“Digital transformation and labor market indicators in the EU: Evidence from the COVID-19 shock using difference-in-differences”

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DIGITAL TRANSFORMATION AND LABOR MARKET INDICATORS IN THE EU: EVIDENCE FROM THE COVID-19 SHOCK USING DIFFERENCE-IN-DIFFERENCES

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Abstract

Digital transformation has emerged as a key driver of structural change in labor markets worldwide, especially in the aftermath of the COVID-19 shock. In the European Union, the pandemic particularly accelerated the adoption of digital technologies and remote work across economic activities. This study estimates the causal effect of the digitalization potential of economic activity (proxied by a binary classification into highly and less digitalized groups based on telework feasibility and digital intensity) on three labor market indicators: employment, hourly wages, and remote work. Using the COVID-19 shock as a quasi-natural experiment within a difference-in-differences (DiD) framework, the empirical analysis draws on quarterly panel data for a consistent sample of 27 EU Member States (excluding the United Kingdom) over 2018–2024 (N = 36,685). The results indicate that higher sectoral digitalization potential (telework feasibility and digital intensity) does not significantly affect aggregate employment levels, as evidenced by a near-zero DiD coefficient (0.06, $p \approx 0.98$). In contrast, it has a statistically significant positive effect on wages, with a DiD coefficient of 0.52 €/hour ($p < 0.001$), corresponding to an increase of approximately 4.6% in the wage gap between highly and less digitalized activities. The strongest effect is found for remote work: the DiD estimate is 40.74 percentage points ($p < 0.001$). Remote work rose from 17.6% to 82.1% in highly digitalized sectors, compared with only 1.3% to 6.6% in less digitalized economic activities.

Keywords digital transformation, labor market, difference-in-differences, COVID-19 shock, remote work, wage inequality, European Union, management, social responsibility

JEL Classification J21, J31, O33, J24

INTRODUCTION

Digital transformation has become one of the defining structural shifts in contemporary labor markets. This process gained particular importance during the COVID-19 pandemic, which triggered an unprecedented disruption to global employment by affecting working hours, job security, and the organization of work itself (ILO, 2021). At the same time, digital technologies helped mitigate these disruptions by enabling remote work and sustaining economic activity in selected sectors. Evidence from the World Bank (2021) and the IMF (2021) shows that economies with higher levels of digital readiness were more resilient during the crisis, experiencing faster labor market recovery and lower employment losses. These developments highlight the dual role of digitalization as both a buffer against external shocks and a driver of longer-term structural change in employment dynamics.

Reports from the ILO (2022) further show that the capacity to shift to remote work remained highly uneven, with workers in less digitalized sectors facing a greater risk of job loss and income instability. As a result, digital transformation has intensified concerns about labor-market polarization, skill mismatches, and new forms of inequality linked to digital access and capabilities.

In the European Union, these changes were especially visible. According to the EC (2022), the pandemic accelerated digitalization trends and contributed to a reconfiguration of sectoral employment patterns and work organization. The rapid expansion of telework, particularly in knowledge-intensive activities, increased flexibility but also exposed structural inequalities between workers and industries.

Despite the growing body of evidence on the digitalization of labor markets, there is still a need for rigorous causal analysis that distinguishes between correlation and structural impact. Existing institutional reports from the World Bank (2022), IMF (2022), and the EC (2023) rely mainly on descriptive or cross-sectional approaches, which are less suited to identifying the dynamic and heterogeneous effects of digital transformation across sectors and countries. In this context, the COVID-19 shock provides a useful quasi-natural experiment for examining the causal mechanisms of labor market adjustment. Such analysis is particularly relevant for EU policymakers, as the scale and speed of digital transformation continue to reshape employment structures, wage distribution, and the future of work.

1. LITERATURE REVIEW

The COVID-19 pandemic is widely regarded as a major exogenous shock that disrupted labor markets and accelerated broader structural change across economies. It affected employment, business operations, and global value chains, generating declines in labor demand, workplace closures, and shifts in production and service delivery systems (Forsythe et al., 2020; Richardson, 2024; Gabrielczak et al., 2025). These disruptions were not confined to employment alone, but extended to financial systems, sectoral performance, and the wider organization of economic activity, indicating that the pandemic should be understood as a system-wide shock rather than a temporary labor-market disturbance (Issam et al., 2024; Hariyanto & Safitri, 2026; Zohaib & Ismail, 2024). At the same time, the crisis intensified socioeconomic vulnerabilities, including job insecurity, inequality, and dissatisfaction, while also affecting consumption, housing, and the sharing economy, thereby reinforcing the uneven distribution of adjustment costs across populations and economic activities (Akinyemi, 2024; Zhang et al., 2020; Hossain, 2021; Hebdzyński, 2024; Macovei et al., 2024). This broader context is important for the present study because it suggests that labor-market changes during the pandemic cannot be understood without considering the structural role of digitalization in mediating sectors' capacity to absorb and adapt to the shock.

Within this broader adjustment process, digital transformation emerged as one of the main mechanisms through which economies maintained continuity under pandemic restrictions. The shift from "high-touch" to "high-tech" models accelerated digital adoption across healthcare, retail, public administration, and other activities, enabling remote coordination, online service provision, and more resilient business operations (Zeng et al., 2020; Conley, 2025; Crăciun et al., 2025). In the European context, digitalization has also been associated with post-pandemic recovery, macroeconomic stability, improved governance, and better quality of life, suggesting that it functions not only as a technological adjustment but also as a broader institutional and developmental force (Kuzior et al., 2024a, 2024b; Vysochyna et al., 2024; Yarovenko et al., 2025). However, the digital transition is not uniformly beneficial. It may increase volatility in technology-intensive activities and alter risk structures, creating new forms of economic exposure and differentiation across sectors and countries (Pollák et al., 2026; Benameur et al., 2025). For this reason, the literature increasingly treats digital transformation not simply as a growth-enhancing trend, but as a source of differentiated labor-market adjustment whose effects depend on sectoral digital intensity and the feasibility of remote work.

These distinctions are especially important for understanding employment dynamics. Existing re-

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search suggests that digitalization did not affect all parts of the labor market equally during the pandemic. Rather than producing a uniform employment response, it changed the capacity of specific activities to continue operating, preserve jobs, and reorganize production under lockdown conditions. This is why the sectoral perspective adopted in the present study is particularly relevant. Sectors with greater digital intensity and stronger telework feasibility were better positioned to buffer employment shocks, whereas less digitalized activities were more exposed to closure, income losses, and labor-demand contraction (Forsythe et al., 2020; Spurk & Straub, 2020; Raišienė et al., 2020; Šafránková & Šikýř, 2024). At the same time, the literature also indicates that the pandemic-induced move toward flexible and remote work fundamentally altered labor relations, career trajectories, and the organization of work. Although these changes increased adaptability and autonomy for some workers, they also created tensions around commitment, work-life balance, and well-being, suggesting that digital transformation affects not only the quantity of employment but also its qualitative dimensions (Kamp et al., 2024; Sarwar et al., 2026). This distinction between quantitative and qualitative labor-market effects directly motivates the present analysis of employment, wages, and remote work as separate but related indicators of labor-market adjustment.

The literature also provides strong reasons to expect digital transformation to affect wage structures. The expansion of digital work has increased demand for advanced digital, cognitive, and soft skills, thereby strengthening the labor-market premium associated with human capital and adaptability (Mishchuk et al., 2025; Poláková et al., 2023). Workers' ability to benefit from digital transformation depends on training motivation, education, and institutional support for reskilling and lifelong learning, which means that digitalization is likely to generate differentiated wage effects rather than uniform gains across the labor force (Śledziewska et al., 2025; Yeremenko, 2026; Zindi & Majam, 2025). Emerging evidence on artificial intelligence reinforces this argument by showing that advanced technologies are already reshaping employment structures and unemployment dynamics, including in the short run (Kuzior et al., 2025). At the organizational level, digital transformation affects job performance, productivity, and innovation processes, further contributing to heterogeneous wage and employment outcomes across firms and workers (H. Saifi & F. Saifi, 2025; Tutar et al., 2024). These studies imply that digital transformation is likely to increase wage dispersion between more and less digitalized activities, especially when a large external shock such as COVID-19 accelerates the reallocation of work toward digitally enabled sectors.

A central mechanism through which these inequalities materialized during the pandemic was remote work. The ability to shift tasks online became a key dividing line between activities that could continue functioning with limited interruption and those that remained dependent on physical presence. However, access to remote work has been highly uneven across sectors, occupations, and demographic groups. Existing studies show that the benefits of telework were concentrated in more knowledge-intensive and digitally prepared activities, while workers in less digitalized sectors faced greater risks of job loss, reduced income stability, and broader forms of exclusion (Del Boca et al., 2020; Jesus et al., 2021). The consequences of this transformation also extended beyond the labor market itself, affecting urban systems and office markets through longer-term changes in the spatial organization of labor demand (Jerobon, 2026). This literature is directly relevant to the present study because it suggests that remote work is not merely an auxiliary variable, but one of the clearest observable manifestations of sectoral digitalization during and after the COVID-19 shock.

Despite these important insights, the literature still leaves several gaps that are central to the present research. First, much of the existing evidence remains descriptive, cross-sectional, or sector-specific, limiting the identification of generalizable causal mechanisms linking digitalization to labor-market adjustment. Second, while many studies discuss employment disruption, remote work, or digital skills separately, fewer analyses examine these dimensions jointly in a coherent empirical framework that distinguishes between employment volume, wage inequality, and work organization. Third, certain forms of labor, especially unpaid and care work, remain underrepresented in mainstream economic analysis, which produces an incomplete account of how shocks and digitalization restructure labor systems more broadly (Goyal & Bhardwaj, 2025; Sitnicki et al., 2022). Fourth, the interaction between digital transformation and other structural pressures, including energy transitions and geopolitical shocks such as the war in Ukraine, remains insufficiently explored despite its increasing relevance for European economies (Vasylieva et al., 2025). These limitations point to the need for research designs that can isolate causal effects and identify whether highly digitalized activities experienced systematically different labor-market trajectories than less digitalized ones during and after the pandemic.

The literature shows that the COVID-19 pandemic acted as a catalyst, accelerating digital transformation and reshaping labor markets through changes in employment structures, wage formation, skill demand, and work organization. At the same time, the evidence indicates that these effects were uneven across activities, workers, and institutional contexts, contributing to new forms of labor-market inequality and structural divergence. What remains insufficiently established, however, is the causal extent to which sectoral digitalization altered employment, wages, and remote work during the COVID-19 shock, particularly in a comparable cross-country European setting. This is the specific gap addressed by the present study, which applies a quasi-experimental difference-in-differences approach to assess how highly and less digitalized economic activities in the European Union adjusted to the pandemic.

This study aims to estimate the causal effect of the digitalization potential of economic activity (proxied by a binary classification into highly and less digitalized groups based on telework feasibility and digital intensity) on three labor market indicators: employment, hourly wages, and remote work.

2. METHODOLOGY

This study employs a difference-in-differences (DiD) approach to estimate the causal impact of digital transformation on labor market outcomes across the European Union. The COVID-19 pandemic is treated as a natural experiment that imposed an exogenous shock, forcing a rapid, large-scale transition to remote work and digital modes of production. This setting provides a suitable empirical framework for identifying the differential effects of digitalization across economic activities with varying capacities for digital adaptation.

The DiD method is widely used to identify causal effects in non-experimental settings by comparing changes in outcomes between a treated group and a control group over time. In this study, highly digitalized economic activities constitute the treated group, while less digitalized economic activities serve as the control group. The analysis distinguishes between the pre-crisis period (2018–2019) and the post-crisis period (2021–2024), with 2020 considered the shock year and excluded from the main DiD estimation window to avoid contamination from transition dynamics.

The empirical model is specified as follows:

$$\begin{aligned} Y_{it} &= \alpha + \beta D_i + \gamma Post_t \\ &+ \delta\left(D_i \cdot Post_t\right) + \theta X_{it} + \varepsilon_{it}, \end{aligned} \tag{1}$$

where Y_{it} denotes the outcome variable for the unit i at time t. Three dependent variables are analyzed: employment level (thousand persons), average hourly wages (euros per hour), and the share of employees working remotely (percentage). The binary variable D_i equals 1 for highly digitalized economic activities and 0 for less digitalized economic activities. The time indicator $Post_t$ equals 1 for the post-crisis period and 0 for the pre-crisis period. The interaction term ($D_i \cdot Post_t$) captures the DiD effect and represents the Average Treatment Effect on the Treated (ATET).

The coefficient δ is the primary parameter of interest, measuring the differential change in outcomes across highly digitalized and less digitalized economic activities after the COVID-19 shock. The vector X_{it} includes country fixed effects to control for time-invariant heterogeneity across EU Member States, such as institutional quality, labor market structures, and baseline levels of digital infrastructure. The error term ε_{it} captures unobserved factors affecting the outcome variables.

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Table 1. Classification of economic activities by digitalization potential

Source: Our calculations based on Dingel and Neiman (2020) and Eurostat (n.d.).

Sector	NACE code	Group	Telework potential (%)	Average employment (thousand)	Average wage (€/hour)
Information and communication	J	Highly digitalized	70–85	51.41	18.35
Financial and insurance	K	Highly digitalized	60–80	69.99	19.71
Professional and scientific	M	Highly digitalized	50–70	65.78	16.65
Administrative services	N	Highly digitalized	40–60	57.86	12.87
Manufacturing	C	Less digitalized	5–15	61.54	11.56
Construction	F	Less digitalized	0–5	163.58	11.52
Retail trade	G	Less digitalized	10–20	322.36	10.67
Transportation	H	Less digitalized	5–10	91.90	11.21
Accommodation and food services	I	Less digitalized	0–5	164.50	8.65

The classification of economic activities is based on the methodology of Dingel and Neiman (2020), adapted to the NACE Rev. 2 classification. The grouping reflects differences in telework feasibility and digital intensity. The detailed classification is presented in Table 1.

The identification strategy relies on the parallel trends assumption, which states that, in the absence of the treatment, both groups would have followed similar trajectories over time. This assumption is empirically tested through pre-trend analysis using pre-crisis data. In addition, placebo tests with fictitious treatment periods are conducted to assess the robustness of the estimated effects and to rule out spurious correlations driven by underlying trends.

From the perspective of the potential outcomes framework, each observational unit is associated with two potential states, one with and one without treatment. The DiD estimator recovers the average treatment effect on the treated under the assumption that unobserved differences between groups are time-invariant. The inclusion of fixed effects further strengthens identification by accounting for structural heterogeneity across countries.

The empirical analysis is conducted using panel data for all 27 European Union Member States over the period 2018–2024 at quarterly frequency, yielding 36,685 observations. The dataset includes Austria, Belgium, Bulgaria, Croatia, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden. Data are obtained from the Eurostat database (Eurostat, n.d.), ensuring consistency and comparability across countries. The study is limited to EU Member States because their shared regulatory and statistical framework ensures greater comparability of labor-market and digitalization indicators. In contrast, the United Kingdom is excluded in order to maintain a consistent EU-27 panel throughout the observation period following Brexit.

Descriptive statistics indicate substantial differences between sector groups. Highly digitalized economic activities exhibit higher average wages and significantly greater shares of remote work, while less digitalized economic activities account for larger employment volumes but demonstrate greater heterogeneity. The use of multiple outcome variables allows for a comprehensive assessment of both quantitative (employment levels) and qualitative (wages and work organization) dimensions of labor market transformation.

All statistical analyses are performed using Python (version 3.10). Data processing and manipulation are conducted with the pandas library (version 2.0.3), while regression models are estimated using statsmodels (version 0.14.0) with ordinary least squares (OLS). Numerical computations rely on numpy (version 1.24.3). Visualizations are produced using matplotlib (version 3.7.1) and seaborn (version 0.12.2).

3. RESULTS

Table 2 presents the descriptive statistics of the key variables across highly and less digitalized economic activities over the period 2018–2024, highlighting substantial structural differences

Table 2. Descriptive statistics of key variables by sector group (2018–2024)

Source: Our calculations based on Eurostat (n.d.).

Sector group	Indicator	Mean	Std. Dev.	Minimum	Maximum
Less digitalized	Employment (thousand)	108.11	243.22	0.50	3388.10
	Wages (€/hour)	11.23	6.77	3.00	36.29
	Remote work (%)	4.88	3.75	0.00	17.42
Highly digitalized	Employment (thousand)	60.58	111.64	0.50	1194.00
	Wages (€/hour)	16.55	9.92	3.00	53.47
	Remote work (%)	63.11	30.25	1.03	85.00

between the two groups before the econometric analysis. Less digitalized economic activities exhibit significantly higher average employment levels (108.11 thousand) than highly digitalized economic activities (60.58 thousand), reflecting their greater role in labor absorption within the EU economy. However, highly digitalized economic activities are characterized by markedly higher average wages (16.55 €/hour versus 11.23 €/hour), indicating a strong skill premium associated with digital intensity. The most pronounced disparity is observed in remote work, where the average share reaches 63.11% in highly digitalized economic activities compared to only 4.88% in less digitalized economic activities, representing a more than twelvefold difference. Furthermore, the substantially higher standard deviation of employment in less digitalized economic activities suggests greater heterogeneity across countries and industries. In contrast, the wide dispersion of remote work in highly digitalized economic activities reflects varying degrees of digital adoption. Overall, these descriptive patterns provide preliminary evidence of structural asymmetries between sector groups and motivate the subsequent causal analysis using the difference-in-differences framework.

The validity of the DiD design was first assessed by testing the parallel trends assumption over the pre-crisis period (2018–2019). The regression of employment levels on the high-digitalization indicator, a time trend, and their interaction yields an interaction coefficient of 0.012 (SE = 0.158, p = 0.995), indicating no statistically significant differences in pre-treatment trends between highly and less digitalized economic activities. This confirms that the parallel trends assumption is satisfied. Visual inspection (Figure 1) further supports this result: before 2020, both groups exhibit modest, closely aligned upward trajectories, whereas the onset of the COVID-19 pandemic is associated with a clear structural break, particularly pronounced in less digitalized economic activities.

Source: Our calculations using the matplotlib and seaborn libraries in Python.

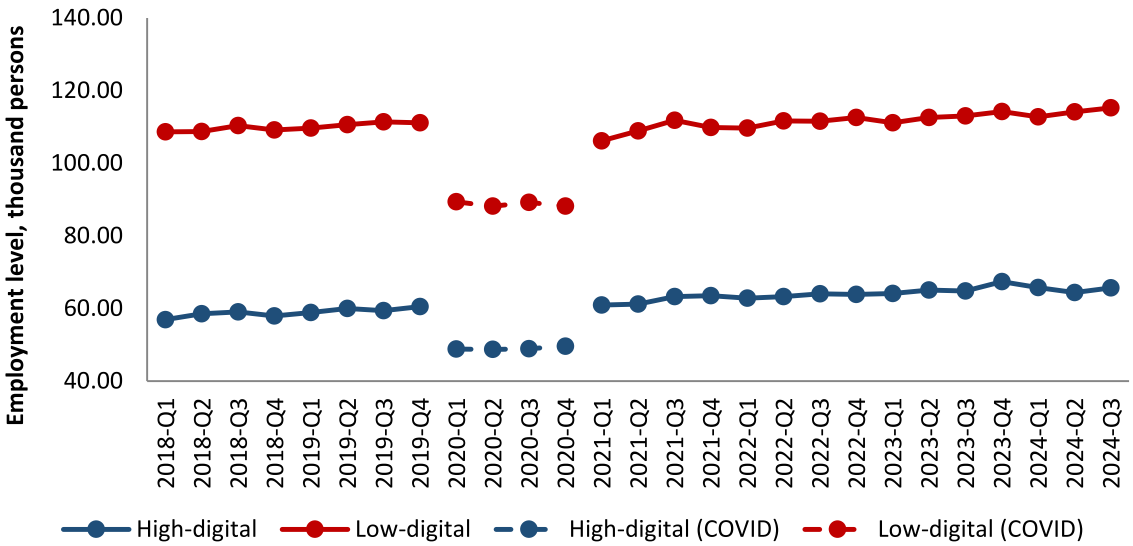

Figure 1. Test of the parallel trends assumption

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Figure 1 shows the dynamics of average employment levels in highly and less digitalized economic activities over 2018–2024. Before the COVID-19 shock, both groups followed broadly parallel trajectories, with only modest fluctuations and no visible divergence in trend, which supports the validity of the parallel trends assumption underlying the difference-in-differences design. After 2020, the trajectories separate more clearly: employment in less digitalized economic activities remains markedly higher in absolute terms, while employment in highly digitalized economic activities demonstrates comparatively stronger resilience and a more favorable post-crisis adjustment. Thus, the visual evidence is consistent with the formal pre-trend test and indicates that the observed post-2020 divergence can be interpreted as the effect of differential exposure to digitalization rather than as a continuation of pre-existing trends.

The baseline DiD estimates with country fixed effects reveal substantial structural differences between sector groups. The coefficient on the high_digital variable is −48.35 (SE = 2.87, p < 0.001), reflecting lower absolute employment levels in highly digitalized economic activities (60.58 thousand on average) than in less digitalized economic activities (108.11 thousand), consistent with sectoral size differences across the EU economy. The post-COVID coefficient is positive but not statistically significant (3.75; SE = 2.33; p = 0.108), suggesting only a weak aggregate recovery effect. The key DiD interaction term (treat_post) equals 0.06 (SE = 3.78, p = 0.987), indicating no statistically significant differential impact of digitalization on total employment levels. The model explains approximately 27.98% of the variation in employment.

The main DiD results across all three dependent variables are summarized in Table 3.

The absence of a statistically significant DiD effect for employment suggests that accelerated digitalization during the pandemic primarily affected the qualitative rather than quantitative dimensions of labor markets. In contrast, wages exhibit a strong and statistically significant effect: The DiD coefficient of 0.52 €/hour (SE = 0.06, p < 0.001) implies that the wage gap between highly and less digitalized economic activities increased by approximately 4.6% relative to the baseline average wage in less digitalized economic activities (11.23 €/hour). This finding is consistent with a skill-biased technological change mechanism, whereby digitalization disproportionately rewards workers in more technologically advanced economic activities.

The most pronounced effect is observed for telework. The DiD coefficient of 40.74 percentage points (SE = 0.28, p < 0.001) indicates a substantial structural transformation in work organization. In highly digitalized economic activities, the share of remote work increased from approximately 17.6% in the pre-crisis period to 82.1% post-2020. In contrast, in less digitalized economic activities, the increase was modest (from 1.3% to 6.6%). This divergence highlights the limited adaptability of traditional economic activities to remote work arrangements and underscores the role of digital infrastructure in enabling labor market resilience.

Figure 2 illustrates the dynamics of three key labor market indicators (employment, wages, and remote work) across highly and less digitally advanced economic activities during the pre-COVID, COVID, and post-COVID periods. Panel (a) shows that both groups experienced a decline in

Table 3. Difference-in-differences estimates of digitalization effects on labor market outcomes

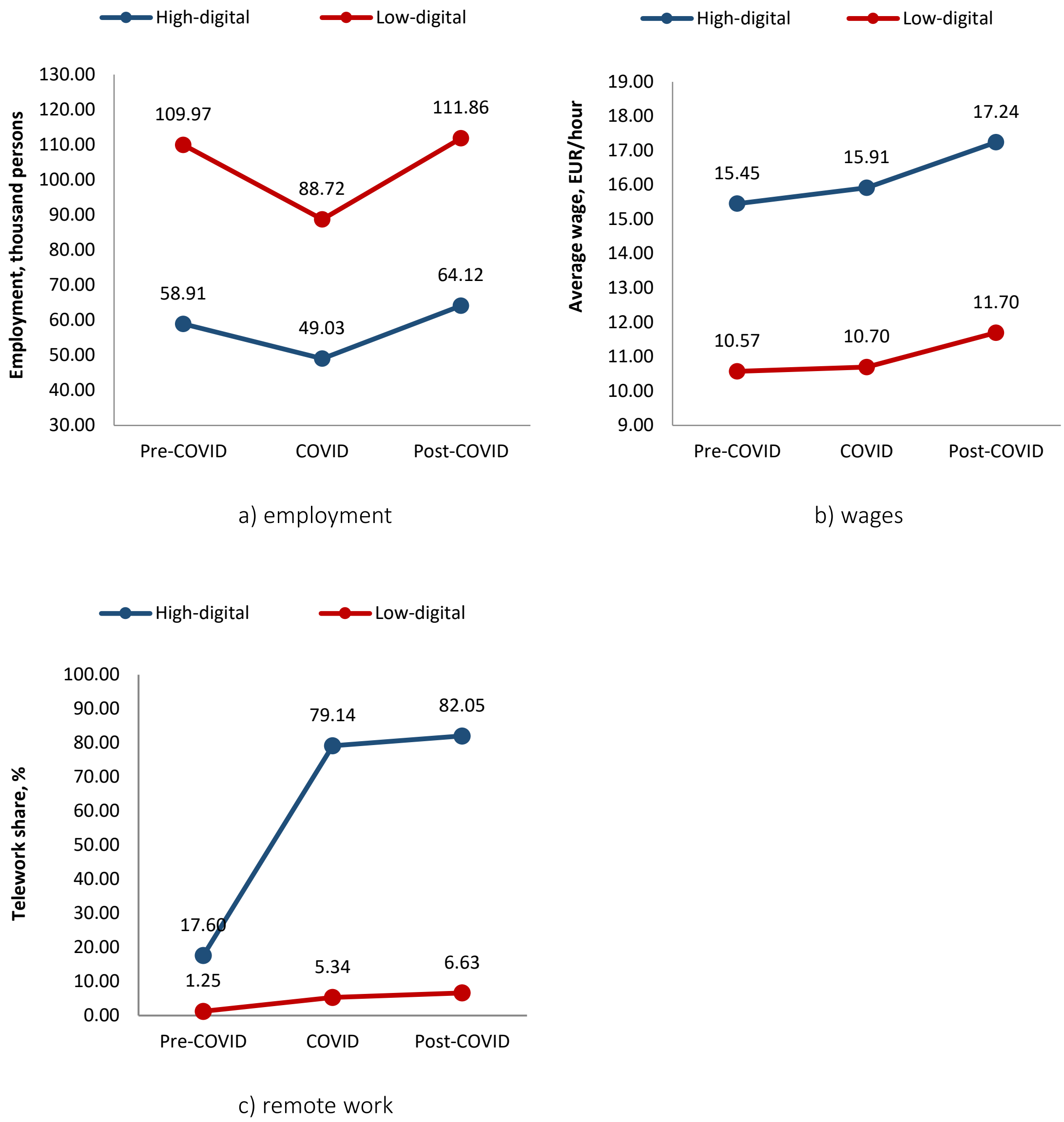
Outcome variable	DiD coefficient	Std. Error	p-value	Significance	Interpretation
Employment (thousand)	0.06	3.78	0.987	–	No statistically significant effect on employment levels; digitalization does not alter total job volumes in the short run
Wages (€/hour)	0.52	0.06	< 0.001	***	Significant increase in wage premium for highly digitalized economic activities (+4.6% relative gap expansion)
Telework (%)	40.74	0.28	< 0.001	***	Large structural shift towards remote work in highly digitalized economic activities

Note: *** denotes statistical significance at the 1% level. All models include country fixed effects for the 27 EU Member States. Standard errors are clustered at the sector–country level. N = 36,685.

employment during the pandemic, followed by a recovery in the post-crisis period. However, highly digitalized economic activities exhibit a relatively stronger rebound. In contrast, less digitalized economic activities do not fully recover to their pre-crisis trajectory, indicating a modest but visible divergence in employment dynamics. Panel (b) demonstrates a steady increase in wages in both sector groups, with a more pronounced upward trajectory in highly digitalized economic activities. The widening gap in the post-COVID period confirms the presence of a positive DiD effect, reflecting an increase in the wage premium associated with digitalization. Panel (c) reveals the most substantial divergence: remote work expands dramatically in highly digitalized economic activities, rising sharply during the COVID period and remaining at elevated levels thereafter, while less digitalized economic activities show only marginal increases. This pattern highlights the structural nature of digital transformation, particularly in terms of work organization and flexibility.

Figure 2 provides clear visual evidence that the impact of digitalization is primarily manifested in qualitative changes, especially wages and remote work, rather than in substantial differences in aggregate employment levels.

Source: Our calculations using the matplotlib and seaborn libraries in Python.



Note: Highly digitalized = blue; Less digitalized = red.

Figure 2. Visualization of DiD effects for three indicators

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Table 4. Sectoral employment dynamics across periods (thousand persons)

Sector	Pre-COVID (2018–2019)	COVID (2020)	Post-COVID (2021–2024)	Δ COVID vs Pre	Δ Post vs Pre	Interpretation
Information and communication	45.62	40.79	56.77	–4.83	+11.15	Strong rebound; digital economic activities expand beyond pre-crisis levels
Financial and insurance	70.28	57.46	72.80	–12.82	+2.52	Moderate recovery with structural stability
Professional and scientific	63.67	54.51	69.45	–9.16	+5.77	Robust recovery driven by knowledge-intensive activities
Administrative services	59.76	45.54	59.82	–14.21	+0.06	Near full recovery but limited growth
Manufacturing	63.07	49.35	63.72	–13.71	+0.65	Recovery to baseline without structural expansion
Construction	164.26	136.63	169.71	–27.62	+5.46	Strong rebound linked to investment cycles
Retail trade	333.10	268.39	329.99	–64.71	–3.11	Persistent losses; structural decline
Transportation	91.96	77.02	95.46	–14.94	+3.50	Gradual recovery with moderate growth
Accommodation and food services	172.68	132.33	168.21	–40.34	–4.47	Incomplete recovery; long-term vulnerability

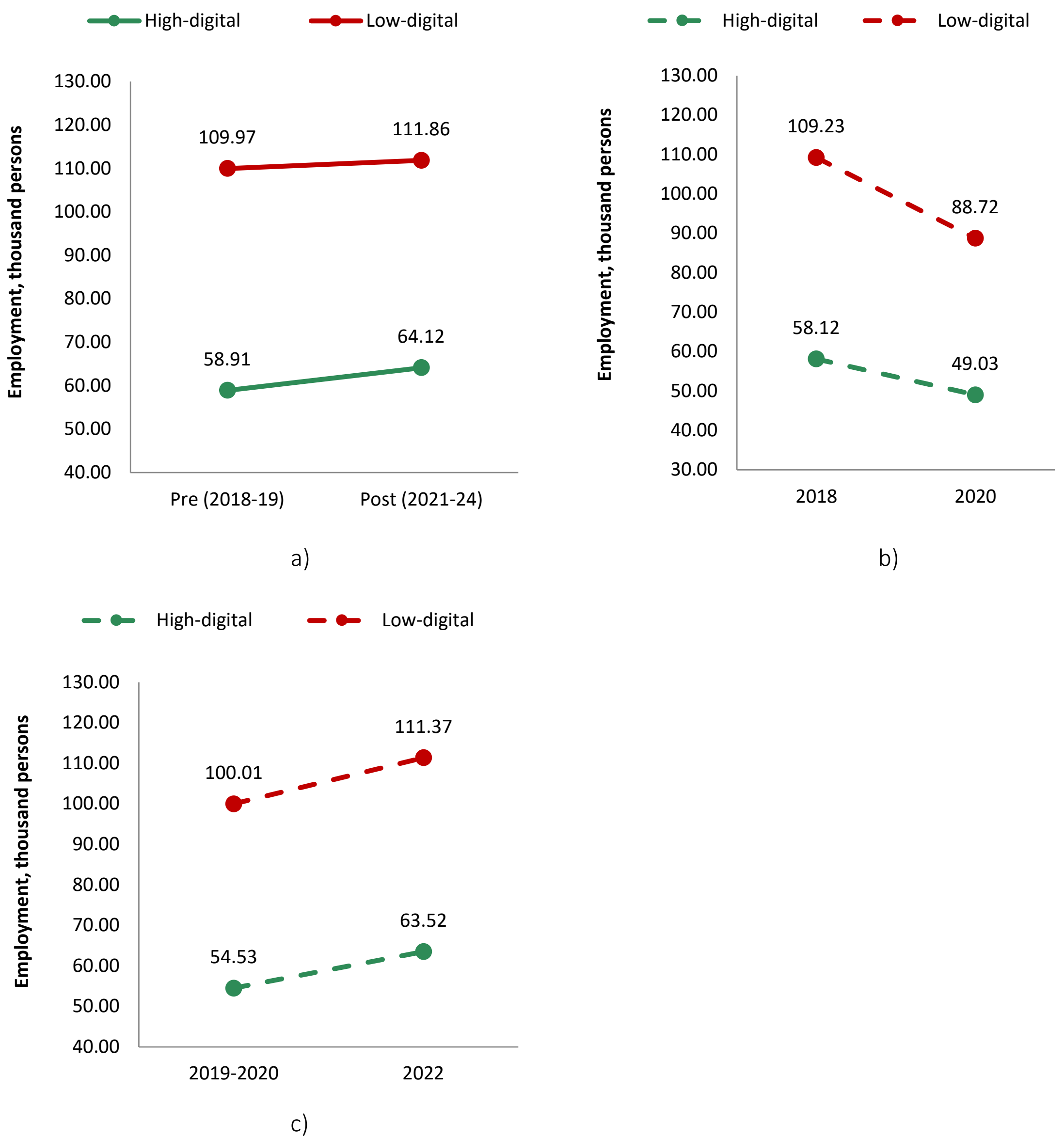
Sectoral dynamics further reveal heterogeneous adjustment patterns (Table 4). The largest employment losses during the pandemic occurred in retail trade (–64.71 thousand) and accommodation and food services (–40.34 thousand). Post-crisis recovery is led by highly digitalized economic activities, particularly information and communication (+11.15 thousand; +24.4% relative to pre-crisis levels) and professional and scientific activities (+5.77 thousand). In contrast, less digitalized economic activities exhibit incomplete recovery, with persistent net losses in accommodation and food services (–4.47 thousand) and retail trade (–3.11 thousand).

Robustness checks using placebo tests confirm the validity of the identification strategy (Table 5). Assigning a fictitious treatment year to 2019 yields a DiD coefficient of 11.31 (SE = 7.36, p = 0.125), while a placebo shock in 2021 produces a coefficient of –1.23 (SE = 1.99, p = 0.536). In both cases, the effects are statistically insignificant, indicating the absence of spurious pre- or post-trends and supporting the causal interpretation of the main results.

Figure 3 compares the estimated difference-in-differences (DiD) effects for employment across the actual COVID-19 shock (2020) and two placebo specifications. In the left panel (actual DiD), both highly digitalized (green) and less digitalized (red) economic activities exhibit similar upward changes between the pre- and post-periods, resulting in a near-zero and statistically insignificant DiD coefficient (0.059, p = 0.987), which indicates the absence of a differential employment effect attributable to digitalization. The middle panel (placebo 1, false shock in 2019) shows a larger apparent divergence between the two groups; however, this effect is also statistically insignificant (coef. = 11.307, p = 0.125), suggesting that it reflects random variation rather than a systematic structural break. The right panel (placebo 2, false shock in 2021) again reveals only minor differences between highly digitalized (green) and less digitalized (red) economic activities, with a small and insignificant coefficient (–1.230, p = 0.536). Taken together, the absence of statistically significant effects in both placebo tests, alongside the null result for the actual DiD, supports the robustness of the empirical strategy and confirms that there are no spurious pre- or post-treatment trends driving the results.

Table 5. Placebo tests for DiD validity (employment, thousand persons)

Specification	DiD coefficient	Std. Error	p-value	95% CI	Interpretation
Actual DiD (COVID-19, 2020)	0.06	3.78	0.987	[–7.36; 7.47]	No effect on employment levels
Placebo 1 (fake shock 2019)	11.31	7.36	0.125	[–3.13; 25.74]	No pre-trend differences
Placebo 2 (fake shock 2021)	–1.23	1.99	0.536	[–5.12; 2.66]	No spurious post-trend effects



Note: (a) actual DiD estimate for the COVID-19 shock in 2020; (b) placebo test 1 with a false treatment year in 2019; (c) placebo test 2 with a false treatment year in 2021. Highly digitalized = green; Less digitalized = red.

Figure 3. Comparison of actual DiD and placebo tests (employment)

Country-level heterogeneity analysis reveals substantial variation in DiD effects. The largest positive effects are observed in France (22.21 thousand), Spain (12.93 thousand), Poland (10.79 thousand), Sweden (8.61 thousand), and the Czech Republic (6.84 thousand). Negative effects are identified in Germany (–3.46 thousand), Denmark (–2.98 thousand), Greece (–2.96 thousand), Romania (–2.32 thousand), and Ireland (–1.36 thousand). The median effect is 1.69 thousand, indicating that positive impacts dominate across most EU Member States. This heterogeneity reflects differences in digital infrastructure, labor-market flexibility, and pandemic policy responses.

Detailed country-level estimates of the DiD effect are reported in Table 6 and reveal substantial cross-country heterogeneity in the post-COVID adjustment of highly digitalized relative to less digitalized economic activities. The largest positive effects are observed in France (22.21 thousand), Spain (12.93 thousand), Poland (10.79 thousand), Sweden (8.61 thousand), and the Czech Republic (6.84 thousand). In these countries, employment in highly digitalized economic ac-

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tivities increased more strongly, or declined less sharply, than in less digitalized economic activities between the pre-crisis and post-crisis periods. France stands out most clearly: employment in highly digitalized economic activities rose from 199.61 to 226.66 thousand, whereas employment in less digitalized economic activities increased only modestly from 314.78 to 319.62 thousand, producing the largest relative advantage for digital economic activities. A similar pattern is evident in Spain and Poland, where high-digital employment expanded considerably faster than low-digital employment, indicating that digitalized activities were better positioned to absorb the shock and recover in the medium term.

At the same time, the results show that this pattern was not universal across the European Union. Negative DiD effects are identified in Germany (–3.46 thousand), Denmark (–2.98 thousand), Greece (–2.96 thousand), Romania (–2.32 thousand), and Ireland (–1.36 thousand), suggesting that in these cases, less digitalized economic activities performed comparatively better, or that highly digitalized economic activities did not gain a relative employment advantage after the pandemic. In Germany, for example, employment increased in both sector groups, but the expansion was stronger in less digitalized economic activities, leading to a negative differential effect. Overall, however, the median DiD effect remains positive at 1.69 thousand, which indicates that the relative employment advantage of highly digitalized economic activities prevailed in most EU Member States. These findings point to the importance of national context, as the labor-market effects of digitalization appear to depend on country-specific conditions such as the pace of digital transformation, the quality of digital infrastructure, the sectoral composition of the economy, and labor-market adaptability.

Table 6. Heterogeneity of the DiD effect across EU countries

Country	DiD effect (thousand)	High-digital Pre	High-digital Post	Low-digital Pre	Low-digital Post
France	22.21	199.61	226.66	314.78	319.62
Spain	12.93	136.50	155.21	257.40	263.17
Poland	10.79	84.32	99.91	228.61	233.42
Sweden	8.61	44.82	51.61	55.78	53.96
The Czech Republic	6.84	29.89	31.05	78.91	73.24
Belgium	6.29	38.38	43.94	58.65	57.92
Lithuania	4.97	9.81	13.05	25.86	24.14
Hungary	3.89	22.78	28.42	65.62	67.36
Latvia	3.26	8.32	7.86	20.11	16.38
Bulgaria	3.03	21.80	22.53	50.41	48.11
Finland	2.42	20.50	22.64	29.47	29.19
Austria	2.26	30.55	32.65	63.87	63.71
Slovakia	1.73	15.73	24.21	43.14	49.89
Slovenia	1.69	6.68	8.07	15.51	15.20
Italy	1.40	165.11	170.41	303.56	307.46
Cyprus	0.75	3.70	4.62	7.72	7.88
Estonia	0.67	8.73	10.13	13.69	14.42
Croatia	0.60	13.16	13.27	26.82	26.34
Malta	0.56	3.39	4.62	5.60	6.26
The Netherlands	0.52	72.78	88.05	87.39	102.15
Luxembourg	0.46	6.72	8.09	5.82	6.72
Portugal	0.24	33.90	32.68	68.35	66.88
Ireland	–1.36	21.64	27.21	36.17	43.10
Romania	–2.32	36.81	37.04	123.45	126.00
Greece	–2.96	23.56	25.08	48.71	53.18
Denmark	–2.98	21.70	22.49	37.20	40.97
Germany	–3.46	311.65	316.64	551.89	560.34

Note: The DiD effect is calculated as the difference between the change in employment in highly digitalized economic activities and that in less digitalized economic activities in the post-crisis period, relative to the pre-crisis period. Pre = 2018–2019; Post = 2021–2024.

Table 7. SDG-related labor market indicators by sector digitalization

Indicator (SDG)	High-digital Pre	High-digital Post	Low-digital Pre	Low-digital Post	Gap change	Interpretation
8.5.1 Wages (€/hour)	15.45	17.24	10.57	11.70	+0.66	Wage inequality increases
8.5.2 Employment (thousand)	58.91	64.12	109.97	111.86	+3.32	Faster growth in digital economic activities
4.4.1 Digital skills (%)	17.6	82.1	1.3	6.6	+59.2 pp	Sharp expansion of the digital divide

Finally, the analysis of Sustainable Development Goal (SDG) indicators highlights a widening structural gap between sector groups (Table 7). Wage growth (SDG 8.5.1) is faster in highly digitalized economic activities (+11.6% vs +10.7%), resulting in a larger absolute wage gap (+0.66 €/hour). Employment growth (SDG 8.5.2) is also stronger in these economic activities (+8.8% vs. +1.7%), indicating a structural shift toward knowledge-intensive activities. The most pronounced divergence is observed in digital skills (SDG 4.4.1, proxied by telework), where the gap increases by 59.2 percentage points. Together, these findings point to a polarization of labor market outcomes driven by digitalization.

The results demonstrate that digitalization did not significantly affect aggregate employment levels but did induce substantial structural changes in wages and work organization, contributing to increased inequality between highly and less digitalized economic activities.

4. DISCUSSION

The empirical findings of this study provide important insights into the role of digital transformation in shaping labor market adjustment during the COVID-19 shock. The absence of a statistically significant effect on aggregate employment (DiD = 0.06; $p \approx 0.98$) suggests that digitalization did not act as a primary driver of job creation or destruction in the short run but rather influenced the composition and resilience of employment across economic activities. This result aligns with evidence indicating that the pandemic primarily affected labor demand through sector-specific disruptions rather than uniform employment declines (Forsythe et al., 2020; Richardson, 2024). At the same time, the observed resilience of highly digitalized economic activities is consistent with broader findings that digital readiness mitigated the negative effects of the crisis and supported faster recovery trajectories (World Bank, 2021; IMF, 2021). Thus, while digitalization did not expand total employment volumes, it contributed to stabilizing labor markets amid unprecedented uncertainty.

In contrast, the results reveal a strong and statistically significant impact of digitalization on wages and work organization, supporting the hypothesis of skill-biased technological change. The estimated increase in the wage gap (DiD = 0.52 €/hour; $p < 0.001$) confirms that digital transformation disproportionately benefits workers in high-skill, technology-intensive economic activities, reinforcing existing inequalities. This finding is consistent with previous research highlighting the growing importance of digital competences and human capital in determining labor market outcomes (Mishchuk et al., 2025; Poláková et al., 2023; Kuzior et al., 2025). Moreover, the substantial expansion of remote work (DiD = 40.74 percentage points; $p < 0.001$) reflects a structural shift in work organization, in line with evidence documenting the rapid adoption of flexible and digital working arrangements during the pandemic (Spurk & Straub, 2020; Raišienė et al., 2020; Šafránková & Šikýř, 2024). However, the uneven distribution of telework opportunities across economic activities confirms that digital transformation has intensified labor market segmentation, as also observed in studies on inequality and differential vulnerability during COVID-19 (Del Boca et al., 2020; Jesus et al., 2021).

The heterogeneity of results across countries further emphasizes that the impact of digital transformation is context-dependent and shaped by institutional and structural factors. The presence of both positive and negative DiD effects across EU Member States suggests that digitalization interacts with national labor market structures, sectoral composition, and policy responses. This observation is consistent with findings that post-pandemic recovery dynamics vary significantly

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across European economies depending on macroeconomic stability, institutional capacity, and the pace of digital transformation (Kuzior et al., 2024b; Vysochyna et al., 2024). In addition, broader structural processes, including geopolitical shocks such as the war in Ukraine and the transition toward energy security, may further influence labor market adjustment by reshaping sectoral demand and investment patterns (Vasylieva et al., 2025). Overall, the results support the view that digital transformation acts as a catalyst for qualitative labor market change, reinforcing structural divergence and inequality, rather than as a uniform driver of employment growth across the European Union.

This study is subject to several limitations that open avenues for further research. First, the analysis relies on sector-level aggregation, which may mask within-sector heterogeneity and individual-level dynamics, particularly in terms of skill composition, job transitions, and worker-level inequality. Second, although the difference-in-differences framework with fixed effects and robustness checks strengthens causal inference, the identification strategy still depends on the parallel trends assumption and may not fully capture unobserved time-varying shocks or policy interventions that differ across countries. Third, the classification of economic activities by digitalization potential, while grounded in established methodology, remains relatively static and may not fully reflect the rapid evolution of digital adoption during and after the pandemic. Fourth, using telework as a proxy for digital skills, although informative, does not capture broader dimensions of digital capability or task complexity. Future research could extend this analysis by incorporating firm-level or micro-level data, allowing for a more granular assessment of labor market adjustments and distributional effects. Additionally, dynamic models capturing longer-term impacts, including lagged effects of digital transformation and structural reallocation across economic activities, would provide deeper insights. Finally, integrating institutional variables, such as education systems, labor market policies, and the quality of digital infrastructure, could help explain cross-country heterogeneity and deepen understanding of how digitalization interacts with national economic contexts.

CONCLUSION

This study estimates the causal effect of the digitalization potential of economic activity (proxied by a binary classification into highly and less digitalized groups based on telework feasibility and digital intensity) on three labor market indicators: employment, hourly wages, and remote work.

The results show that digitalization did not significantly change aggregate employment levels. By contrast, it increased wages and had an especially strong effect on the expansion of remote work. The findings also reveal considerable cross-country variation, indicating that the labor-market effects of digitalization depend on national context.

These findings show that digital transformation is reshaping labor markets primarily through qualitative rather than quantitative change. Although aggregate employment levels do not appear to respond significantly, digitalization is associated with higher wages and a much stronger expansion of remote work, indicating that its main effects are concentrated in work organization and the distribution of labor-market advantages. In this sense, digitalization functions less as a driver of overall job creation and more as a force that redefines how work is performed, rewarded, and spatially organized. The results also point to growing divergence between highly and less digitalized economic activities, suggesting that the benefits of technological adaptation are unevenly distributed across the economy. Moreover, the substantial variation across countries indicates that differences in institutional capacity, labor-market structures, and existing levels of digital development shape these effects. The study suggests that digital transformation has become a major channel of post-pandemic labor-market restructuring, simultaneously strengthening resilience in some areas while deepening inequality and structural fragmentation in others.

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