Digitization and the Limits of Productivity Growth in Aging Industries

Nazif Durmaz* Eli Kochersperger† Alka Bishnoi‡ Irina Gioaba§

Abstract

This paper studies whether the productivity returns to information and communication technology (ICT) capital are attenuated in industries with older workforces. Using a country–industry–year panel of European productivity, capital, and labor-market data from 1995–2019, we estimate labor-productivity models that allow the marginal association between ICT intensity and productivity to vary with the share of older workers. ICT intensity is positively associated with labor productivity on average, but the interaction between ICT intensity and older-worker shares is negative and statistically significant, indicating weaker realized productivity gains from ICT in aging industries. Instrumental-variables estimates using predetermined 1995 ICT exposure, global ICT price declines, and historical European research-backbone connectivity support the same heterogeneous-return pattern. We also examine ICT accumulation, age-specific employment shares, and technostress-related outcomes from the European Working Conditions Survey. These mechanism results do not show that older workers who remain employed in digitally intensive environments report disproportionately worse technostress-related outcomes; instead, they are consistent with selection, adjustment costs, or organizational frictions. The findings suggest that workforce aging may limit the productivity gains from digitization even when ICT investment raises productivity on average.

Keywords: Digitization, Aging, Labor Productivity, Technostress.

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*Department of Marketing, Global Business & Economics, Kean University, 303-P Hynes Hall Union, NJ 07083. Tel: (908)-737-4188. Email:ndurmaz@kean.edu

†Department of Marketing, Global Business & Economics, Kean University, 303-V Hynes Hall Union, NJ 07083. Tel: (908)-737-4179. Email:ekochers@kean.edu

‡Department of Physical Therapy, Kean University, 425 NAAB Union, NJ 07083. Tel: (908)-737-6177. Email:abishnoi@kean.edu

§Department of Management, Kean University, 203-P Hynes Hall Union, NJ 07083. Tel: (908)-737-4132. Email:igioaba@kean.edu

1. Introduction

Recent studies concerning information and communication technologies and economic growth have been substantially influenced by inspiring contributions to endogenous growth theory, which hypothesize that technological advancement is an integral component of the growth process. Romer (1990) and Aghion and Howitt (1990) argue that investments in human capital and technology yield increasing returns, which can lead to sustained long-term economic development. Technological advancements have revolutionized work environments, requiring employees to adapt to new digital tools and processes in terms of easing the knowledge distribution and refining the structural productivity (Bresnahan and Trajtenberg (1995)). Autor et al. (2003) found that computers replace routine tasks but enhance complex problem-solving and communication roles. This dynamic helps explain why middle-skill jobs are declining while both high- and low-skill jobs grow.

While these changes have generated new job prospects for younger cohorts, older adults often struggle to keep pace, leading to performance issues, disengagement, and even early retirement. Recent empirical research examined these labor market transformations and pointed out how some groups of workers, in particular older workers, face the greatest risk. Acemoglu et al. (2022) developed a firm-level measure to evaluate how much companies are exposed to AI and found that demand for AI jobs grew quickly from 2010 to 2018, especially in businesses where tasks closely align with what AI can do. In these firms, adopting AI led to fewer hires for non-AI roles and increased skill requirements for remaining jobs, favoring analytical and non-routine abilities.

This paper examines whether workforce aging attenuates the productivity returns to ICT capital. Our central contribution is to estimate heterogeneous ICT-productivity returns across European country–industry cells from 1995–2019, focusing on whether the marginal productivity association of ICT intensity is smaller in industries with larger older-worker shares. We then use auxiliary evidence on ICT accumulation, age-specific employment shares, and technostress-related working conditions to help interpret the mechanisms behind the aggregate productivity patterns. These mechanism analyses are not intended to establish technostress as the primary causal channel;

rather, they assess whether the evidence is more consistent with direct health burdens, selection, adjustment costs, or organizational frictions.

Section 2 reviews related literature. Section 3 presents the conceptual framework. Section 4 describes the empirical strategy and Section 5 the data. Section 6 reports the main results, while Section 7 reports the results of some mechanisms analyses. Section 8 discusses interpretation and policy implications, and Section 9 concludes.

2. Literature Review

This paper contributes to three related literatures: the productivity effects of ICT capital, the economic consequences of workforce aging, and the organizational and worker-level frictions that accompany digital transformation. A large empirical literature finds that ICT investment is positively associated with productivity growth, especially in settings where digital capital is combined with complementary organizational change and human-capital investments (Jorgenson et al., 2008; Cardona et al., 2013). More recent work has extended this discussion to artificial intelligence and related digital technologies, emphasizing both their potential contribution to productivity growth and their uneven effects across tasks, industries, and worker groups (Chui et al., 2016; Aghion & Bunel, 2024; Farach et al., 2025).

The central question in this paper is not whether ICT capital is productive on average, but whether its productivity returns vary systematically with workforce age composition. This question is motivated by the view that digital technologies are not simple capital deepening devices: their productivity effects depend on worker skills, task organization, learning costs, and the ability of firms to adapt production processes. If older workforces face higher adjustment costs or if firms adopt ICT less effectively in aging industries, then the realized productivity gains from digitization may be attenuated even when ICT capital is productive on average.

A related literature studies the implications of population aging for labor markets, productivity, and technological change. Population aging changes the composition of employment and may affect productivity through several competing channels. Some evidence suggests that aging workforces may experience slower productivity growth when technological change places greater weight on new skills, adaptation, or retraining (Feyrer, 2008; Friedberg, 2003). At the same time, experience, firm-specific human capital, and accumulated knowledge may offset age-related declines in some settings (Börsch-Supan & Weiss, 2016; Viviani et al., 2021). Recent work on automation and demographic change further emphasizes that aging and technology adoption are jointly determined: firms facing older labor forces may have different incentives to automate, while technological change can alter the demand for older workers' skills (Acemoglu & Restrepo, 2022).

These mechanisms are especially relevant because digital transformation may interact with age-related differences in training, task reassignment, and technology use. Research in organizational psychology and information systems has emphasized technostress as one potential channel through which ICT adoption affects workers. Technostress, originally defined by Brod (1984) as stress arising from difficulty adapting to computer technologies, includes dimensions such as techno-overload, techno-invasion, and techno-complexity. These stressors have been linked to burnout, anxiety, lower job satisfaction, and reduced work performance (Ragu-Nathan et al., 2008; Tarafdar et al., 2019; Nedeljko et al., 2024). From a person–environment fit perspective, stress may arise when workplace technological demands exceed workers' perceived capabilities or available support (Edwards et al., 1998). This channel may be particularly salient for older workers if digital technologies increase learning demands or alter established work routines.

The evidence on older workers and technology, however, does not imply a simple relationship between digitization, technostress, and productivity. Older workers who remain employed in digitally intensive environments may be selected on adaptability, health, occupation, or employer support. Firms may also redesign tasks, provide training, or sort workers across roles in ways that weaken any direct relationship between ICT intensity and self-reported stress. The COVID-19 shift toward remote and digitally mediated work renewed attention to these issues, especially in education and health-related occupations (Bahamondes-Rosado et al., 2023; Gualano et al., 2023; Nascimento et al., 2025). Recent measurement work also highlights the expanding set of instruments used to study digital stress and technology-related working conditions (Ragu-Nathan et al., 2008; Argyriadi et al., 2025).

Our contribution is to connect these literatures by estimating whether the productivity returns to ICT capital are attenuated in industries with older workforces. Unlike studies focused solely on worker-level technostress or technology use, we begin from country–industry productivity data and then use worker-level health and working-conditions measures to discipline the interpretation of the aggregate results. We therefore treat technostress and related outcomes as potential mechanisms rather than as the central contribution. The primary empirical question is whether ICT capital generates systematically weaker productivity gains in aging industries, and whether the auxiliary evidence is more consistent with direct health burdens, selection, adjustment costs, or organizational frictions.

3. Conceptual Framework

We develop a parsimonious framework linking digitization, workforce age composition, and labor productivity. Competitive firms combine non-ICT capital, ICT capital, and labor to produce value added. The key mechanism is that the productivity effect of ICT capital depends on the age composition of the workforce: as the share of older workers rises, the marginal productivity of ICT is attenuated.

The framework is intentionally stylized. Our empirical analysis does not estimate the full dynamic general-equilibrium system; instead, we focus on reduced-form relationships that map directly into observable objects in the data, in particular the interaction between ICT intensity and workforce aging in a labor-productivity equation. To motivate auxiliary outcomes, we also allow digitization to affect older workers' labor supply decisions and ICT adjustment costs (formal derivations in Appendix A).

3.1. Demographics

Time is discrete, $t = 0, 1, 2, \ldots$. At each date there are two overlapping generations: a mass N_t^Y of young individuals and a mass N_t^O of old individuals. Demographic stocks evolve exogenously and slowly over time, reflecting fertility, mortality, and aging. For the purposes of our empirical application, N_t^Y and N_t^O are treated as predetermined demographic state variables. In the empirical implementation, "older" corresponds to workers aged 50 and above (or the closest available age bin in the Eurostat tabulations).

Young individuals supply labor inelastically. Old individuals choose whether to work, generating an old-age labor-force participation rate $n_t \in [0,1]$. Labor supplied to firms is therefore

$$L_t^Y = N_t^Y, \qquad L_t^O = n_t N_t^O, \qquad L_t = L_t^Y + L_t^O. \tag{1}$$

We define the share of older workers among those employed as

$$s_{O,t}^{\text{work}} = \frac{L_t^O}{L_t} = \frac{n_t N_t^O}{N_t^Y + n_t N_t^O}. \tag{2}$$

3.2. Firms

A representative competitive firm produces value added Y_t using non-ICT physical capital K_t^{NI}, ICT capital K_t^{ICT}, and labor L_t:

$$Y_t = A_t \left(K_t^{NI}\right)^{\alpha} L_t^{1-\alpha}, \qquad \alpha \in (0,1), \tag{3}$$

where A_t denotes total factor productivity. We model ICT as shifting productivity through A_t, with effectiveness that depends on workforce age composition.

We assume that ICT capital enhances productivity through organizational and task-level complementarities, but that its effectiveness depends on the age composition of the workforce. Specifically,

$$\ln A_t = a_t + \left(\theta + \gamma s_{O,t}^{\text{work}}\right) \ln\left(\frac{K_t^{ICT}}{L_t}\right), \qquad \theta > 0,\ \gamma < 0, \tag{4}$$

where $s_{O,t}^{\text{work}}$ is the share of older workers among those employed. Parameter θ captures the baseline elasticity of productivity with respect to ICT intensity, while $\gamma < 0$ captures attenuation as the share of older workers rises.

Dividing output by labor and taking logs yields

$$\ln\left(\frac{Y_t}{L_t}\right) = a_t + \alpha \ln\left(\frac{K_t^{NI}}{L_t}\right) + \theta \ln\left(\frac{K_t^{ICT}}{L_t}\right) + \gamma \left[\ln\left(\frac{K_t^{ICT}}{L_t}\right) \times s_{O,t}^{\text{work}}\right]. \tag{5}$$

This expression is the basis for our main estimating equation in Section 4, where we identify γ using within-country, within-industry changes in ICT intensity and workforce age composition.

The elasticity of labor productivity with respect to ICT intensity is

$$\frac{\partial \ln(Y_t/L_t)}{\partial \ln(K_t^{ICT}/L_t)} = \theta + \gamma s_{O,t}^{\text{work}}, \tag{6}$$

which declines with workforce aging when $\gamma < 0$.

3.3. Households

There are two types of households: *young* and *old*. To motivate a third implication, we allow digitization to increase the disutility of work at older ages (e.g., through learning burdens or task reorganization). This generates a reduced-form prediction that higher ICT intensity reduces older workers' labor-force participation. Formal expressions for the participation cutoff and the implied participation rate are provided in Appendix A.

3.4. Testable Implications

The framework yields three testable implications that guide the empirical analysis:

Prediction 1: Age-dependent returns to ICT. ICT capital increases labor productivity on average ($\theta > 0$), but its marginal product is smaller in industries with a larger share of older workers ($\gamma < 0$).

Prediction 2: Slower ICT deepening. ICT intensity grows more slowly in industries with older workforces due to higher adjustment and training costs.

Prediction 3: Older-age labor supply. Higher ICT intensity is associated with lower employment shares at older ages due to higher non-pecuniary costs of work.

4. Empirical Strategy

Guided by the framework above, we estimate reduced-form relationships that map directly to the model's testable implications. Our primary specification examines whether the productivity effect of ICT capital depends on workforce age composition. We then study two auxiliary outcomes: ICT capital accumulation and age-specific employment shares.

From the model, labor productivity satisfies

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = a_{it} + \alpha \ln\left(\frac{K_{it}^{NI}}{L_{it}}\right) + \theta \ln\left(\frac{K_{it}^{ICT}}{L_{it}}\right) + \gamma \left[\ln\left(\frac{K_{it}^{ICT}}{L_{it}}\right) \times s_{O,it}^{\text{work}}\right] + \varepsilon_{it}. \tag{7}$$

We estimate Equation (7) using country–industry–year panel data with high-dimensional fixed effects. Baseline specifications include country×industry, year×industry, and year×country fixed effects, absorbing time-invariant industry characteristics, common industry-specific shocks, and country-specific macroeconomic trends. Standard errors are clustered at the country×industry level.

Under the structural interpretation, θ captures the baseline elasticity of productivity with respect to ICT intensity, while γ measures how that elasticity varies with workforce aging. A negative γ indicates attenuated ICT returns in older workforces.

4.1. Identification and Instrumental Variables

A central concern is that ICT adoption is endogenous to expected productivity growth, demand conditions, or demographic change. Firms may invest in ICT in anticipation of future productivity gains, and aging itself may respond to technology-driven labor demand shifts. Ordinary least squares estimates may therefore conflate causal productivity effects with reverse causality or omitted shocks.

To address these concerns, we exploit predetermined differences in digital infrastructure connectivity arising from the historical European research backbone network. Our strategy isolates variation in ICT adoption driven by pre-existing connectivity interacted with common global ICT cost shocks.

Our instrument is based on the planned and early realized topology of the European research backbone network (EuropaNET and NORDUnet) in the early 1990s, prior to widespread commercial internet diffusion. Figure 1 illustrates the reconstructed network topology.

We construct a country-level measure of predetermined connectivity based on distance to backbone hubs and network centrality. Countries closer to major backbone gateways faced lower marginal costs of accessing international data flows once ICT prices declined.

This approach follows a growing empirical literature that exploits variation in digital infrastructure rollout and network access as an instrument for ICT adoption and usage when studying productivity, employment, and organizational outcomes (Czernich et al., 2011; Akerman et al., 2015; Falck et al., 2014). While the backbone network primarily served research institutions, prior work shows that early research and academic connectivity strongly predicts subsequent commercial internet penetration and broadband availability, as these networks shaped peering locations, capacity expansion, and routing decisions in later periods (Greenstein, 2000; Forman et al., 2005).

A key feature of our design is that the backbone network is constructed from historical and planned maps produced before the widespread adoption of digital technologies. The location of nodes and links was determined by engineering constraints, legacy telecommunications routes, and political coordination among national research networks, rather than by contemporaneous local economic conditions. This mirrors a well-established practice in applied urban and regional economics that uses planned or historical infrastructure—such as railroads, highways, ports, or canals—to obtain exogenous variation in market access or transportation costs (Redding & Turner, 2015; Donaldson & Hornbeck, 2016; Faber, 2014).

Using planned and early backbone topology strengthens the excludability of the instrument: conditional on fixed effects and controls, historical network design should not directly affect labor

Figure 1: Planned European research backbone network, early 1990s

The figure illustrates the planned and early realized topology of the European research backbone network—including EuropaNET and NORDUnet—during the early 1990s. Backbone nodes represent major national research gateways and exchange points, while links indicate planned or operational international connections prior to the widespread diffusion of commercial internet services. Link thickness reflects indicative transmission capacities where available. The network structure is reconstructed from historical maps and archival documentation, drawing on information from Bersee (1994), Lehtisalo (2005), and Graham and Sundblad (2014).

productivity except through its impact on the cost and intensity of ICT adoption. Importantly, our instrument varies only through interactions with common time shocks, ensuring that it is not absorbed by country or year fixed effects.

The identifying variation is therefore not the level of historical backbone connectivity itself. Country$\times$Year fixed effects absorb all country-specific time-varying shocks, including national broadband policy, macroeconomic conditions, and aggregate productivity trends. Year×Industry fixed effects absorb global industry-specific technology trends and common changes in ICT prices. Country×Industry fixed effects absorb permanent differences in productivity, capital intensity, workforce composition, and industrial structure across country–industry cells. Identification comes from whether common ICT price declines translate into greater ICT deepening in country–industry cells with higher predetermined ICT exposure, and whether this translation is amplified by historical backbone connectivity.

We operationalize our instrument using an industry-level shift–share design that interacts predetermined differences in digital connectivity and ICT dependence with common global shocks to the cost of ICT investment. Identification exploits variation in how global declines in ICT prices translate into industry-specific ICT capital accumulation across countries.

We construct two excluded instruments:

$$Z_{cit}^{base} = ICTExposure_{ci,1995} \times ICTCostShock_t,$$

and

$$Z_{cit}^{backbone} = ICTExposure_{ci,1995} \times BackboneExposure_c \times ICTCostShock_t.$$

Here $ICTExposure_{ci,1995}$ is predetermined 1995 country–industry ICT intensity, $BackboneExposure_c$ is a time-invariant measure of country c's historical exposure to the European research backbone network, and $ICTCostShock_t$ is the common global decline in the real cost of ICT capital, proxied by the Private Fixed Investment, Chained Price Index for Information Processing Equipment and Software from the U.S. Bureau of Economic Analysis. We instrument both ICT intensity and its interaction with the older-worker share using these exposure measures and their interactions with the older-worker share. In a robustness specification, the interaction instruments are formed using lagged older-worker shares.

This design is related to the modern shift–share literature, which clarifies that Bartik-style instruments can be justified either by the exogeneity of predetermined exposure shares or by the quasi-random assignment of common shocks, depending on the empirical setting (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022, 2024). In our application, the exposure components are predetermined: baseline ICT intensity is measured in 1995, before the subsequent productivity outcomes used in the main panel, and historical backbone exposure is constructed from planned and early realized research-network topology prior to widespread commercial internet diffusion. The time-varying shift is a common global ICT price decline, rather than an outcome-specific country–industry shock. We therefore view the instrument as combining predetermined exposure to ICT adoption with a common technology-cost shock, while using the historical backbone measure to capture cross-country differences in the cost of translating global ICT price declines into realized ICT investment.

The exclusion restriction requires that, conditional on the fixed effects and controls, the excluded instruments affect labor productivity through ICT adoption rather than through other contemporaneous determinants of productivity. The exclusion restriction cannot be verified directly, so we report several diagnostics in Appendix C. These include first-stage regressions, reduced-form event-style estimates, placebo regressions for non-ICT capital, R&D capital, and older-worker shares, and baseline correlates of the backbone-amplified exposure component.

4.2. ICT Accumulation

The framework predicts that ICT capital accumulates more slowly in industries with older workforces. While we do not estimate the firm's dynamic investment problem structurally, we examine this implication using the reduced-form relationship:

$$\Delta \ln\left(\frac{K_{it}^{ICT}}{L_{it}}\right) = \eta_0 + \eta_1 s_{O,it}^{\text{work}} + X_{it}'\eta + \mu_i + \tau_t + u_{it}, \tag{8}$$

A negative η_1 indicates slower ICT deepening in older workforces, consistent with higher adjustment or training costs.

4.3. Age-Specific Employment Shares

To assess whether digitization affects older workers' labor supply, we examine age-specific employment shares within country–industry–year cells. Because individual retirement decisions are not directly observed, these shares capture the combined effects of retirement, reallocation, and selection. Our estimating equation is therefore a reduced-form relationship of the form:

$$\text{EmpShare}_{it,a} = \beta_0 + \beta_1 \ln\left(\frac{K_{it}^{ICT}}{L_{it}}\right) + \beta_2 \left[\ln\left(\frac{K_{it}^{ICT}}{L_{it}}\right) \times \mathbb{1}\{a \geq a_O\}\right] + X'_{it,a}\beta + \alpha_{it,a} + \varepsilon_{it,a}, \quad (9)$$

where $\text{EmpShare}_{it,a}$ denotes the employment share of age group a in country i, industry j, and year t, constructed as employment in that age group divided by the total population of the same age group at the country–year level. The indicator $\mathbb{1}\{a \geq a_O\}$ identifies older age groups (e.g. ages 50–59 or 60+), allowing the association between ICT intensity and employment shares to vary by age.

A negative β_2 indicates that ICT intensity is associated with disproportionately lower employment shares among older workers. However, because the outcome is an aggregate employment share rather than an individual participation indicator, the estimates capture equilibrium responses that combine retirement, cross-industry reallocation, and compositional changes in the employed workforce. Specifications include the same high-dimensional fixed effects as in the baseline productivity regressions, with standard errors clustered at the country×industry×age-group level.

5. Data

Our analysis combines harmonized European labor market, demographic, and industry-level productivity data to construct a country–industry–year panel spanning 1995–2019. The unit of observation is a country × one-digit industry × year cell. The panel is unbalanced due to changes in industry classification and differential data availability across countries and sectors. Figure 2 in Appendix B illustrates the coverage of the estimation sample across countries and years.

5.1. Data Sources

Employment by age and industry is drawn from the European Union Labour Force Survey (LFS), accessed via Eurostat.[1] We use annual employment counts by age group, country, and economic activity. To ensure comparability over time, we aggregate to one-digit NACE industries, which remain consistent across revisions. These data are used to construct industry-level workforce age composition measures.

Population counts by age and country are obtained from Eurostat's demographic statistics and merged at the country–year level.[2] These data are merged at the country–year level and used to construct employment shares by age group and to verify consistency of age-group totals.

Industry-level output, labor input, and capital stocks are drawn from the EUKLEMS and INTANProd productivity accounts, accessed via the Luiss Lab distribution (of European Economics & Transition, 2024). These data provide harmonized measures of value added, hours worked, and capital stocks, including detailed ICT and R&D capital components. For selected extensions, we incorporate wage data from the Structure of Earnings Survey (SES), which provides industry-level average earnings by age group for selected years.[3]

5.2. Variable Construction

Labor productivity is defined as real value added per hour worked. Our baseline measure of digitization is ICT intensity, constructed as the ratio of aggregate ICT capital stock to hours worked. ICT capital is defined as the sum of information technology, communications equipment, and software/database capital. Non-ICT capital and R&D capital intensity are constructed analogously relative to hours worked.

Our primary measure of workforce aging is the share of employed workers aged 50–64 within each country–industry–year cell. Employment counts by age and industry are harmonized to one-

[1] Annual employment tabulations from Eurostat datasets `lfsa_egana` (NACE Rev. 1.1) and `lfsa_egan2` (NACE Rev. 2).

[2] Population by age group from Eurostat demographic statistics (dataset `demo_pjangroup`). See `https://ec.europa.eu/eurostat`.

[3] Datasets `earn_ses_agt27`, `earn_ses06_27`, `earn_ses10_27`, `earn_ses14_27`, and `earn_ses18_27`.

Table 1: Summary statistics for productivity and age-specific participation analyses

Panel A: Summary statistics for productivity analysis

Statistic	N	Mean	St. Dev.	Min	Max
Log labor productivity, $\ln(VA_{it}/L_{it})$	6,639	−2.824	1.348	−6.309	1.503
Log ICT intensity, $\ln\left(K_{it}^{ICT}/L_{it}\right)$	6,639	−6.035	1.778	−12.536	−0.233
Older-worker share (ages 50–64), $s_{O,it}^{\text{work}}$	6,639	0.258	0.083	0.053	0.634
Log non-ICT intensity, $\ln\left(K_{it}^{nonICT}/L_{it}\right)$	6,639	−2.060	1.884	−5.642	4.020
Log R&D intensity, $\ln\left(K_{it}^{RD}/L_{it}\right)$	6,243	−7.163	2.650	−15.848	−0.717
Log hours worked, $\ln(L_{it})$	6,639	13.275	1.659	7.616	17.015

Panel B: Summary statistics for participation analysis, by age group
(Long panel; unbalanced across age groups)

Statistic	N	Mean	St. Dev.	Min	Max
Age 40–49					
Log ICT capital intensity (per hour)	961	−5.860	1.717	−9.807	−0.372
Average annual wage (10,000 EUR, age-specific)	961	3.273	1.932	0.241	16.104
Employment share within age group	961	0.053	0.043	0.001	0.288
Age 50–59					
Log ICT capital intensity (per hour)	961	−5.857	1.718	−9.807	−0.372
Average annual wage (10,000 EUR, age-specific)	961	3.343	1.951	0.237	11.259
Employment share within age group	961	0.044	0.036	0.001	0.210
Age ≥ 60					
Log ICT capital intensity (per hour)	920	−5.830	1.730	−9.807	−0.372
Average annual wage (10,000 EUR, age-specific)	920	3.560	2.309	0.229	18.074
Employment share within age group	920	0.007	0.006	0.000	0.038

Panel A reports summary statistics for the country–industry–year panel used in the productivity analysis corresponding to Equations 7 & 8. Labor productivity is measured as value added per hour worked. ICT capital intensity is constructed from the aggregate ICT capital stock—defined as the sum of information technology, communications equipment, and software and database capital—relative to labor input. The older-worker share is defined as the fraction of employed persons aged 50–64 among the working-age employed population. Capital intensity measures are expressed in inverse hyperbolic sine form. The sample corresponds to the baseline estimation sample used in Table 2. Panel B reports summary statistics for the long panel used in the participation analysis corresponding to Equation 9, stratified by age group. For each age group, the table reports ICT capital intensity, average annual wages (tens of thousands of EUR), and age-specific employment shares within country–industry–year cells. Employment shares are defined as the ratio of employed persons in a given age group to the total population of that age group at the country–year level. The sample corresponds to the baseline estimation sample used in Table 4 digit NACE industries to maintain consistency across classification changes and data sources. The resulting estimation sample is a country $\times$ one-digit industry $\times$ year panel.

Capital intensity and productivity variables are transformed using the inverse hyperbolic sine transformation, which approximates the logarithm for large positive values while retaining observations with zero or near-zero quantities. For readability, tables refer to these transformed variables as log or ln intensity measures. Appendix B provides additional detail on source harmonization, panel coverage, and variable construction.

5.3. European Working Conditions Survey (Mechanisms Analysis)

To examine potential mechanisms linking digitization and workforce aging, we use individual-level data from the European Working Conditions Survey (EWCS), a repeated cross-sectional survey conducted between 1995 and 2015. These data are used exclusively for supplemental mechanisms analysis and are not incorporated into the construction of the main panel.

From the EWCS, we construct individual-level measures of technostress-related health outcomes, including indicators for headaches or eyestrain, anxiety or stress, fatigue, and sleep problems, as well as a composite technostress index defined as the unweighted mean of these components. We also use information on gender, age, and job quality, the latter measured using Eurofound's harmonized job quality indices capturing skills use and task discretion. Older workers are defined as individuals aged 50 and above. The EWCS includes survey weights, which we apply in all micro-level regressions. EWCS respondents are matched to industry-level ICT intensity using a harmonized 11-industry NACE classification by country and survey year. This procedure assigns each worker the ICT intensity of their country–industry–year cell.

6. Results

We begin by estimating the baseline productivity specification implied by Equation (7). The central question is whether the marginal product of ICT capital declines with the share of older workers.

Table 2 reports baseline estimates from increasingly saturated fixed-effects specifications. ICT capital intensity is positively and statistically significantly associated with labor productivity across all specifications. The interaction between ICT intensity and the older-worker share is negative and statistically significant once rich fixed effects are introduced, indicating that the productivity gains from ICT are systematically smaller in industries with older workforces.

The magnitude of the interaction effect is economically meaningful. Evaluated at the sample mean, the implied elasticity of productivity with respect to ICT intensity declines substantially as the share of older workers increases, suggesting that workforce aging materially dampens the realized gains from digitization.

The stability of the interaction term across Columns (2) and (3) is notable. These specifications include country–industry, year–industry, and year–country fixed effects, absorbing time-invariant industry differences, global sectoral trends, and country-specific macroeconomic conditions. The persistence of the negative interaction suggests that the attenuation effect reflects within-industry variation in how ICT translates into productivity as workforce age composition evolves.

Table 3 examines the relationship between workforce aging and subsequent ICT accumulation. The dependent variable is the forward change in ICT intensity over one- and two-year horizons. The results show that industries with older workforces experience significantly slower subsequent ICT deepening, particularly in sectors that are already more ICT-intensive. Both the level effect of the older-worker share and its interaction with initial ICT intensity are negative and statistically significant in the more saturated specifications. These patterns are consistent with higher adjustment costs, slower adoption, or reduced effective utilization of digital technologies in older work environments, and they suggest that workforce aging may dampen not only the productivity returns to ICT, but also the pace of future digital investment.

Table 4 examines whether ICT intensity is associated with changes in age-specific employment shares within industries. We find little evidence that higher ICT intensity reduces older-age employment shares within industries. If anything, ICT intensity is weakly positively associated with employment shares among workers aged 60 and above in some specifications. This suggests that the attenuation of ICT productivity is unlikely to be driven by displacement of older workers.

Table 2: ICT capital intensity, workforce aging, and labor productivity

Dependent Variable:	$\ln(VA_{it}/L_{it})$		
Model:	(1)	(2)	(3)
Variables			
Older-worker share, $s_{O,it}^{\text{work}}$	-0.4509	-0.5471	-0.6581*
	(0.5582)	(0.4162)	(0.3805)
Log ICT intensity, $\ln\left(K_{it}^{ICT}/L_{it}\right)$	0.1108***	0.0842***	0.0578**
	(0.0338)	(0.0237)	(0.0267)
$s_{O,it}^{\text{work}} \times \ln\left(K_{it}^{ICT}/L_{it}\right)$	-0.0211	-0.1433**	-0.1300**
	(0.0934)	(0.0615)	(0.0555)
Log non-ICT intensity, $\ln\left(K_{it}^{nonICT}/L_{it}\right)$			0.3123***
			(0.0514)
Log R&D intensity, $\ln\left(K_{it}^{RD}/L_{it}\right)$			0.0162*
			(0.0090)
Fixed-effects			
Year	Yes		
Country	Yes		
Industry	Yes		
Country $\times$ Industry		Yes	Yes
Year $\times$ Industry		Yes	Yes
Year $\times$ Country		Yes	Yes
Fit statistics			
Observations	6,639	6,639	6,243
R^2	0.95379	0.99278	0.99404
Within R^2	0.05483	0.02506	0.13595

Clustered (Country × Industry) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports reduced-form estimates of the relationship between ICT capital intensity, workforce aging, and labor productivity, corresponding to the level specification in Equation 7. The dependent variable is value-added labor productivity, $\ln(VA_{it}/L_{it})$. The key regressor is ICT intensity, $\ln\left(K_{it}^{ICT}/L_{it}\right)$, interacted with the older-worker share, $s_{O,it}^{\text{work}}$, to allow the productivity association of ICT capital to vary with workforce age composition. The coefficient on ICT intensity captures the association between ICT intensity and labor productivity when the older-worker share is zero, while the interaction term captures how this association changes as the older-worker share increases. A negative interaction indicates that the estimated productivity return to ICT intensity is smaller in country–industry cells with older workforces. Columns (2) and (3) absorb unobserved heterogeneity through Country×Industry fixed effects, Year×Industry fixed effects, and Year×Country fixed effects. Column (3) additionally controls for non-ICT capital intensity and R&D intensity. Standard errors are clustered at the Country×Industry level.

Table 3: Workforce Aging and ICT Accumulation

Dependent Variable:	$\Delta\ln\left(K^{ICT}/L\right)_{t\to t+1}$		$\Delta\ln\left(K^{ICT}/L\right)_{t\to t+2}$
Model:	(1)	(2)	(3)
Variables			
Older-worker share, $s^{\text{work}}_{O,it}$	-0.3689	-0.5557***	-1.076***
	(0.3088)	(0.2047)	(0.3688)
Log ICT intensity, $\ln\left(K^{ICT}_{it}/L_{it}\right)$	-0.1525***	-0.0942***	-0.2258***
	(0.0532)	(0.0143)	(0.0254)
$s^{\text{work}}_{O,it}\times\ln\left(K^{ICT}_{it}/L_{it}\right)$	-0.0737	-0.1094***	-0.2172***
	(0.0549)	(0.0359)	(0.0639)
Log non-ICT intensity, $\ln\left(K^{nonICT}_{it}/L_{it}\right)$		-0.0364	-0.0760
		(0.0241)	(0.0467)
Log R&D intensity, $\ln\left(K^{RD}_{it}/L_{it}\right)$		0.0044	0.0089
		(0.0044)	(0.0087)
Log labor productivity, $\ln(VA_{it}/L_{it})$		0.0060	0.0163
		(0.0266)	(0.0488)
Fixed effects			
Country $\times$ Industry	Yes	Yes	Yes
Year $\times$ Industry	Yes	Yes	Yes
Year $\times$ Country	Yes	Yes	Yes
Fit statistics			
Observations	6,326	5,936	5,633
R^2	0.38634	0.38463	0.50670
Within R^2	0.12404	0.07478	0.16801

Clustered (Country $\times$ Industry) standard errors in parentheses.
Significance codes: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.10$.

This table reports reduced-form estimates of the ICT-accumulation implication of Equation 8. The dependent variable is the forward change in ICT capital intensity, $\Delta\ln\left(K^{ICT}/L\right)$, measured either over one year (columns 1–2) or cumulatively over two years (column 3). The key regressor is the older-worker share, $s^{\text{work}}_{O,it}$, interacted with initial ICT intensity, $\ln\left(K^{ICT}_{it}/L_{it}\right)$, to test whether ICT accumulates more slowly in older workforces and whether this drag is stronger in sectors/countries that are more ICT-intensive. Negative coefficients on $s^{\text{work}}_{O,it}$ and on $s^{\text{work}}_{O,it}\times\ln\left(K^{ICT}_{it}/L_{it}\right)$ indicate slower subsequent ICT deepening as workforce age increases, consistent with higher ICT adjustment costs in older work environments. Columns (2) and (3) additionally control for non-ICT capital intensity, R&D intensity, and contemporaneous labor productivity. All specifications include Country×Industry fixed effects, Year×Industry fixed effects (absorbing global sector-specific shocks), and Year×Country fixed effects (absorbing country-specific macro shocks). Standard errors are clustered at the Country×Industry level. The two-year horizon estimates in column (3) reflect cumulative adjustment and are presented as a robustness check.

Table 4: ICT intensity and age-specific employment shares within industries

Dependent Variable:	Age-specific employment share, $\text{EmpShare}_{it,a}$	
Model:	(1)	(2)
Variables		
Log ICT intensity, $\ln\left(K_{it}^{ICT}/L_{it}\right)$	-0.0019	-0.0036
	(0.0029)	(0.0042)
Log non-ICT intensity, $\ln\left(K_{it}^{nonICT}/L_{it}\right)$	-0.0114**	-0.0111***
	(0.0045)	(0.0031)
Log R&D intensity, $\ln\left(K_{it}^{RD}/L_{it}\right)$	9.77×10^{-5}	0.0002
	(0.0013)	(0.0009)
Average annual wage (age-group specific, tens of thousands of EUR)	0.0011	0.0018***
	(0.0007)	(0.0007)
$\ln\left(K_{it}^{ICT}/L_{it}\right) \times \mathbb{1}\{a = 50\text{–}59\}$	-0.0003	0.0035
	(0.0012)	(0.0053)
$\ln\left(K_{it}^{ICT}/L_{it}\right) \times \mathbb{1}\{a \geq 60\}$	0.0044***	0.0051
	(0.0016)	(0.0044)
Fixed-effects		
Country × Industry	Yes	
Year × Industry	Yes	
Year × Country	Yes	
Age group × Year	Yes	
Age group × Country	Yes	
Age group × Industry	Yes	
Country × Industry × Age group		Yes
Year × Industry × Age group		Yes
Year × Country × Age group		Yes
Fit statistics		
Observations	2,694	2,694
R^2	0.85489	0.95293
Within R^2	0.01196	0.02460

Clustered (Country × Industry × Age group) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports panel regressions relating digitization to age-group-specific employment shares within country–industry cells, corresponding to Equation 9. The dependent variable, $\text{EmpShare}_{it,a}$, is the ratio of employed persons in age group a within country i and industry j at year t to the total population in that age group at the country–year level. The key regressors are log ICT capital intensity, $\ln\left(K_{it}^{ICT}/L_{it}\right)$, and its interactions with age-group indicators (baseline group: ages 40–49), which allow the association between digitization and employment shares to vary by age. Column (1) includes a rich set of two-way fixed effects, absorbing time-invariant country–industry heterogeneity, country- and industry-specific shocks, and age-specific country, industry, and time factors. Column (2) further saturates the fixed-effects structure with age-group-specific country–industry and time interactions. These aggregate relationships combine the effects of retirement, job-to-job reallocation across industries, and selection into employment; they therefore do not separately identify individual retirement responses to digitization. Standard errors are clustered at the Country×Industry×Age-group level.

Instead, it points to mechanisms operating within continuing employment relationships, such as differences in task adaptability, learning costs, or organizational frictions.

Table 5 reports instrumental-variables estimates that address potential endogeneity in ICT capital accumulation. ICT intensity and its interaction with workforce aging are instrumented using predetermined 1995 country–industry ICT exposure, global ICT price declines, and historical research-backbone connectivity. In the preferred specification, the coefficient on ICT intensity is positive but imprecisely estimated, while the interaction between ICT intensity and the older-worker share is negative and statistically significant. This pattern suggests that the IV evidence is strongest for the heterogeneous-return result: productivity gains from ICT are smaller in industries with older workforces. The interaction remains negative and statistically significant when the excluded instruments for the interaction term are formed using lagged older-worker shares.

Appendix B describes the data inputs used to construct the instrument, while Appendix C reports first-stage, placebo, event-style, and baseline-correlate diagnostics. First-stage regressions show strong relevance for both endogenous regressors. Baseline diagnostic regressions show that the backbone-amplified exposure component is not systematically related to baseline productivity, workforce age composition, non-ICT capital intensity, or R&D intensity after conditioning on baseline ICT exposure and country and industry fixed effects. Reduced-form event-style estimates show no systematic association between predetermined exposure and productivity across the sample period. Placebo regressions show that the excluded instruments do not jointly predict changes in non-ICT capital intensity, R&D intensity, or older-worker shares.

Taken together, the productivity, ICT-accumulation, employment-share, and IV results provide consistent evidence that workforce aging moderates both the productivity impact of digitization and the subsequent accumulation of ICT capital. While ICT investment is positively associated with productivity on average, its effectiveness depends critically on workforce age composition. This interaction offers a coherent explanation for why economies and industries with aging workforces may experience slower realized productivity gains from ongoing digital transformation, even in the absence of large-scale employment reallocation away from older workers.

Table 5: Instrumental-variables estimates: ICT capital intensity, workforce aging, and labor productivity

Dependent Variable:	$\ln(VA_{it}/L_{it})$	
Model:	(1)	(2)
Variables		
Older-worker share, $s^{\text{work}}_{O,it}$	-1.493***	-1.829***
	(0.4934)	(0.6119)
Log ICT intensity, $\ln\left(K^{ICT}_{it}/L_{it}\right)$	0.1036	0.1175
	(0.0967)	(0.0980)
$s^{\text{work}}_{O,it} \times \ln\left(K^{ICT}_{it}/L_{it}\right)$	-0.3049***	-0.3666***
	(0.0784)	(0.1000)
Log non-ICT intensity, $\ln\left(K^{nonICT}_{it}/L_{it}\right)$	0.2130***	0.2107***
	(0.0780)	(0.0779)
Log R&D intensity, $\ln\left(K^{RD}_{it}/L_{it}\right)$	0.0098	0.0098
	(0.0100)	(0.0101)
Fixed-effects		
Country $\times$ Industry	Yes	Yes
Year $\times$ Industry	Yes	Yes
Year $\times$ Country	Yes	Yes
Instrument construction		
Current older-worker share in IV interactions	Yes	
Lagged older-worker share in IV interactions		Yes
Fit statistics		
F-test (1st stage), $\ln\left(K^{ICT}_{it}/L_{it}\right)$	135.09	132.58
F-test (1st stage), $s^{\text{work}}_{O,it} \times \ln\left(K^{ICT}_{it}/L_{it}\right)$	647.53	313.79
Observations	4,004	4,004

Clustered (Country $\times$ Industry) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports two-stage least squares (2SLS) estimates of the relationship between ICT capital intensity, workforce aging, and labor productivity, corresponding to Equation 7. The dependent variable is log value-added labor productivity, $\ln(VA_{it}/L_{it})$. ICT intensity, $\ln\left(K^{ICT}_{it}/L_{it}\right)$, and its interaction with the older-worker share, $s^{\text{work}}_{O,it} \times \ln\left(K^{ICT}_{it}/L_{it}\right)$, are treated as endogenous. Instruments are constructed using predetermined 1995 country–industry ICT intensity interacted with a common global ICT price-decline shifter and a country-level historical research-backbone exposure measure; the corresponding excluded instruments are also interacted with the older-worker share to identify heterogeneous ICT effects by workforce age composition. Column (1) forms these interaction instruments using the contemporaneous older-worker share. Column (2) instead uses the lagged older-worker share when forming the excluded instruments for the interaction term, reducing concerns that contemporaneous workforce age composition adjusts endogenously with ICT adoption. Both specifications include Country$\times$Industry fixed effects, Year$\times$Industry fixed effects, and Year$\times$Country fixed effects. Reported first-stage F-tests assess instrument relevance for each endogenous regressor. Standard errors are clustered at the Country$\times$Industry level.

7. Mechanisms: Health and Working Conditions

The baseline results establish that workforce aging attenuates the productivity returns to ICT. We next examine whether this attenuation operates through differential exposure to technostress-related health outcomes among older workers.

A growing literature emphasizes that digitization reshapes not only productivity and capital accumulation but also the organization and experience of work. Digital technologies can alter task content, monitoring intensity, learning requirements, and work pace, potentially affecting workers' well-being and job satisfaction. These changes may be particularly salient at older ages, when adjustment costs associated with new technologies or intensified work organization could influence workers' decisions about continued employment.

In our conceptual framework, digitization affects labor supply at older ages not only through productivity or wage channels, but also through non-pecuniary aspects of work. More digitally intensive production environments may raise the disutility of work for older workers by increasing cognitive demands, stress, or fatigue, thereby lowering the attractiveness of continued employment even absent sharp declines in physical capacity. This channel is modeled parsimoniously as a digitization-related increase in the reservation utility of non-employment for older individuals.

To assess the empirical plausibility of this mechanism, we examine reduced-form relationships between exposure to digitally intensive work environments and technostress-related health and working-conditions outcomes. Rather than modeling individual labor supply decisions directly, we use microdata from the European Working Conditions Survey (EWCS) to study whether older workers exhibit systematically different associations between industry-level ICT intensity and self-reported health outcomes.

At the individual level, we estimate regressions of the form:

$$\begin{aligned}\text{Health}_{ijct} = \beta_0 + \beta_1 \ln\left(K^{ICT}_{jct}/L_{jct}\right) + \beta_2 \text{Older}_i + \beta_3 \ln\left(K^{ICT}_{jct}/L_{jct}\right) \times \text{Older}_i \\ + X'_{ijct}\beta + \mu^{(1)}_{jct} + \mu^{(2)}_{jct} + \mu_{ct} + \varepsilon_{ijct},\end{aligned}$$

where Health_{ijct} denotes a technostress-related health outcome for individual i employed in industry j, country c, and survey wave t. Outcomes include a composite technostress index and indicators for headaches or eyestrain, anxiety or stress, fatigue, and sleep problems. The variable $\ln\left(K^{ICT}_{jct}/L_{jct}\right)$ measures log ICT capital intensity at the industry–country–year level, constructed from external data and harmonized to a consistent 11-industry NACE classification. Older_i is an indicator equal to one for workers aged 50 and above.

The coefficient of interest, β_3, captures whether the association between industry-level ICT intensity and health or working-conditions outcomes differs systematically for older workers relative to younger workers within the same industry, country, and year. All specifications include a rich set of fixed effects—11-industry NACE $\times$ year, 11-industry NACE $\times$ country, and country $\times$ year—which absorb common technological trends, institutional features, and macroeconomic conditions. Regressions are estimated using EWCS survey weights, and standard errors are clustered at the industry–country level.

To further probe the interpretation of these associations, we also estimate stratified versions of this specification across subsamples defined by job characteristics related to technology exposure and work organization, including computer use at work, learning requirements, employer-provided training, work intensity, and task autonomy. These stratifications allow us to assess whether age-differentiated associations between ICT intensity and health outcomes are concentrated in work environments where digital task demands are more salient.

Taken together, this analysis provides micro-level evidence on how digitization correlates with working conditions and well-being across age groups. While these reduced-form results do not establish a causal effect of digitization on health, they help discipline the interpretation of our macro-level findings by clarifying whether slower productivity growth in older workforces is plausibly linked to selection and exit responses rather than heightened vulnerability to digitized work environments.

Table 6 examines whether the interaction between digitization and workforce aging operates through differential exposure to technostress-related health outcomes among older workers. Across the baseline specifications reported in Panel A, higher industry-level ICT intensity is associated with modest increases in certain technostress indicators on average—particularly headaches or eyestrain and fatigue. However, the interaction between ICT intensity and being an older worker is consistently negative or statistically indistinguishable from zero across outcomes. This pattern indicates that, within the same industry, country, and year, older workers do not experience disproportionately worse technostress-related health outcomes as ICT intensity rises. If anything, older workers appear less exposed to the adverse health correlates of digitized work environments than their younger counterparts.

Panel B reinforces this interpretation by showing that the negative interaction between ICT intensity and older age is most pronounced in work environments where digital task demands and organizational pressures are plausibly higher—such as jobs requiring continuous learning, computer use, employer-provided training, high work intensity, or low task autonomy. These estimates are obtained using the same regression specification as in Panel A, differing only by sample stratification. The fact that older workers exhibit weaker associations between ICT intensity and technostress outcomes precisely in these settings is consistent with a selection mechanism: older individuals who remain employed in more digitally intensive environments may be positively selected on adaptability, task matching, or health, while others sort into less digitally intensive roles or exit employment altogether.

Taken together, the results in Table 6 do not support an interpretation in which digitization disproportionately harms the health or well-being of older workers conditional on employment. Instead, they are consistent with a participation and selection channel, whereby digitization alters working conditions in ways that affect older workers' employment decisions, contributing to slower observed productivity growth in older workforces without requiring heightened vulnerability to technostress among those who remain employed.

Table 6: ICT Intensity, Aging, and Technostress-Related Health Outcomes

	Dependent Variables				
	Technostress Index (1)	Headache Eyestrain (2)	Anxiety Stress (3)	Fatigue (4)	Sleep Problems (5)
Panel A: Baseline Estimates					
Log ICT Intensity (11-industry)	0.0037	0.0183^{**}	-0.0002	0.0171^{**}	-0.0018
	(0.0043)	(0.0090)	(0.0069)	(0.0080)	(0.0039)
Older Worker (Age $\geq$ 50)	-0.0302^{***}	-0.0526^{**}	-0.0274^{*}	-0.0623^{***}	0.0088
	(0.0102)	(0.0205)	(0.0164)	(0.0203)	(0.0098)
Job Quality (Skills & Discretion)	0.0004^{***}	0.0010^{***}	0.0005^{***}	0.0004^{***}	$7.87 \times 10^{-5**}$
	(5.32×10^{-5})	(9.47×10^{-5})	(7.04×10^{-5})	(0.0001)	(3.23×10^{-5})
Female	0.0438^{***}	0.1203^{***}	0.0338^{***}	0.0544^{***}	0.0199^{***}
	(0.0024)	(0.0056)	(0.0033)	(0.0051)	(0.0021)
Log ICT Intensity $\times$ Older Worker	-0.0050^{***}	-0.0033	-0.0056^{**}	-0.0118^{***}	-0.0012
	(0.0016)	(0.0031)	(0.0025)	(0.0032)	(0.0014)
Observations	107,399	82,320	82,245	82,286	107,399
R^2	0.195	0.063	0.092	0.123	0.427
Within R^2	0.009	0.017	0.004	0.004	0.002
Panel B: Stratified Log ICT Intensity $\times$ Older Worker Coefficients					
Job Requires Learning New Things	-0.0038^{**}	-0.0010	-0.0051^{**}	-0.0098^{***}	-0.0007
	(0.0016)	(0.0035)	(0.0023)	(0.0038)	(0.0016)
Employer-Provided Training	-0.0061^{**}	-0.0030	-0.0092^{**}	-0.0124^{***}	-0.0032
	(0.0024)	(0.0047)	(0.0041)	(0.0044)	(0.0024)
Computer Use at Work	-0.0065^{***}	-0.0063	-0.0069^{**}	-0.0148^{***}	-0.0041^{*}
	(0.0022)	(0.0042)	(0.0033)	(0.0043)	(0.0024)
High Work Intensity	-0.0034^{**}	-0.0025	-0.0042	-0.0100^{**}	-0.0002
	(0.0017)	(0.0034)	(0.0029)	(0.0041)	(0.0018)
Low Task Autonomy	-0.0046^{**}	-0.0056	-0.0044	-0.0080^{**}	1.86×10^{-5}
	(0.0019)	(0.0037)	(0.0028)	(0.0040)	(0.0017)

Clustered (11-industry NACE $\times$ Country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel A reports estimates from individual-level regressions using pooled microdata from the European Working Conditions Survey (EWCS), covering employed respondents across participating European countries and survey waves from 1991 to 2015. Dependent variables measure technostress-related health outcomes, including a composite Technostress Index (the unweighted mean of indicators for headaches/eyestrain, anxiety or stress, fatigue, and sleep problems) and each component separately. The main explanatory variable is log ICT capital intensity at the industry–country–year level, harmonized to a consistent 11-industry NACE classification. Older Worker is an indicator for respondents aged 50 and above. All specifications control for gender and job quality (skills use and task discretion) and are estimated using survey weights. Regressions include 11-industry NACE $\times$ year, 11-industry NACE $\times$ country, and country $\times$ year fixed effects, with standard errors clustered at the 11-industry NACE $\times$ country level. The interaction term captures differential associations between ICT intensity and technostress-related outcomes for older workers relative to younger workers within the same industry, country, and year.
Panel B reports stratified estimates of the log ICT intensity $\times$ Older Worker interaction, obtained by re-estimating the Panel A specification within subsamples defined by indicators of workplace technology exposure and work organization: learning requirements, employer-provided training, computer use at work, high work intensity, and low task autonomy. Each coefficient corresponds to the interaction term from a separate subsample regression. All stratified models use the same controls, fixed effects, survey weights, and clustering as in Panel A, though sample sizes vary across strata. Panel B assesses whether the interaction between ICT intensity and worker age is concentrated in work environments where digital task demands and organizational pressures are more pronounced.

8. Discussion

Our findings emphasize that the productivity gains from ICT capital depend on workforce age composition. Across the baseline fixed-effects specifications, ICT intensity is positively associated with labor productivity, but the ICT–productivity association is systematically weaker in industries with larger older-worker shares. The IV estimates support the same heterogeneous-return pattern, although the average ICT coefficient is less precisely estimated. These results are consistent with a broader literature emphasizing that aging workforces may face adjustment frictions when technological change alters task requirements, work organization, and skill demands (Ilmarinen, 2006; Acemoglu & Restrepo, 2022). They also suggest that the productivity consequences of digitization depend not only on the availability of digital capital, but on how effectively firms integrate that capital into production environments with different workforce structures.

The mechanism evidence points toward adjustment costs, selection, and organizational frictions rather than a simple story in which digitization disproportionately harms older workers who remain employed. Older workers in more digitally intensive environments do not report disproportionately worse technostress-related outcomes conditional on employment. If anything, the weaker association between ICT intensity and technostress outcomes among older workers is consistent with positive selection into digitally intensive jobs, sorting away from high-demand digital environments, or organizational accommodations that allow some older workers to remain employed. This interpretation is consistent with the view that the productivity effects of new technologies depend on complementary investments in skills, task redesign, and organizational change (Bessen, 2018). Rather than treating technostress as the primary explanation for attenuated ICT returns, our results suggest that technostress and related working-conditions measures are useful for interpreting how older workers are selected into, adapt to, or are supported within digitized work environments.

These findings have implications for firms and policymakers facing simultaneous digital transformation and population aging. Policies that encourage ICT investment alone may be insufficient if older workforces face higher adjustment costs or if firms underinvest in complementary organizational practices. Training, digital literacy programs, ergonomic ICT implementation, and age-inclusive job design may help workers adapt to changing task demands and may increase the realized productivity returns to ICT capital. This is consistent with recent work emphasizing the importance of supporting older workers as automation and digital technologies reshape labor demand (Aisa et al., 2023). More generally, the results suggest that productivity policy in aging economies should treat ICT adoption and workforce development as complementary margins, rather than as separate policy domains.

9. Conclusion

This paper examines whether workforce aging attenuates the productivity returns to ICT capital. Using a European country–industry–year panel from 1995–2019, we find that ICT intensity is positively associated with labor productivity on average, but that this association is weaker in industries with larger older-worker shares. We also find evidence that industries with older workforces experience slower subsequent ICT deepening, suggesting that workforce aging may affect both the realized returns to digital capital and the pace of future digital investment.

Instrumental-variables estimates based on predetermined 1995 ICT exposure, global ICT price declines, and historical research-backbone connectivity support the central heterogeneous-return result. Supplemental diagnostics provide no evidence that the instruments operate through broad non-ICT capital deepening, R&D accumulation, or endogenous workforce aging. The IV evidence should be interpreted as reinforcing the main attenuation result rather than as definitive proof of the exclusion restriction.

Mechanism analyses using the European Working Conditions Survey do not indicate that older workers who remain employed in digitally intensive environments experience disproportionately worse technostress-related health outcomes. Instead, the evidence is more consistent with selection, adjustment costs, or organizational frictions. These findings suggest that the productivity consequences of digitization in aging economies depend not only on the availability of ICT capital, but also on the ability of firms and workers to adapt organizationally to digital production.

References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, *40*(S1), S293–S340.

Acemoglu, D., & Restrepo, P. (2022). Demographics and automation. *The Review of Economic Studies*, *89*(1), 1–44.

Aghion, P., & Bunel, S. (2024). Ai and growth: where do we stand? *Policy Note*.

Aghion, P., & Howitt, P. (1990). *A model of growth through creative destruction.* National Bureau of Economic Research Cambridge, Mass., USA.

Aihounton, G. B. D., & Henningsen, A. (2021). Units of measurement and the inverse hyperbolic sine transformation. *The Econometrics Journal*, *24*(2), 334–351. doi: 10.1093/ectj/utaa032

Aisa, R., Cabeza, J., & Martin, J. (2023). Automation and aging: The impact on older workers in the workforce. *The Journal of the Economics of Ageing*, *26*, 100476.

Akerman, A., Gaarder, I., & Mogstad, M. (2015). The skill complementarity of broadband internet. *Quarterly Journal of Economics*, *130*(4), 1781–1824.

Argyriadi, A., Katsarou, D., Patelarou, A., Megari, K., Patelarou, E., Kotrotsiou, S., … others (2025). Digital stress scale (dsc): Development and psychometric validation of a measure of stress in the digital age. *International Journal of Environmental Research and Public Health*, *22*(7), 1080.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, *118*(4), 1279–1333.

Bahamondes-Rosado, M. E., Cerdá-Suárez, L. M., Dodero Ortiz de Zevallos, G. F., & Espinosa-Cristia, J. F. (2023). Technostress at work during the covid-19 lockdown phase (2020–2021): a systematic review of the literature. *Frontiers in psychology*, *14*, 1173425.

Bellemare, M. F., & Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, *82*(1), 50–61. doi: 10.1111/obes.12325

Bersee, J. (1994). DANTE and EuropaNET: A Profile. *ConneXions: The Interoperability Re-*

port, *8*(6). Retrieved from `https://new-archive.dante.net/Documents/DiP04.pdf` (Reprinted in *DANTE in Print*, No. 4)

Bessen, J. (2018). Artificial intelligence and jobs: The role of demand. In *The economics of artificial intelligence: an agenda* (pp. 291–307). University of Chicago Press.

Börsch-Supan, A., & Weiss, M. (2016). Productivity and age: Evidence from work teams at the assembly line. *The Journal of the Economics of Ageing*, *7*, 30–42.

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *Review of Economic Studies*, *89*(1), 181–213. doi: 10.1093/restud/rdab030

Borusyak, K., Hull, P., & Jaravel, X. (2024). *A practical guide to shift-share instruments* (Working Paper No. 33236). National Bureau of Economic Research.

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'engines of growth'? *Journal of econometrics*, *65*(1), 83–108.

Brod, C. (1984). *Technostress: The human cost of the computer revolution*. Reading, MA: Addison-Wesley.

Burbidge, J. B., Magee, L., & Robb, A. L. (1988). Alternative transformations to handle extreme values of the dependent variable. *Journal of the American Statistical Association*, *83*(401), 123–127.

Cardona, M., Kretschmer, T., & Strobel, T. (2013). Ict and productivity: conclusions from the empirical literature. *Information Economics and policy*, *25*(3), 109–125.

Chen, J., & Roth, J. (2024). Logs with zeros? some problems and solutions. *The Quarterly Journal of Economics*, *139*(2), 891–936.

Chui, M., Manyika, J., & Miremadi, M. (2016). Where machines could replace humans-and where they can't (yet). *The McKinsey Quarterly*, 1–12.

Czernich, N., Falck, O., Kretschmer, T., & Woessmann, L. (2011). Broadband infrastructure and economic growth. *Economic Journal*, *121*(552), 505–532.

Donaldson, D., & Hornbeck, R. (2016). Railroads and american economic growth: A market access approach. *Quarterly Journal of Economics*, *131*(2), 799–858.

Edwards, J. R., Caplan, R. D., & Harrison, R. V. (1998). Person–environment fit theory: Conceptual foundations, empirical evidence, and directions for future research. In C. L. Cooper (Ed.), *Theories of organizational stress* (pp. 28–67). Oxford: Oxford University Press.

Faber, B. (2014). Trade integration, market size, and industrialization: Evidence from china's national trunk highway system. *Review of Economic Studies*, *81*(3), 1046–1070.

Falck, O., Gold, R., & Heblich, S. (2014). E-lections: Voting behavior and the internet. *American Economic Review*, *104*(7), 2238–2265.

Farach, A., Cambon, A., & Spataro, J. (2025). Evolving the productivity equation: Should digital labor be considered a new factor of production? *arXiv preprint arXiv:2505.09408*.

Feyrer, J. (2008). Aggregate evidence on the link between age structure and productivity. *Population and Development Review*, *34*, 78–99.

Forman, C., Goldfarb, A., & Greenstein, S. (2005). How did location affect adoption of the commercial internet? global village vs. urban density. *Journal of Urban Economics*, *58*(3), 389–420.

Friedberg, L. (2003). The impact of technological change on older workers: Evidence from data on computer use. *ILR review*, *56*(3), 511–529.

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *110*(8), 2586–2624. doi: 10.1257/aer.20181047

Graham, P., & Sundblad, Y. (2014). Nordic internet infrastructure development 1988–2007. In *Ifip conference on history of nordic computing* (pp. 205–214).

Greenstein, S. (2000). Building and delivering the virtual world: Commercializing services for internet access. *Journal of Industrial Economics*, *48*(4), 391–411.

Gualano, M. R., Santoro, P. E., Borrelli, I., Rossi, M. F., Amantea, C., Daniele, A., & Moscato, U. (2023). Telework-related stress (terra), psychological and physical strain of working from home during the covid-19 pandemic: a systematic review. *Workplace Health and Safety*, *71*(2), 58–67.

Ilmarinen, J. (2006). The ageing workforce—challenges for occupational health. *Occupational*

Medicine, *56*(6), 362–364.

Jorgenson, D. W., Ho, M. S., & Stiroh, K. J. (2008). A retrospective look at the us productivity growth resurgence. *Journal of Economic perspectives*, *22*(1), 3–24.

Lehtisalo, K. (2005). The history of nordunet. *Twenty-Five Years of Networking Cooperation in the Nordic Countries, Hørsholm*.

Nascimento, L., Correia, M. F., & Califf, C. B. (2025). Techno-eustress under remote work: a longitudinal study in higher education teachers. *Education and Information Technologies*, 1–38.

Nedeljko, M., Gu, Y., & Bostan, C. M. (2024). The dual impact of technological tools on health and technostress among older workers: an integrative literature review. *Cognition, Technology and Work*, *26*(1), 47–61.

of European Economics, L. L., & Transition, E. (2024). *Euklems and intanprod productivity accounts.* Data portal.

Ragu-Nathan, T., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. *Information systems research*, *19*(4), 417–433.

Redding, S. J., & Turner, M. A. (2015). Transportation costs and the spatial organization of economic activity. In *Handbook of regional and urban economics* (Vol. 5, pp. 1339–1398). Elsevier.

Romer, P. M. (1990). Endogenous technological change. *Journal of political Economy*, *98*(5, Part 2), S71–S102.

Tarafdar, M., Cooper, C. L., & Stich, J.-F. (2019). The technostress trifecta-techno eustress, techno distress and design: Theoretical directions and an agenda for research. *Information systems journal*, *29*(1), 6–42.

Viviani, C., Bravo, G., Lavallière, M., Arezes, P., Martínez, M., Dianat, I., . . . Castellucci, H. (2021). Productivity in older versus younger workers: A systematic literature review. *Work*, *68*(3), 577–618.

A. Model Details

Firm problem (ICT investment). Within period t, the firm takes the predetermined stocks (K_t^{NI}, K_t^{ICT}) and labor input L_t as given and produces Y_t. After production, the firm chooses ICT investment $I_t^{ICT} \geq 0$ to determine next period's ICT stock:

$$K_{t+1}^{ICT} = (1 - \delta_{ICT})K_t^{ICT} + I_t^{ICT}. \tag{10}$$

Accumulating ICT capital entails organizational and training costs that rise with the share of older workers:

$$C\left(I_t^{ICT}, s_{O,t}^{\text{work}}\right) = \frac{\kappa}{2}\left(I_t^{ICT}\right)^2\left(1 + \phi_s s_{O,t}^{\text{work}}\right), \qquad \phi_s > 0. \tag{11}$$

Let $V(\cdot)$ denote the continuation value of entering period $t+1$ with ICT stock K_{t+1}^{ICT}. An interior optimum satisfies

$$\kappa I_t^{ICT}\left(1 + \phi_s s_{O,t}^{\text{work}}\right) = \frac{\partial V}{\partial K_{t+1}^{ICT}}, \tag{12}$$

implying that a higher share of older workers reduces optimal ICT investment for a given marginal value of ICT capital.

Old households and retirement Old individuals choose whether to work after observing wages and the predetermined ICT capital stock K_t^{ICT}. Digitization increases the disutility of work for older individuals.

Utility if working:

$$U_t^W = u\Big((1 + r_t)a_t + w_t^O\Big) - \chi \ln\left(\frac{K_t^{ICT}}{L_t}\right). \tag{13}$$

Utility if retiring:

$$U_t^R = u((1 + r_t)a_t) + \psi. \tag{14}$$

Under quasi-linear utility $u(c) = c$, an old individual works if

$$w_t^O \geq \psi + \chi \ln\left(\frac{K_t^{ICT}}{L_t}\right). \tag{15}$$

Let $\Psi(\cdot)$ denote the distribution of heterogeneous retirement preferences. Then the old-age participation rate is

$$n_t = 1 - \Psi\left(\psi + \chi \ln(K_t^{ICT}/L_t) - w_t^O\right), \qquad \frac{\partial n_t}{\partial K_t^{ICT}} < 0. \tag{16}$$

Competitive Equilibrium A competitive equilibrium consists of sequences

$$\{K_t^{NI}, K_t^{ICT}, I_t^{ICT}, n_t, w_t^Y, w_t^O, r_t\}_{t \geq 0}$$

such that:

(i) Given predetermined capital stocks, firms produce according to the production function and factor prices clear markets.

(ii) Old households choose labor supply optimally, determining n_t.

(iii) Labor markets clear: $L_t = N_t^Y + n_t N_t^O$.

(iv) Firms choose ICT investment I_t^{ICT} to determine next period's ICT stock.

Our empirical analysis focuses on the within-period productivity implications of ICT capital and workforce aging rather than on the full dynamic path of capital accumulation.

Key Predictions

Proposition 1 (Age-Dependent Returns to ICT)**.** *Under $\theta > 0$ and $\gamma < 0$, the marginal productivity of ICT capital is strictly decreasing in the share of older workers:*

$$\frac{\partial^2 \ln(Y_t/L_t)}{\partial \ln(K_t^{ICT}/L_t)\, \partial s_{O,t}^{\text{work}}} = \gamma < 0.$$

Proposition 2 (Slower ICT Accumulation in Older Workforces)**.** *If* $\phi_s > 0$*, environments with a larger share of older workers exhibit slower accumulation of ICT capital.*

Proposition 3 (Digitization-Induced Retirement)**.** *If* $\chi > 0$*, higher ICT intensity reduces old-age labor-force participation:*

$$\frac{\partial n_t}{\partial K_t^{ICT}} < 0.$$

Together, these predictions imply that aging economies or industries will exhibit weaker productivity gains from ICT capital and slower technology adoption, consistent with the interaction effects estimated in the data.

B. Data Sources and Variable Construction

This appendix provides additional detail on the construction of the country–industry–year panel, the harmonization of industry and age categories, the transformation of productivity and capital variables, and the supplemental microdata used in the mechanisms analysis.

B.1. Country–industry–year panel construction

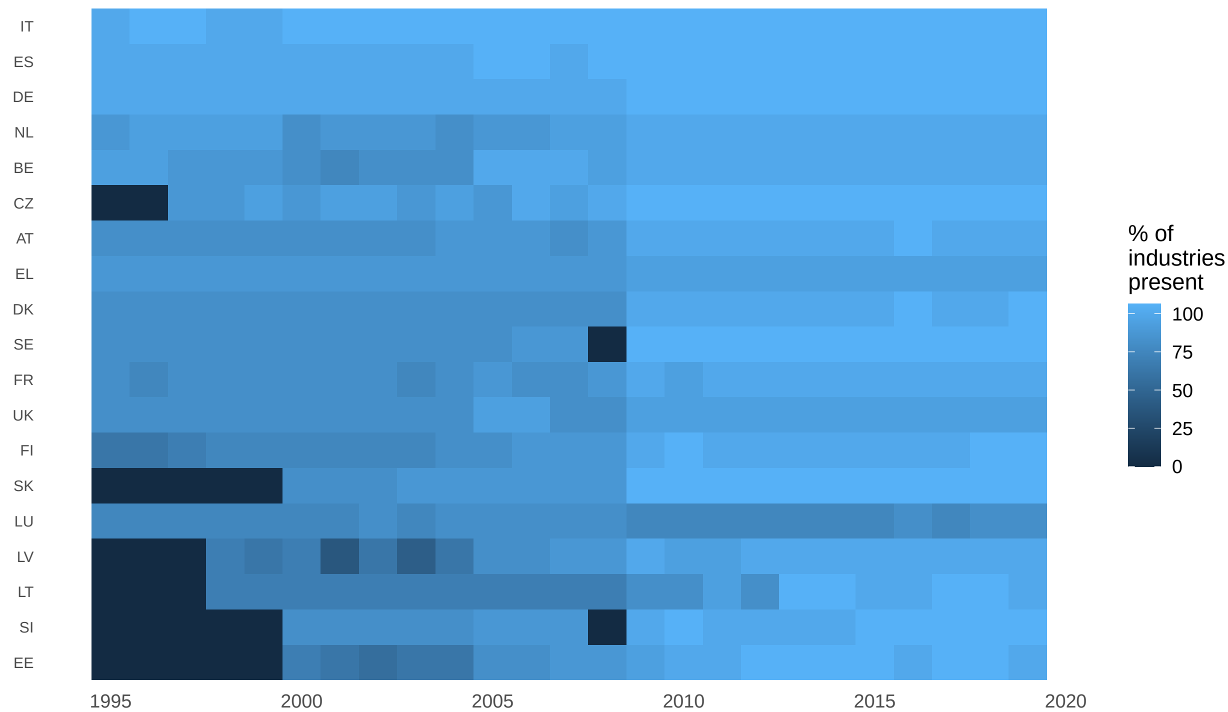
The main analysis uses a country $\times$ one-digit industry $\times$ year panel covering 1995–2019. The panel combines labor-market and demographic information from Eurostat with industry-level productivity and capital-account measures from the EUKLEMS and INTANProd productivity accounts. The panel is unbalanced because data availability differs across countries, years, industries, and capital-asset categories. Figure 2 reports panel coverage by country and year.

Employment by age, country, industry, and year is drawn from the European Union Labour Force Survey (LFS), accessed through Eurostat. We use the annual employment tabulations from `lfsa_egana` for the NACE Rev. 1.1 period and `lfsa_egan2` for the NACE Rev. 2 period. In both sources, we retain total-sex employment counts, restrict attention to one-digit NACE industries, and exclude aggregate regional units such as EU-wide or euro-area aggregates. The Rev. 1.1 data are used from 1995 onward, while the Rev. 2 data are used after 2008. The two sources are appended after harmonizing country, industry, age, and year identifiers.

Population counts by age and country are obtained from Eurostat demographic statistics, dataset `demo_pjangroup`. These data are merged to the employment panel at the country–year level and are used to construct age-specific employment shares in the supplemental employment-share analysis.

Industry-level output, labor input, and capital-stock measures are drawn from the EUKLEMS and INTANProd productivity accounts, accessed through the Luiss Lab distribution (of European Economics & Transition, 2024). We merge the national-accounts and capital-accounts files by country, one-digit industry, and year. These data provide real value added, hours worked,

Figure 2: Panel coverage by country and year: share of one-digit industries observed



This figure illustrates the temporal and cross-country coverage of the country–industry panel used in the baseline analysis. Each cell reports the percentage of one-digit NACE industries observed for a given country–year combination, with darker shading indicating more complete industry coverage. The panel is unbalanced due to differences in data availability across countries, years, and industry classifications, including the transition from NACE Rev. 1.1 to Rev. 2 and incomplete reporting of capital asset components in earlier years for some countries.

employment, gross fixed capital formation, and capital stocks by asset type, including information technology, communications equipment, software/database capital, and R&D capital. We restrict the productivity panel to country–industry–year cells that can be matched to the Eurostat employment-by-age data.

B.2. Industry harmonization and one-digit NACE aggregation

The main productivity analysis is conducted at the one-digit NACE industry level. This aggregation is used because it provides the most consistent industry classification across the transition from NACE Rev. 1.1 to NACE Rev. 2 and across the productivity, labor-force, and demographic sources. We retain one-letter NACE sections in the LFS and productivity accounts and harmonize the industry identifiers to a common `nace` variable.

For the European Working Conditions Survey analysis, we use a coarser 11-industry classification available in the EWCS. To match country–industry ICT intensity to individual respondents, one-digit NACE sections in the productivity panel are mapped to the 11 EWCS industry groups. ICT capital and hours worked are then aggregated within country, year, and 11-industry group before constructing the matched ICT-intensity measure.

B.3. Labor productivity and capital intensity measures

The baseline dependent variable is value-added labor productivity, measured as real value added per hour worked. Let VA_{cit} denote real value added and L_{cit} denote hours worked in country c, industry i, and year t. Because the empirical variables are transformed using the inverse hyperbolic sine transformation, our constructed productivity measure is

$$\widetilde{\ln}\left(\frac{VA_{cit}}{L_{cit}}\right) = \operatorname{asinh}(VA_{cit}) - \operatorname{asinh}(L_{cit}),$$

which approximates $\ln(VA_{cit}/L_{cit})$ for positive values away from zero. In the tables and text, we refer to this variable as log value-added labor productivity for readability.

ICT capital is constructed as the sum of information technology, communications equipment, and software/database capital:

$$K_{cit}^{ICT} = K_{cit}^{IT} + K_{cit}^{CT} + K_{cit}^{SoftDB}.$$

The primary ICT-intensity measure is ICT capital per hour worked, transformed as

$$\widetilde{\ln}\left(\frac{K_{cit}^{ICT}}{L_{cit}}\right) = \operatorname{asinh}(K_{cit}^{ICT}) - \operatorname{asinh}(L_{cit}).$$

The same transformation is used for non-ICT capital intensity and R&D capital intensity. Non-ICT capital is constructed as total gross fixed capital formation less ICT capital, with a small positive floor imposed before transformation when necessary:

$$K_{cit}^{nonICT} = \max\{K_{cit}^{GFCF} - K_{cit}^{ICT}, 10^{-6}\}.$$

R&D intensity is constructed analogously using the R&D capital stock.

We also construct an ICT capital-share measure,

$$D_{cit}^{ICT} = \frac{K_{cit}^{ICT}}{K_{cit}^{GFCF}},$$

which is used in exploratory specifications but not as the primary measure in the main results.

B.4. Older-worker shares

The primary workforce-aging measure is the share of workers aged 50–64 among workers aged 15–64 within each country–industry–year cell:

$$s_{O,cit}^{work} = \frac{Emp_{50\text{–}64,cit}}{Emp_{15\text{–}64,cit}}.$$

This measure is constructed from Eurostat LFS age-by-industry employment counts. We use the 50–64 age range because it is consistently available in the industry-by-age employment tabulations over the sample period and captures late-career employment before the age ranges most affected by retirement eligibility and sparse reporting. In the mechanisms analysis using EWCS microdata, older workers are defined as individuals aged 50 and above.

B.5. Logarithmic and inverse-hyperbolic-sine transformations

Several productivity and capital-stock measures in the panel are highly skewed, and some asset components take zero or near-zero values in particular country–industry–year cells. To avoid dropping these observations or adding arbitrary constants before logging, we transform continuous productivity and capital-intensity variables using the inverse hyperbolic sine transformation,

$$\operatorname{asinh}(x) = \log\left(x + \sqrt{x^2+1}\right).$$

The inverse hyperbolic sine transformation is widely used in applied economics as a log-like transformation that remains defined at zero and, unlike the natural logarithm, can also accommodate negative values (Burbidge et al., 1988; Bellemare & Wichman, 2020). For large positive values, $\operatorname{asinh}(x)$ differs from $\log(x)$ only by an additive constant, so differences of transformed quantities approximate log ratios.

Accordingly, our transformed value-added labor productivity measure is

$$\widetilde{\ln}\left(\frac{VA_{cit}}{H_{cit}}\right) = \operatorname{asinh}(VA_{cit}) - \operatorname{asinh}(H_{cit}),$$

and ICT intensity is constructed as

$$\widetilde{\ln}\left(\frac{K_{cit}^{ICT}}{H_{cit}}\right) = \operatorname{asinh}(K_{cit}^{ICT}) - \operatorname{asinh}(H_{cit}).$$

Non-ICT capital intensity and R&D capital intensity are constructed analogously. For readability, the tables refer to these variables as "log" or ln measures, but the empirical variables are inverse-hyperbolic-sine transformations.

Recent econometric work emphasizes that coefficients from inverse-hyperbolic- sine transformed variables should not always be interpreted mechanically as percentage effects, especially when zeros are common or when rescaling the underlying variable would change the relative weight placed on extensive and intensive margins (Aihounton & Henningsen, 2021; Chen & Roth, 2024). We therefore interpret the estimates as log-like associations rather than exact elasticities. In our setting, the transformation is used primarily to retain country–industry–year cells with zero or near-zero capital components while reducing the influence of extreme values. The underlying measurement units are kept fixed throughout the analysis, and all specifications use the same transformation across baseline, robustness, and IV estimates.

B.6. Age-specific employment-share and wage extension

For the age-specific employment-share analysis, we combine the main country–industry panel with wage information from Eurostat's Structure of Earnings Survey (SES). We use the SES datasets `earn_ses_agt27`, `earn_ses06_27`, `earn_ses10_27`, `earn_ses14_27`, and `earn_ses18_27`. We retain total-sex average earnings in euros and one-digit NACE industries. For SES waves in which establishment-size restrictions are available, we retain establishments with at least 10 employees.

The employment-share analysis is organized around three age groups: 40–49, 50–59, and 60 and above. Employment shares are constructed by dividing industry employment in each age group by the corresponding country–year population in that age range. Specifically, the 50–59 share uses employment aged 50–59 divided by population aged 50–54 and 55–59, while the 60+ share uses employment aged 60 and above divided by population aged 60–64, 65–69, 70–74, and 75+. Earnings variables are merged by country, industry, year, and age group and are used as controls in the age-specific employment-share regressions.

B.7. European Working Conditions Survey mechanism sample

To examine potential mechanisms linking digitization, workforce aging, and working conditions, we use individual-level data from the European Working Conditions Survey (EWCS), a repeated cross-sectional survey covering multiple waves through 2015. These data are used only for the mechanisms analysis and are not used to construct the main country–industry productivity panel.

We retain respondents with non-missing country, year, industry, and survey-weight information. Older workers are defined as individuals aged 50 and above. The baseline controls include gender and Eurofound job-quality measures, especially the skills-and-discretion index used to proxy job content and autonomy.

The main mechanism outcomes are technostress-related health and working-conditions indicators. We construct binary indicators for headaches or eyestrain, anxiety or stress, fatigue, and sleep problems. The sleep-problem measure equals one when the respondent reports at least one sleep-related problem occurring monthly or more frequently. We also construct a composite technostress-related index as the unweighted mean of the available component indicators:

$$TS_{ijct} = \frac{1}{M_{ijct}} \sum_{m=1}^{M_{ijct}} TS^m_{ijct},$$

where TS^m_{ijct} denotes component m for individual j in industry i, country c, and year t, and M_{ijct} is the number of non-missing components.

To match EWCS respondents to industry-level ICT exposure, we aggregate the productivity panel to the EWCS 11-industry classification. Within each country–year–11-industry cell, we sum ICT capital and hours worked across the matched one-digit NACE sections and construct

$$\widetilde{\ln}\left(\frac{K^{ICT}_{cgt}}{L_{cgt}}\right) = \text{asinh}(K^{ICT}_{cgt}) - \text{asinh}(L_{cgt}),$$

where g indexes the EWCS 11-industry group. This country–industry–year ICT-intensity measure is merged to individual EWCS respondents by country, survey year, and 11-industry group.

We also construct stratification variables used in the mechanism analysis. These include an indicator for jobs involving learning new things, an indicator for employer-provided training, an indicator for computer use at work, an indicator for high work intensity based on the sample median of the EWCS work-intensity index, and an indicator for low autonomy based on the sample median of the skills-and-discretion index. The EWCS regressions use survey weights and cluster standard errors at the industry–country level.

B.8. Instrument inputs and IV construction

The historical-backbone instrument is described in the main text and in Appendix C. The data inputs are: (i) the reconstructed early-1990s EuropaNET and NORDUnet research-backbone topology, (ii) population-weighted country centroids constructed from NUTS-3 regions and population, (iii) predetermined 1995 country–industry ICT intensity from the productivity panel, and (iv) the

U.S. BEA Private Fixed Investment chained price index for Information Processing Equipment and Software.

IV construction uses predetermined 1995 country–industry ICT intensity. Let

$$ICTExposure_{ci,1995} = \widetilde{\ln}\left(\frac{K^{ICT}_{ci,1995}}{L_{ci,1995}}\right).$$

The baseline shift–share exposure is

$$Z^{base}_{cit} = ICTExposure_{ci,1995} \times ICTCostShock_t,$$

where $ICTCostShock_t$ is the common decline in the ICT investment price index relative to 1995. The backbone-amplified exposure is

$$Z^{backbone}_{cit} = ICTExposure_{ci,1995} \times BackboneExposure_c \times ICTCostShock_t.$$

The endogenous regressors in the IV productivity specifications are ICT intensity and its interaction with the older-worker share. The excluded instruments are Z^{base}_{cit}, $Z^{backbone}_{cit}$, and their interactions with the older-worker share. In the lagged-share robustness specification, the interaction instruments are formed using the lagged older-worker share rather than the contemporaneous older-worker share.

C. Supplemental Instrumental-Variables Evidence

This appendix reports additional evidence supporting the instrumental-variables strategy described in Section 4. The instrument combines predetermined 1995 country–industry ICT exposure, a common global ICT price-decline shifter, and historical exposure to the European research-backbone network. The identifying assumption is that, conditional on the fixed effects and controls included in the main specification, the excluded instruments affect labor productivity through ICT adoption rather than through other contemporaneous productivity determinants. The results below assess this assumption along three dimensions: first-stage relevance, reduced-form event-style patterns, and placebo relationships with alternative channels.

Table 7 reports the first-stage regressions corresponding to the main IV specifications in Table 5. The excluded instruments are strongly related to both endogenous regressors: ICT intensity and its interaction with the older-worker share. This confirms that the shift–share instruments generate meaningful predicted variation in ICT intensity after absorbing Country$\times$Industry, Year$\times$Industry, and Year$\times$Country fixed effects.

Figure 3 reports year-specific reduced-form associations between predetermined backbone-amplified ICT exposure and log labor productivity. This exercise is not a formal pre-trend test, since the main panel begins in the baseline period used to construct exposure. Instead, it provides a diagnostic check for whether the exposure measure is systematically associated with differential productivity changes throughout the sample. The estimated coefficients are small and statistically indistinguishable from zero across the period, providing no evidence that the predetermined exposure measure directly tracks productivity growth outside the ICT-adoption channel.

Table 8 examines whether the excluded instruments predict changes in outcomes that should not be directly affected by ICT-specific price declines and historical backbone exposure. The placebo outcomes are changes in non-ICT capital intensity, R&D capital intensity, and the older-worker share. These tests address the concern that the instrument may be capturing broader capital deepening, innovation investment, or endogenous workforce aging rather than ICT-specific adop-

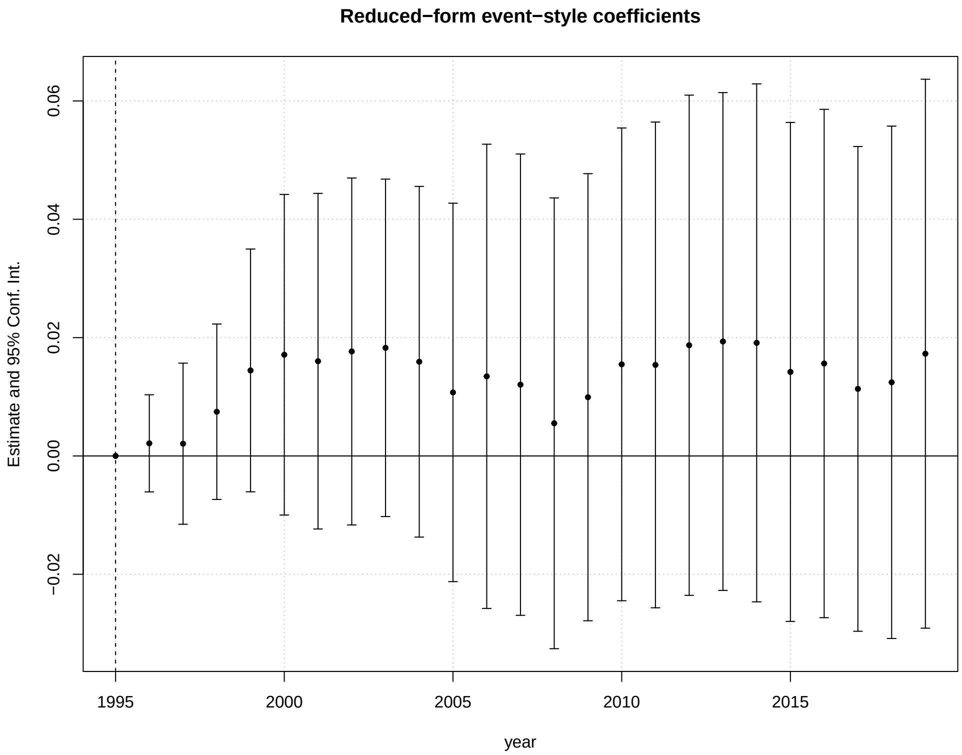
Table 7: First-stage regressions for ICT intensity and heterogeneous exposure

Dependent Variable:	$\ln\left(K_{it}^{ICT}/L_{it}\right)$	$\ln\left(K_{it}^{ICT}/L_{it}\right) \times s_{O,it}^{\text{work}}$	$\ln\left(K_{it}^{ICT}/L_{it}\right)$	$\ln\left(K_{it}^{ICT}/L_{it}\right) \times s_{O,it}^{\text{work}}$
Model:	(1)	(2)	(3)	(4)
Variables				
Baseline ICT exposure × price decline	-0.7875***	-0.6607***	-0.7502***	-0.5182***
	(0.1304)	(0.0536)	(0.1327)	(0.0527)
Baseline ICT exposure × price decline × backbone	0.0814	0.0922**	0.0669	0.0893**
	(0.1169)	(0.0385)	(0.1063)	(0.0413)
Baseline ICT exposure × price decline × older-worker share	0.2965	1.722***	0.1868	1.292***
	(0.3289)	(0.1094)	(0.3189)	(0.1054)
Backbone-amplified exposure × price decline × older-worker share	-0.4086	-0.2155*	-0.3710	-0.2216*
	(0.3824)	(0.1120)	(0.3539)	(0.1251)
Older-worker share, $s_{O,it}^{\text{work}}$	0.1392	-5.584***	0.1696	-5.487***
	(0.3624)	(0.1338)	(0.3534)	(0.1677)
Log non-ICT intensity, $\ln\left(K_{it}^{nonICT}/L_{it}\right)$	0.3546***	0.0660*	0.3522***	0.0606
	(0.1320)	(0.0381)	(0.1325)	(0.0414)
Log R&D intensity, $\ln\left(K_{it}^{RD}/L_{it}\right)$	0.0520**	0.0081	0.0514**	0.0079
	(0.0243)	(0.0072)	(0.0243)	(0.0076)
Fixed-effects				
Country × Industry	Yes	Yes	Yes	Yes
Year × Industry	Yes	Yes	Yes	Yes
Year × Country	Yes	Yes	Yes	Yes
Instrument construction				
Current older-worker share in IV interactions	Yes	Yes		
Lagged older-worker share in IV interactions			Yes	Yes
Fit statistics				
Observations	4,004	4,004	4,004	4,004
R^2	0.98688	0.98975	0.98684	0.98673
Within R^2	0.18486	0.85430	0.18271	0.81140

Clustered (Country × Industry) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports first-stage regressions corresponding to the 2SLS estimates in Table 5. The endogenous regressors are ICT capital intensity, $\ln\left(K_{it}^{ICT}/L_{it}\right)$, and its interaction with the older-worker share, $\ln\left(K_{it}^{ICT}/L_{it}\right) \times s_{O,it}^{\text{work}}$. Instruments are constructed from a shift–share design that interacts predetermined 1995 country–industry ICT intensity with a common global ICT price-decline shifter and a country-level historical research-backbone exposure measure. Columns (1)–(2) correspond to the preferred specification, in which the excluded instruments for the interaction term are formed using the contemporaneous older-worker share. Columns (3)–(4) instead form the interaction instruments using the lagged older-worker share. All specifications include Country×Industry, Year×Industry, and Year×Country fixed effects and control for non-ICT capital intensity and R&D intensity. Standard errors are clustered at the Country×Industry level.

Figure 3: Reduced-form event-style diagnostic for backbone-amplified ICT exposure



This figure reports year-specific reduced-form associations between predetermined backbone-amplified ICT exposure and log value-added labor productivity. The omitted reference year is 1995. The estimating equation includes Country×Industry, Year×Industry, and Year×Country fixed effects, as well as the same controls used in the main IV specification. Standard errors are clustered at the Country×Industry level. The flat coefficient profile provides no evidence that the predetermined exposure measure is directly associated with differential productivity changes over the sample period.

tion. The excluded instruments are not jointly significant in any of the placebo regressions, with Wald test p-values of 0.363, 0.263, and 0.925, respectively. The exclusion restriction cannot be verified directly, but these results provide no evidence that the instrument operates through these observable alternative channels.

Finally, Table 9 reports baseline diagnostic regressions relating the backbone-amplified exposure component to 1995 country–industry characteristics. These regressions condition on baseline ICT exposure, country fixed effects, and industry fixed effects; the coefficient on baseline ICT exposure is omitted from the table for compactness. The reported coefficient therefore captures whether the incremental historical-backbone component is associated with baseline productivity,

Table 8: Placebo reduced-form tests for alternative IV channels

Dependent Variable:	$\Delta \ln\left(K_{it}^{nonICT}/L_{it}\right)$	$\Delta \ln\left(K_{it}^{RD}/L_{it}\right)$	$\Delta s_{O,it}^{\text{work}}$
Model:	(1)	(2)	(3)
Variables			
Baseline ICT exposure × price decline	0.0069	-0.0431	0.0014
	(0.0125)	(0.0769)	(0.0063)
Backbone-amplified exposure × price decline	0.0104	0.0397	0.0039
	(0.0064)	(0.0373)	(0.0045)
Baseline ICT exposure × price decline × older-worker share	-0.0133	0.1253	-0.0102
	(0.0350)	(0.1987)	(0.0196)
Backbone-amplified exposure × price decline × older-worker share	-0.0357*	-0.0063	-0.0123
	(0.0199)	(0.1080)	(0.0153)
Older-worker share, $s_{O,it}^{\text{work}}$	0.0162	0.0750	0.2960***
	(0.0415)	(0.1819)	(0.0232)
Log R&D intensity, $\ln\left(K_{it}^{RD}/L_{it}\right)$	0.0058**		-0.0004
	(0.0025)		(0.0010)
Log non-ICT intensity, $\ln\left(K_{it}^{nonICT}/L_{it}\right)$		0.0221	-0.0007
		(0.0517)	(0.0034)
Fixed-effects			
Country × Industry	Yes	Yes	Yes
Year × Industry	Yes	Yes	Yes
Year × Country	Yes	Yes	Yes
Joint tests			
Wald test of excluded instruments	1.084	1.311	0.224
p-value	0.363	0.263	0.925
Fit statistics			
Observations	4,004	3,993	4,004
R^2	0.39346	0.34448	0.50305
Within R^2	0.00568	0.00309	0.15387

Clustered (Country × Industry) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports reduced-form placebo regressions designed to assess whether the excluded instruments predict alternative channels other than ICT adoption. The dependent variables are changes in non-ICT capital intensity, R&D capital intensity, and the older-worker share. The excluded instruments are not jointly significant in any placebo regression, with Wald test p-values of 0.363, 0.263, and 0.925, respectively. These results provide no evidence that the instrument primarily captures broad capital deepening, R&D accumulation, or endogenous workforce aging.

workforce age composition, non-ICT capital intensity, or R&D intensity. The estimates are small and statistically insignificant across outcomes, suggesting that the backbone-amplified component is not simply proxying for observable baseline differences in productivity, capital structure, or workforce aging.

Table 9: Baseline correlates of backbone-amplified ICT exposure

Dependent Variable:	$\ln\left(VA_{i,1995}/L_{i,1995}\right)$	$s^{\text{work}}_{O,i,1995}$	$\ln\left(K^{nonICT}_{i,1995}/L_{i,1995}\right)$	$\ln\left(K^{RD}_{i,1995}/L_{i,1995}\right)$
Model:	(1)	(2)	(3)	(4)
Variables				
Backbone-amplified baseline ICT exposure	0.0002	0.0010	0.0396	-0.2241
	(0.0289)	(0.0037)	(0.0275)	(0.2027)
Controls and fixed-effects				
Baseline ICT exposure control	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Fit statistics				
Observations	178	178	178	163
R^2	0.94411	0.71838	0.94552	0.71438
Within R^2	0.03057	0.01677	0.06406	0.03821

Clustered country-level standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table reports baseline cross-sectional diagnostic regressions relating 1995 country–industry characteristics to the backbone-amplified exposure component used in the IV design. All regressions include country and industry fixed effects and condition on baseline 1995 ICT exposure; the coefficient on baseline ICT exposure is omitted from the table for compactness. The reported coefficient therefore captures whether the incremental backbone-amplified component is systematically associated with baseline productivity, workforce age composition, non-ICT capital intensity, or R&D intensity.