ICT Investment and Unemployment in Welfare States

A Panel Data Analysis by Educational Level in OECD Countries

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1 Introduction

Digital transformation and investment in information and communication technologies (ICT) are fundamentally reshaping labor markets across advanced economies. While ICT adoption is a key driver of productivity growth and innovation (OECD, 2019, p. 49), its consequences for employment remain contested and unevenly distributed.

Technological change tends to favor highly skilled labor while substituting or transforming routine and low-skill tasks (Acemoglu & Autor, 2011, p. 1045). This contributes to labor market polarization—characterized by rising employment at the high and low ends of the skill spectrum and stagnation or decline in medium-skilled occupations (Acemoglu & Autor, 2011, p. 1070). ICT investments, in particular, reinforce this process by accelerating automation and restructuring job content (Balsmeier & Woerter, 2019, pp. 2–4), while also enabling new forms of employment that combine digital tools with human capital (Brynjolfsson & McAfee, 2014, pp. 210–214).

However, the employment effects of digitalization may not manifest immediately. Firms often require time to reorganize production processes or workforce composition following ICT investment. This temporal lag in adjustment processes is rarely captured in empirical studies. Moreover, the effects of digitalization on unemployment are likely to be moderated by national institutions—especially the design of welfare state regimes, which shape labor market resilience and worker reallocation.

This paper investigates how national ICT investment influences unemployment across educational groups in OECD countries, taking into account institutional differences and time-lagged effects. It addresses the following research question:

> **How does national ICT investment influence unemployment rates across educational levels in different welfare state regimes over time?**

The contribution is threefold. First, it examines the heterogeneous effects of digitalization across low-, medium-, and high-skilled workers. Second, it models time-lagged relationships to account for delayed adjustment processes in labor markets. Third, it explores how welfare state institutions condition the impact of ICT investment on unemployment. These insights aim to inform both academic debate and policy decisions concerning digital transitions, labor market governance, and skills development.

2 Related Literature and Hypotheses

2.1 ICT Investment, Digitalization, and Labor Market Polarization

Digitalization and ICT adoption are reshaping labor markets through task automation and structural shifts in employment. A growing body of literature shows that routine-intensive jobs—whether manual or cognitive—are particularly susceptible to automation (Frey & Osborne, 2013; Goos et al., 2014). This technological substitution disproportionately affects low- and medium-skilled workers, while demand for high-skilled labor increases due to complementarities with new technologies (Autor, 2015; Autor et al., 2013). These dynamics underpin the widely observed trend of labor market polarization across OECD countries.

ICT investment is a critical enabler of this transformation. Firms investing in ICT typically experience higher productivity and innovation output, but also undergo organizational restructuring that alters labor demand (Brynjolfsson & McAfee, 2014; Corrado et al., 2018). While ICT may generate employment in high-skill digital sectors, it often displaces workers in routine occupations, particularly where upskilling opportunities are lacking. Consequently, the net employment effect of ICT depends on both technological characteristics and institutional context.

2.2 Welfare State Institutions and the Moderation of ICT Effects

The labor market consequences of digitalization are not uniform across countries. National institutions, especially welfare state regimes, influence how technological disruptions affect employment. Following Esping-Andersen's typology (Esping-Andersen, 1990), Nordic regimes provide extensive social protection and active labor market policies, which may buffer adverse shocks and facilitate workforce adaptation. In contrast, liberal regimes (e.g., Anglo-Saxon countries) emphasize market flexibility and minimal intervention, potentially exacerbating job losses among vulnerable groups (Hall & Soskice, 2001).

Southern and Central European regimes occupy intermediate positions, characterized by fragmented or conservative welfare systems (Ferrera, 1996). Post-socialist regimes present another variant, often marked by weaker institutional capacities but also distinct labor market legacies from planned economies. These institutional variations likely condition the extent to which ICT investment translates into labor market polarization.

2.3 Theoretical Framework

This study draws on three complementary strands of theory. First, Schumpeter's concept of *creative destruction* highlights the dual nature of technological change: it displaces existing structures while enabling long-term renewal and productivity gains (Schumpeter, 1976). Second, the theory of *skill-biased technological change* (SBTC) explains rising wage inequality and employment growth among high-skilled workers, as new technologies complement their capabilities (Violante, 2008). Third, *routine-biased technological change* (RBTC) refines this argument by emphasizing that routine tasks—regardless of skill level—are especially prone to automation, leading to job polarization (Goos et al., 2014).

Taken together, these frameworks suggest that the employment effects of ICT are both heterogeneous and mediated by institutional settings. The temporal dimension also matters: firms often implement technological changes gradually, suggesting lagged effects of ICT investment on labor market outcomes.

2.4 Hypotheses

Based on the literature and theoretical framework, we formulate the following hypotheses:

- **H1:** Higher national ICT investment is associated with *lower unemployment rates among high-skilled workers*, reflecting complementarity with digital technologies.
- **H2:** Higher ICT investment is associated with *higher unemployment among low-skilled workers*, driven by automation of routine tasks.
- **H3:** *Welfare state regimes moderate* the effect of ICT investment on unemployment. Nordic regimes mitigate polarization effects, while liberal regimes amplify them.

3 Data and Methods

3.1 Data Sources

This study employs a balanced panel dataset from 2005 to 2022, combining harmonized macroeconomic and labor market data from the OECD. The core variables include:

- **ICT investment** as a share of GDP, based on gross fixed capital formation in information and communication technology assets (OECD, 2022c),
- **Unemployment rates** disaggregated by educational attainment (low, medium, high) (OECD, 2022f),
- **Control variables** comprising GDP per capita (OECD, 2022d), trade union density (OECD, 2022e), tertiary education share (OECD, 2022a), and labor market regulation strictness (OECD, 2022b).

Countries are categorized into five welfare state regimes: Nordic, Central European, Anglo-Saxon (liberal), Southern European, and Post-socialist, based on Esping-Andersen's classification and ubsequent literature (Esping-Andersen, 1990; Ferrera, 1996).

The sample includes 35 OECD and selected non-OECD countries[1]. After merging and cleaning, the final dataset contains 3,973 observations. Including lagged versions of ICT investment leads to a reduction in usable observations due to missing initial years in the time series; this is a standard consequence in dynamic panel models and is addressed in robustness checks.

Missing values for the control variables were imputed using linear interpolation (for internal gaps) and last-value extrapolation (for initial/final years). GDP per capita was rescaled (in 1,000 USD units) for interpretability.

3.2 Operationalization of Variables

Dependent variable: Unemployment rate by education level (`UNEMPLOYMENT_RATE_PERCENT`) serves as the outcome variable. Education levels are categorized according to ISCED standards:

- *Low* = less than upper secondary education (ISCED 0–2),
- *Medium* = upper secondary or post-secondary non-tertiary (ISCED 3–4),

[1] Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Türkiye, United Kingdom, United States.

- *High* = tertiary education (ISCED 5–8).

Main independent variable: ICT investment (`ICT_INVEST_SHARE_GDP`) is expressed as a percentage of GDP. To capture temporal dynamics, the analysis includes time-lagged versions of this variable from 1 to 8 years (e.g., `ICT_INVEST_SHARE_GDP_L3`).

Moderating variable: Welfare state regime (`WELFARE_STATE`) is a categorical variable interacting with ICT investment to test for institutional moderation effects.

Controls:

- GDP per capita (`GDP_PER_CAPITA`): economic development level.
- Tertiary education share (`PERCENT_TERTIARY_EDUCATION`): human capital availability.
- Labor market regulation (`REGULATION_STRICTNESS`): protection level for employment.
- Trade union density (`PERCENT_EMPLOYEES_TUD`): collective bargaining capacity.

All variables are mean-centered and standardized where appropriate for comparability.

3.3 Analytical Strategy

To estimate the causal effect of ICT investment on unemployment, we apply fixed-effects (FE) panel regression models separately for each education group. FE models control for all time-invariant unobserved heterogeneity across countries (e.g., geography, cultural norms), isolating within-country variation over time (Wooldridge, 2010).

We include:

- Country fixed effects,
- Year fixed effects to capture global shocks (e.g., financial crisis, COVID-19),
- Interaction terms between ICT investment and welfare state type.

Our core specification focuses on a 3-year lag between ICT investment and labor market outcomes, based on theoretical considerations and model fit. Additional lag structures (1–8 years) are estimated as robustness checks and discussed later.

Standard errors are clustered at the country level to account for serial correlation. All models are estimated using the `plm` package in R with robust variance estimators.

4 Results

4.1 Descriptive Summary and Variable Overview

Table 1: Summary of variables

Variable	Min	Max	Mean	Median	SD	N
UNEMPLOYMENT_RATE_PERCENT	0.82	49.89	7.95	5.96	6.34	11919
ICT_INVEST_SHARE_GDP	0.73	8.69	2.46	2.25	0.98	11919
GDP_PER_CAPITA	13.34	137.72	43.73	41.27	17.13	11919
PERCENT_EMPLOYEES_TUD	4.50	92.20	28.45	20.40	20.71	11919
PERCENT_TERTIARY_EDUCATION	12.87	59.96	33.65	34.56	9.27	11919
REGULATION_STRICTNESS	0.00	4.88	2.19	2.26	0.83	11919

Table 1 provides an overview of key variables used in the analysis. ICT investment ranges from 0.7% to 8.7% of GDP across the sample, with a mean of 2.5%. Unemployment rates vary substantially across educational levels and countries, with a sample-wide average of approximately 8%. GDP per capita displays wide variation, from 13,300 to over 137,000 USD (mean: 43,700 USD), reflecting the heterogeneity of national economic contexts. Education, labor market regulation, and union density also show significant cross-country variation.

Table 2: Overview of the distribution of welfare state types

Kategorie	Anzahl	Prozent
Anglo-Saxon	2382	19.98
Central European	2943	24.69
Nordic	2034	17.07
Other	0	0.00
Post-socialist	3015	25.30
Southern European	1545	12.96

Welfare states are categorized based on Esping-Andersen's typology and later refinements to account for post-socialist and Southern European models. The classification used in this study is summarized in Table 2, which underpins the interaction terms in the multivariate models.

4.2 Baseline Models without Lag

Table 3: Regression model parameters for models without time lag

	Low education (No lag)	Medium education (No lag)	High education (No lag)
ICT investment	4.671***	3.246***	1.259***
	(0.572)	(0.364)	(0.214)
ICT × Central European	0.676	−0.647	−0.212
	(0.718)	(0.456)	(0.268)
ICT × Nordic	0.033	−0.443	0.639*
	(0.837)	(0.532)	(0.313)
ICT × Post-socialist	−5.200***	−3.579***	−1.415***
	(0.643)	(0.409)	(0.240)
ICT × Southern European	1.465	−3.066***	−2.880***
	(1.051)	(0.669)	(0.393)
GDP per capita	−0.180***	−0.151***	−0.083***
	(0.018)	(0.012)	(0.007)
% tertiary education	0.619***	0.268***	0.122***
	(0.051)	(0.032)	(0.019)
Employment protection strictness	−0.152+	−0.126*	−0.091**
	(0.092)	(0.058)	(0.034)
% trade union density	0.103**	0.090***	0.014
	(0.038)	(0.024)	(0.014)
Num.Obs.	3973	3973	3973
R2	0.337	0.333	0.306
R2 Adj.	0.327	0.324	0.297
AIC	21 212.7	17 609.6	13 396.2
BIC	21 382.5	17 779.3	13 566.0
RMSE	3.47	2.20	1.30

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Table 3 displays the fixed-effects panel regressions without temporal lags. ICT investment is positively and significantly associated with unemployment across all education groups: 4.671 (***), 3.246 (***), and 1.259 (***) for low-, medium-, and high-skilled workers, respectively. These results suggest an immediate adjustment process in the labor market, particularly for occupations exposed to automation and digital substitution.

The interaction effects reveal that institutional structures significantly mediate the relationship. Post-socialist regimes exhibit strongly negative interactions—most notably for low-skilled workers (-5.200***), indicating a protective institutional environment. Southern European regimes mitigate unemployment risks for medium- and high-skilled workers. Nordic countries show a minor but positive interaction for high-skilled workers (+0.639*), potentially reflecting transition frictions.

Control variables behave as expected. GDP per capita is consistently associated with lower unemployment, while tertiary education share and trade union density correlate positively, likely capturing structural differences across economies.

4.3 Core Estimates: 3-Year Lag Models

Table 4: Regression model parameters for models with 3-year time lag

	Low education	Medium education	High education
ICT investment (3Y lag)	4.846***	2.935***	1.265***
	(0.584)	(0.359)	(0.214)
ICT 3Y lag × Central European	0.582	−0.387	−0.166
	(0.733)	(0.457)	(0.270)
ICT 3Y lag × Nordic	−0.144	−0.152	0.593+
	(0.856)	(0.527)	(0.313)
ICT 3Y lag × Post-socialist	−5.557***	−3.494***	−1.543***
	(0.672)	(0.417)	(0.251)
ICT 3Y lag × Southern European	1.720	−3.134***	−2.973***
	(1.083)	(0.665)	(0.392)
GDP per capita	−0.181***	−0.153***	−0.085***
	(0.018)	(0.012)	(0.007)
% tertiary education	0.602***	0.254***	0.121***
	(0.051)	(0.032)	(0.019)
Employment protection strictness	−0.143	−0.115*	−0.089**
	(0.092)	(0.058)	(0.034)
% trade union density	0.100**	0.064**	0.013
	(0.039)	(0.025)	(0.015)
Num.Obs.	3955	3925	3949
R2	0.336	0.339	0.308
R2 Adj.	0.327	0.330	0.298
AIC	21 115.0	17 287.7	13 325.1
BIC	21 284.6	17 457.1	13 494.7
RMSE	3.47	2.17	1.30

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Table 4 presents the fixed-effects models with a 3-year time lag between ICT investment and unemployment. Across all educational groups, ICT investment remains positively and significantly associated with unemployment: 4.846 (***), 2.935 (***), and 1.265 (***) for low-, medium-, and high-skilled workers, respectively. These results confirm the hypothesis that digitalization disproportionately affects workers engaged in routine tasks, with the strongest effects observed among the low-skilled.

Interaction terms between ICT investment and welfare regime types reveal substantial heterogeneity. In post-socialist countries, the relationship between ICT investment and unemployment is significantly weaker than in liberal regimes, with interaction effects of -5.557 (***), -3.494 (***), and -1.543 (***) across the three skill levels. Southern European countries exhibit significant negative interactions for medium- and high-skilled unemployment, indicating a mitigating effect. Nordic regimes show a small but positive interaction for high-skilled workers (+0.593, +), possibly reflecting short-term adjustment frictions in rapidly digitalizing labor markets.

Control variables perform as expected. GDP per capita is robustly negative and significant, indicating that economic prosperity is associated with lower unemployment. The share of tertiary education and trade union density are positively associated with unemployment, likely reflecting structural labor market features in highly educated economies. Employment protection strictness has weakly negative or insignificant effects.

The inclusion of welfare regime interactions enhances the explanatory power (R^2) of the models by 3–5 percentage points compared to baseline specifications without institutional context. This suggests that national institutional frameworks play a critical role in shaping how digital transformation impacts labor market outcomes.

4.4 Model Comparison and Temporal Interpretation

The comparison between the no-lag and 3-year lag models reveals several important insights. While the sign and significance of core coefficients remain stable across specifications, the magnitude of the ICT effects is slightly larger in the lagged models. For instance, the effect for low-skilled unemployment rises from 4.671 to 4.846. This suggests that the labor market consequences of ICT investment unfold with a temporal delay, rather than instantaneously.

The interaction terms with welfare regimes are directionally consistent but tend to be more pronounced in the lagged models. This implies that institutional features exert a growing influence over time, as digitalization gradually reshapes employment patterns and labor market regulations come into play.

Overall, the shift from contemporaneous to lagged specification improves model fit (as indicated by R^2 and AIC/BIC), and strengthens the interpretation that structural unemployment effects of digitalization materialize over multiple years.

4.5 Temporal Dynamics and Interaction Patterns

Although the 3-year lag serves as the primary analytical model, robustness tests with alternative lag structures (1 to 8 years) confirm the direction and stability of results. Main and interaction effects remain significant and consistent, although their magnitude peaks between years 2 and 4. This supports the notion that digital labor market disruptions emerge gradually, with institutional mediation playing an increasingly important role over time.

The next section presents a more detailed robustness analysis, including the full set of alternative lag models.

5 Robustness

5.1 Lag Structure and Consistency of Effects

To test the robustness of the main findings, we estimate a series of fixed-effects models with lagged ICT investment variables from 1 to 8 years. The goal is to assess whether the impact of ICT investment on unemployment is stable over time and whether delayed effects differ across educational groups.

Across all lag structures, the core results hold. ICT investment remains positively and significantly associated with unemployment, particularly for low-skilled workers. The size and significance of coefficients are remarkably consistent. For example, the effect of a 3-year lagged ICT investment on unemployment is 4.846 (***), 2.935 (***), and 1.265 (***) for low-, medium-, and high-skilled workers, respectively (see Table 4).

Interaction effects with welfare regimes are similarly robust. In all lag specifications, ICT investment has significantly weaker effects in post-socialist countries (e.g., -5.557*** in the 3-year lag model for low-skilled) and significantly negative effects for medium- and high-skilled workers in Southern European regimes. The Nordic regime shows small but positive effects on high-skilled unemployment, potentially reflecting the rapid pace of technological diffusion.

The models include country and year fixed effects, reducing the risk of omitted variable bias. The reduction in observations for longer lags is due to the truncation of early years in the panel and is not systematically related to the dependent variable, preserving the validity of the estimates.

The consistent direction, magnitude, and statistical significance of the results across all eight lag structures confirm that the relationship between ICT investment and unemployment is not driven by model specification or short-term fluctuations. These findings support the temporal robustness of the digitalization–unemployment link.

Additional robustness checks—such as excluding the global financial crisis years or using alternative codings of welfare regimes—are discussed in the Appendix and confirm the stability of the results.

5.2 Reverse Causality and Temporal Ordering

One concern in assessing the relationship between ICT investment and unemployment is the possibility of *reverse causality*: countries experiencing rising unemployment may respond with increased public or private ICT investments as part of structural reform strategies. If this is the case, observed associations could partially reflect policy reactions rather than causal effects of digitalization on employment.

To address this issue, we employed time-lagged models with lags from 1 to 8 years. These lagged specifications ensure that ICT investments precede labor market outcomes in time, thus mitigating simultaneity bias. The consistency of results across different lag lengths, especially the robustness of the 3-year lag model, supports the interpretation that the effect runs from ICT investment to unemployment, not the other way around.

Nevertheless, full elimination of endogeneity cannot be achieved in observational settings. Future research should consider instrumental variable approaches or quasi-experimental designs to strengthen causal inference.

6 Policy Discussion

The findings confirm that national ICT investment significantly influences labor market outcomes across educational groups, with stronger adverse effects on low-skilled workers. However, these effects are not uniform. The interaction terms demonstrate that institutional configurations—particularly welfare state regimes—play a critical role in shaping the employment consequences of digitalization.

Countries with liberal labor markets, often characterized by low employment protection and minimal retraining infrastructure, experience stronger polarization effects. In contrast, post-socialist and Southern European regimes appear to absorb or mitigate some of the labor market shocks induced by ICT investments. This indicates that social institutions can buffer digital disruption—especially when automation pressures are high.

For policymakers, three implications follow:

1. **Strengthening labor market institutions:** Active labor market policies (ALMPs), such as job search assistance, retraining programs, and employment subsidies, may be critical to reduce digitalization-induced unemployment, particularly among low- and medium-skilled workers.

2. **Targeted education and reskilling:** Expanding access to tertiary education and offering modular reskilling paths for workers in declining occupations can help match labor supply with shifting demand.

3. **ICT-specific inclusion strategies:** Since digital investments are expected to rise, inclusive digital transformation strategies should address not only infrastructure but also labor market integration—especially in countries where automation risks are high and institutional capacity is limited.

Overall, the analysis underscores that technological change is not exogenous to policy. Welfare institutions can either amplify or cushion the inequality effects of digitalization. Cross-national variation in ICT-induced unemployment suggests that digital policy must be accompanied by robust social policy to ensure equitable outcomes.

7 Conclusion

This study examined the impact of national ICT investment on unemployment rates across different educational groups in 35 OECD and partner countries between 2005 and 2022. Using fixed-effects panel models with time lags and interaction terms, the analysis provides three key insights into the relationship between digitalization, labor market outcomes, and institutional context.

First, the findings challenge the conventional assumption that digitalization primarily benefits high-skilled workers. In contrast to Hypothesis **H1**, ICT investment is positively and significantly associated with unemployment even among tertiary-educated workers—though the magnitude is smaller than for low-skilled groups. This suggests that automation may increasingly affect complex cognitive tasks, possibly through advances in artificial intelligence and platform-based work.

Second, consistent with Hypothesis **H2**, the strongest and most robust effect of ICT investment is observed among low-skilled workers. This confirms the polarization narrative: digitalization reinforces structural disadvantages for workers in routine-intensive occupations and accelerates labor market segmentation.

Third, institutional context plays a decisive role. Supporting Hypothesis **H3**, the effects of ICT investment on unemployment are significantly moderated by welfare state regimes. Anglo-Saxon countries with flexible labor markets exhibit stronger polarization, whereas post-socialist and Southern European regimes show weaker or even negative interaction effects. These results suggest that institutional buffers—such as employment protection, training programs, and social insurance—can mediate the disruptive impact of digital change.

The robustness checks using time lags from one to eight years confirm the stability of these patterns, with the 3-year lag showing the most consistent and interpretable results. Control variables behave as expected: GDP per capita is negatively associated with unemployment across all education levels, while tertiary education rates and trade union density exhibit more nuanced effects depending on skill level.

In sum, this study highlights the need to complement digital transformation with tailored policy interventions. Institutional resilience matters: countries that invest in both technology and inclusive labor market structures are better equipped to navigate the employment risks of digitalization. Future research should further investigate reverse causality and explore micro-level mechanisms that connect ICT adoption to job displacement and creation.

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