
Digital technology and income inequality: the role of formal institutions

	(1)	(2)	(3)
Dep. Var.: *ln*GINI	FE	FE	FE
lnDT1	0.014***		
	[0.001]		
GOVEFF	−0.013**		
	[0.004]		
lnDT1 x GOVEFF	−0.001***		
	[0.000]		
lnDT2		0.014***	
		[0.002]	
GOVEFF		−0.013***	
		[0.004]	
lnDT2 x GOVEFF		−0.001***	
		[0.000]	
lnDT3			0.015***
			[0.002]
GOVEFF			−0.007**
			[0.004]
lnDT3 x GOVEFF			−0.002***
			[0.000]
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	990	990	1144
R^2 within	0.158	0.159	0.124

Driscoll-Kraay standard errors in parentheses. Controls include *ln*POP, *ln*POPDEN, *ln*HK, *ln*FEMALE, *ln*PATENT, *ln*GVAMAN, and *ln*GVASERV. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DT1 computed using as a weight for DT the regional share of professionals and technicians (ISCO-08 codes 2 and 3). DT2 computed using as a weight for DT the regional share of digital users (ISCO-08 codes 2, 3, 4, and 6). DT3 computed using as a weight for DT the regional intensity of digital skill (as in Castellacci et al., 2020).

Table A5
Digital technology and income inequality: the role of bridging social capital

	(1)	(2)	(3)
Dep. Var.: *ln*GINI	FE	FE	FE
lnDT1	−0.007		
	[0.026]		
BRIDGING	−0.308***		
	[0.065]		
lnDT1 x BRIDGING	−0.026***		
	[0.005]		
lnDT2		−0.007	
		[0.026]	
BRIDGING		−0.306***	
		[0.064]	
lnDT2 x BRIDGING		−0.026***	
		[0.005]	
lnDT3			−0.009
			[0.032]
BRIDGING			−0.326***

(*continued on next page*)

Table A5 (*continued*)

	(1)	(2)	(3)
			[0.064]
lnDT3 x BRIDGING			−0.052***
			[0.011]
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1001	1001	1155
R^2 within	0.136	0.136	0.122

Driscoll-Kraay standard errors in parentheses. Controls include *ln*POP, *ln*POPDEN, *ln*HK, *ln*FEMALE, *ln*PATENT, *ln*GVAMAN, and *ln*GVASERV. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DT1 is computed using as a weight for DT the regional share of professionals and technicians (ISCO-08 codes 2 and 3). DT2 is computed using as a weight for DT the regional share of digital users (ISCO-08 codes 2, 3, 4, and 6). DT3 is computed using as a weight for DT the regional intensity of digital skill (as in Castellacci et al., 2020).

Table A6
Digital technology and income inequality: the role of bonding social capital

	(1)	(2)	(3)
Dep. Var.: *ln*GINI	FE	FE	FE
lnDT1	−0.006		
	[0.026]		
BONDING	−0.222***		
	[0.046]		
lnDT1 x BONDING	−0.019***		
	[0.004]		
lnDT2		−0.006	
		[0.026]	
BONDING		−0.224***	
		[0.046]	
lnDT2 x BONDING		−0.020***	
		[0.004]	
lnDT3			−0.008
			[0.032]
BONDING			−0.151***
			[0.038]
lnDT3 x BONDING			−0.025***
			[0.007]
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1001	1001	1155
R^2 within	0.150	0.150	0.132

Driscoll-Kraay standard errors in parentheses. Controls include *ln*POP, *ln*POPDEN, *ln*HK, *ln*FEMALE, *ln*PATENT, *ln*GVAMAN, and *ln*GVASERV. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DT1 is computed using as a weight for DT the regional share of professionals and technicians (ISCO-08 codes 2 and 3). DT2 is computed using as a weight for DT the regional share of digital users (ISCO-08 codes 2, 3, 4, and 6). DT3 is computed using as a weight for DT the regional intensity of digital skill (as in Castellacci et al., 2020).

Table A7
First-stage IV-GMM regression

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	GOVEFF	lnDT *GOVEFF	BRIDGING	lnDT* BRIDGING	BONDING	lnDT *BONDING
lnTRAINING	6.680***	−4.015***	0.204***	0.011	0.180***	0.209***
	[1.161]	[1.126]	[0.040]	[0.027]	[0.140]	[0.041]
lnTRAINING*GOVEFF	0.068***	1.132***				
	[0.017]	[0.026]				
lnTRAINING*BRIDGING			0.003	1.073***		
			[0.019]	[0.034]		
lnTRAINING*BONDING					−0.052***	1.250***
					[0.017]	[0.044]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nr. obs.	1232	1232	1243	1243	1243	1243
Nr. regions	112	112	113	113	113	113
Sanderson-Windmeijer multivariate F test of excluded instruments	38.25***	2302.2***	25.97***	892.12***	23.37***	30.14***

Note: NUTS-2 region clustered standard errors in parentheses. Controls include GOVEFF (Columns 1 and 2), BRIDGING (Columns 3 and 4), BONDING (Columns 5 and 6), *ln*POP, *ln*POPDEN, *ln*HK, *ln*FEMALE, *ln*PATENT, *ln*GVAMAN, and *ln*GVASERV. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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