DOCTORAL THESIS

Economic Perspectives of Twin-transition: Low-carbon Production and Inclusive Digitalization

Artjom Saia

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

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Rohe-digipöörde majanduslikud perspektiivid: madala süsinikheitega tootmine ja kaasav digitaliseerimine

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Author's Contribution to the Publications

Contribution to the papers in this thesis are:

I The author of the thesis is the sole author of this article.

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Introduction

Human activity in the form of combusting fossil fuels for generating electricity, manufacturing products, and transporting people and goods has led to substantial emissions of carbon dioxide (CO_2) into the atmosphere that evokes climate change. CO_2 has the longest life cycle (Camarero et al., 2011) and constitutes the largest share (72%) of global total greenhouse gas (GHG)[1] emissions (Crippa et al., 2023). Although the economic literature on global warming and CO_2 emissions is expanding (Acemoglu et al., 2016; Lange et al., 2020; Dwivedi et al., 2022), there is a need to further explore the direct and indirect impacts of technological and economic progress on reducing CO_2 emissions.

The concept of sustainable development suggests that maintaining a clean environment and improving the quality of human life are interdependent, and advancing an economy can be sustainable only if it is green and inclusive (Stojkoski et al., 2023). Attention to the environmental effects of digitalization and other technologies has recently reached its peak in response to growing public environmental concerns.

A required condition for green economic growth[2] is the deployment and development of products and technologies with environmental advantages (Mealy and Teytelboym, 2022). Economically, it is highly unlikely that the level of investment in eco-friendly technologies is socially optimal. Market prices may not reflect the environmental gains linked to green products. On the other hand, the positive spillover effects may arise from "learning by doing" and research and development (R&D) in green products. As a result of these externalities, which have been crucial, for instance, in the renewable energy and automotive industries (Aghion et al., 2016), the market is likely undersupplied with green technologies, thus prompting government interventions.

Countries with more complex economies[3] produce more knowledge-intensive and technologically complex goods and achieve higher levels of gross domestic product (GDP) per capita and growth rates (Hausmann et al., 2014), lower income inequality, and greater inclusiveness (Hartmann et al., 2017). Correspondingly, the complexity measure of the green economy (or green complexity) reflects the degree to which a country is able to produce technologically complex and green products competitively. The economies with higher green complexity exhibit reduced CO_2 emissions, markedly higher shares of environmental patents, and stricter environmental regulations (Mealy and Teytelboym, 2022). Path dependence in green complexity implies that earlier and stronger actions to create eco-friendly production capabilities are vital to the development of a prospective green economy (Acemoglu et al., 2016; Aghion et al., 2016).

Reducing carbon emissions is urgent, and this issue is addressed in action plans and policies at the supra-national level; these include the development of a competitive, carbon-free, and digitalized economy. These necessary transitions with introducing the intertwined green and digital technologies have been called "twin transitions" or sustainable digitally-enabled transitions; the twin transition framework is presented in Appendix 4 (European Commission, 2020a, 2020b; Rehman et al., 2023). The European

[1] GHGs include the following: carbon dioxide, perfluorocarbons, hydrofluorocarbons, sulphur hexafluoride, methane, nitrous oxide, and water vapour (EEA, 2023).

[2] „Green growth" refers to the possibility for advancing economic well-being while precisely acknowledging environmental constraints and impacts (EBRD, 2017; Mealy and Teytelboym, 2022).

[3] Economic complexity explains economic growth as involving the development of information and accumulation of knowledge in producing sophisticated goods (Hausmann et al., 2014).

Commission (EC) has stipulated its ambitious climate objectives in the European Green Deal (EGD)[4] and the European Digital Strategy (EDS)[5], which consider the synergetic twin transition as crucial to achieving sustainability goals (Paiho et al., 2023). These initiatives specify challenging goals for all industries with a focus on greening digitalization, which is enabled by information and communication technologies (ICT)[6]. The twin-transition strategy is also fundamental to the EU's COVID-recovery program, the NextGenerationEU, which supports green, digital and equality principles (European Commission, 2023a). Corresponding legislation is also in effect in other developed countries. Policymakers aim to take full advantage of digitalization to enhance efficiency and reduce environmental costs across all industries in the economy.

The green transition relates to areas such as the production of clean energy, the circular economy, the preservation of ecosystems, and a decarbonized environment. The green transition represents a potential pathway for sustainable and inclusive development in the EU (European Commission, 2019).

The influential work of von Neumann and Turing in computing has led to the proliferation of modern digital technologies (Ciarli et al., 2021). The digital transition involves the adoption of digital innovations and technologies, such as computers, smart sensors, machine learning (ML), artificial intelligence (AI), the Internet of Things (IoT), data algorithms, and hubs. The COVID-19 pandemic and the military conflict in Europe have confirmed the vital need for digital technologies for economic development in the EU (European Commission, 2022d). Digital technologies can reduce economies' overall energy consumption but, on their own, increase the demand for electricity (Schulte et al., 2016; Lange et al., 2020). Digitalization is thus a double-edged sword in its environmental effect, and its use can also lead to environmental degradation since it relies heavily on infrastructure, materials, and energy (Strubell et al., 2019). E-waste is also on the rise globally due to the increased use of digital equipment and electronics (Kunkel and Matthess, 2020). Thus, digital transition does not automatically improve environmental quality, and as the idea of the twin transition suggests, it should be integrated with green solutions (Bianchini et al., 2022).

The emergence of digital technologies has spurred confidence that economic, social, and environmental objectives can be achieved alongside goals for inclusive, sustainable development. At the same time, the potentially unfavorable effects of the widespread dissemination of digital technologies have raised concerns that range from escalating inequality (O'Neil, 2016) to increasing unemployment (Brynjolfsson and Mitchell, 2017). This issue thus demands an immediate response, especially given the current transition to green energy, which is supported by innovative policies.

The positive environmental externalities associated with the use of digitalization may considerably reduce CO_2 emissions. For instance, the use of digital tools in teleworking, e-teaching, e-learning, and e-health can substantially reduce time, energy, and travel costs. Digitalization can enhance utility and productivity and can provide even greater

[4] The EU Green Deal is focused on ensuring environmental sustainability, including reducing energy costs and reliance on imported fossil fuels (European Commission, 2019, 2022d).
[5] The EU Digital Strategy is designed to enhance the resilience and competitiveness of the digitalization eco-system (European Commission, 2020a, 2022b).
[6] The ICTs comprise the relevant infrastructure, hardware, software, and information services, that constitute the infrastructural foundation for digitalization. Digitalization can be defined as the ever-increasing adoption of data processing via advanced digital technologies that generate innovative digital processes, products, and business models (Briglauer et al., 2023).

economic prosperity by being an integral part of global net-zero society. Digital technologies allow the deciphering of environmental issues, for instance, through the use of big data and AI that can detect new structures in environmental processes (Vinuesa et al., 2020); encourage consumers to behave in a more eco-friendly manner and increase their environmental awareness (Coeckelbergh, 2021); interconnect smart devices and smart grids for electricity management, transmission and generation (del Río Castro et al., 2021; Higon et al., 2017), and guide policymakers' efforts to ensure environmental sustainability and accurate forecasting of natural disasters.

Thus, the net effects of digitalization are ambiguous, and there is insufficient focus in the literature on how the full potential of digitalization can be harnessed to achieve energy efficiency and environmental sustainability.

In fact, scientists and policymakers have begun to address several vital questions: are technological development in a broad sense (including green energy and low-carbon technologies) and digital transformation compatible? What is the effect of digitalization's expansion on CO_2 emissions, given that it is not supported by the development of overall technology? These are the questions comprehensively addressed in this dissertation. More specifically, this study examines the impact of digitalization, both direct and moderated by technology development, on CO_2 emissions, thus also identifying the twin-transition impact.

These multidirectional digitalization effects imply a high level of heterogeneity, meaning that the all-embracing quantitative effect of digitalization on CO_2 emissions is uncertain and must be tackled empirically to send the right message to policymakers. The contribution of this study (Article I) is in revealing the critical role of R&D in the form of technology patents that transform the relationship between digitalization and CO_2 emissions. In this setting, R&D-induced technology inventions act as a nonlinear transition function that turns digitalization into a mechanism that improves environmental quality. Existing evidence (e.g., Aydin and Cetintas, 2022) shows that progress in R&D enhances energy efficiency and expedites the transition to green energy. This study enriches the relationship between digitalization and R&D output and fills the research gap in two key aspects. First, it estimates the relevance and significance of an R&D-driven regime shift that reduces CO_2 emissions in response to digitalization while controlling for a set of appropriate indicators. Second, the study applies a nonlinear generalized panel estimator, panel smooth transition regression (PSTR) (González et al., 2005), which enables a smooth R&D-induced transition and produces heterogeneous estimates that vary across regimes. Unlike existing research, this study disentangles the R&D-driven technological innovation and digitalization progress while investigating their joint nonlinear smooth regime-effect on CO_2 emissions. In addition, this study uses a worldwide sample of high- and middle-income economies.

Based on the sample obtained, the author estimated several econometric models to find the direct environmental outcomes of digitalization and those moderated by technological development. The results indicate that the advancement of digitalization has opposite effects: in the linear part and under a low level of technology development, digitalization leads to CO_2 emissions' increase, presumably due to its high electricity consumption. However, in the nonlinear part and for higher levels of technological progress, the complex interaction of digitalization and technology reduces CO_2 emissions, with the latter (reducing) effect exceeding the effect that increases emissions. This study supports the environmental Kuznets curve (EKC) hypothesis (Grossman and Krueger, 1995), which states that CO_2 emissions have an inverted U-shaped nexus with the levels of economic and technological development. It shows that carbon emissions increase with digitalization in countries with lower levels of R&D output until they reach an R&D threshold, after which CO_2 emissions begin to decline as economies advance in digitalization.

Environmental disequilibrium and global warming are associated with substantial increases in energy costs and issues of the security of energy supply[7], as its consumption leads to CO_2 emissions. Thus, economic, energy, security, and environmental factors are closely intertwined.

Also, not only digitalization but technology development in general is at the heart of most strategies addressing climate change (Bianchini et al., 2023). In the transformation to a low-carbon economy, green and low-emission technologies provide diverse solutions, spreading from carbon capture (CC) (including CC in electricity generation) to emissions-free steel and cement production technologies, which can successfully decrease the environmental impact.

The EU energy program covers the energy policy of the Baltic States that has three major goals crucial to promoting green economic development: sustainability, competitive ability, and energy security (Bompard et al., 2017). Due to increasing competition and incentives for organizations to invest in cost-decreasing and innovative technologies, energy prices are expected to gradually decline and converge between EU members, leading to increased efficiency and welfare (Böckers and Heimeshoff, 2014). Investments are essential for sustainable development and a precondition for an accelerated digital and green transition (European Commission, 2022d). Also, the energy markets with enhanced interconnection may contribute to strengthening the short- and long-term security of energy supply.

Over the last years, Estonia has transformed its energy industry, making a substantial contribution to reinforcing energy security in the region. According to the "REPowerEU" plan of the EC (2022c) the joint activities are required not only to improve energy efficiency and increase renewable energy production, but also to enhance the capacities of low-carbon production with the help of CC technologies. Regardless of the relative abundance of oil shale (OS) reserves, few countries have chosen this fuel as a reliable energy source for power generation. Estonia is one such country with an extensive knowledge base and production experience in OS use, implying production capabilities and path-dependence in this area. OS is a fossil fuel, and its combustion in power plants results in high CO_2 emissions. Substantially abating the GHG emissions in Estonia requires a reduction in CO_2 emissions from electricity generation. With the spotlight on the EU target of net-zero GHG emissions by 2050 (European Commission, 2019), the introduction of new technologies, including CC, is vital.

Article II presents applied research of specific case study, with inter-phenomenon normative real data and sensitivity analysis (rather than classical hypothesis testing) applied to answer the specific research question. This analysis manifests the real example of CC technology potential implementation with the retrofitting Estonia's OS power plants (OSPPs) to allow direct abatement of CO_2 emissions, which also aligns with the theoretical technological effect of the EKC hypothesis (Grossman and Krueger, 1995). The effect of implementing these CC technologies is observable on the EKC curve after

[7] Energy security is multidimensional construct that relates to uninterrupted (continuous) availability of energy sources at an affordable price (International Energy Agency (IEA), 2023b).

the threshold point, when they contribute to the decoupling of economic growth from environmental degradation.

This dissertation provides a comparative techno-economic analysis of the implementation of CO_2 capture technologies, such as post-combustion capture (PCC) and oxy-fuel combustion capture (OXY) technologies, in existing OS power plants in Estonia. The technical analysis reveals that OXY technology performs better than PCC in OS electricity generation plants. From a financial feasibility perspective (based on the technical feasibility analysis), the possibility of CO_2 capture in the Estonian OSPPs relies on the long-term state of the electricity market and the CO_2 emissions trading system.

The study, thus, seeks to answer the question of whether the actual additional cost of integrating CC technologies in OSPPs exceeds the combined CO_2 emission allowance and environmental fees or if it may lead to a competitive disadvantage. Additionally, this study discusses the potentially high relative cost of CC and the negative externalities arising from CO_2 emissions and national energy security issues if they cannot be practically mitigated using alternative, sustainable and manageable energy sources. Thus, this study makes an original contribution to an area that is largely unexplored.

Digital technologies penetrate and reorganize all aspects of social and economic activities (Ciarli et al., 2021). Organizations need modern skills for innovation, learning, and assimilation of digital technologies that transform the programming code into improved productivity and innovative performance (Ciarli et al., 2021). Digital technologies like AI and ML are fundamentally transforming the tasks distribution between human and technology. Digital technologies also support a fair and sustainable society, for instance, by enabling digital access for unconnected and exposed individuals. However, digitalization can inflate consumption, exacerbate the digital divide, and upset the balance of the labor market. Thus, the positive developments of digital technologies should be addressed in a way that minimizes potential negative externalities.

The accelerated adoption of digital technologies and digital skills allows individuals to be more mobile and flexible in terms of employment and learning (Claro et al., 2018). The COVID-19 pandemic has transformed daily lives and routines of individuals (Feldmann et al., 2021). It exposed an urgent need for infrastructure and highlighted a lack of digital skills of individuals who were unequipped to hold events, study, and work from home online.

Today digitalization goes beyond an incremental change to existing technological advances and represents a fundamental transformation in the technological paradigm, capable of inducing a new cycle of economic growth and profound structural changes (Brynjolfsson and McAfee, 2014; Cirillo et al., 2021). Such digital transformations may have disparate impacts on employment. Some studies predict widespread unemployment caused by technological disruption, while others suggest that the new technological model will create employment opportunities (Frey and Osborne, 2017; Nedelkoska and Quintini, 2018).

The literature contains mixed empirical findings on the influence of digital technologies and digital skills on employment dynamics. These results can mostly be explained by heterogeneity in the level of aggregation and the specificity of the digitalization indicator used, although its choice is often dictated by data availability. Nevertheless, most studies express the consensus position that digitalization has a favorable effect on employment outcomes.

This dissertation contributes to extant literature by defining and empirically exploring the relationship between digital technologies, digital skills, and employment dynamics in the specific occupational context. More specifically, it aims to answer the research question of whether digital skills and digital technology (broadband Internet access) have a positive impact on employment status on the micro level before and after the emergence of the COVID-19. The novel contribution of this study (Article III) is that it identifies the individual-level impacts in the relationship between digital skills and employment and the post-COVID-19 effect on digital transition in European countries. The COVID-19 pandemic has generally triggered growth in employment outcomes for individuals with digital skills, broadband Internet access, and tertiary education. However, in the post-pandemic period, the individuals with basic digital skills have gained employment benefits, while the relative advantage in the labor market of those with advanced digital skills has declined.

The contribution of this dissertation is in detecting favorable effects of the green and digital, or so-called "twin" transitions in mitigating climate change. In evaluating the nexus between the advancement of digitalization and green technologies and their impact on CO_2 emissions, particular focus is placed on the technological component. There are few empirical studies of the twin-transition phenomenon, and those that consider this in the light of technological development are even less (Bianchini et al., 2023); even fewer studies investigate the environmental impacts of the technologies underpinning this transition.

The complexity of interaction between general, green and digital technologies and their environmental, social, and employment-related impacts call also for new investigation approaches. To the best of the author's knowledge, this dissertation makes a novel contribution: it explores the digitalization's impact, moderated by technological development, on CO_2 emissions, evaluates the financial feasibility of implementing specific CC technologies in Estonia, as well as estimates the effects of digital skills and technology on employment outcomes. The econometric methods (PSTR and bivariate ordered probit models) applied in the published articles add to the originality of the contribution.

The remainder of this dissertation is structured as follows. Section 1 sets out the theoretical and empirical background and offers the literature overview on the environmental impacts of digitalization, the effects of implementing CC technologies in Estonia, the digital divide and transformation of the labor markets, as well as the green and digital twin transition and their environmental implications. The research questions and hypotheses are elaborated in Section 2 based on the arguments presented in Section 1. In Section 3, the empirical methodology is outlined, and the data are described. The author discusses the key estimation results in Section 4 and presents conclusions in Section 5 with the policy suggestions most relevant to the ongoing debate on twin transition, including a human-centered focus, the implementation of low-carbon technologies and their economic, environmental, and social implications.

Abbreviations

AI	Artificial Intelligence
CC	CO_2 capture
CSIS	Community Statistics on Information Society
DOE	U.S. Department of Energy
EC	European Commission
EGD	European Green Deal
EKC	Environmental Kuznets curve
ETS	Emissions Trading System
EU	European Union
GDP	Gross domestic product
GHG	Greenhouse gas
ICT	Information and communication technologies
IEA	International Energy Agency
IoT	Internet of Things
ISCED	International Standard Classification of Education
ISCO	International Standard Classification of Occupations
ML	Machine learning
NETL	National Energy Technology Laboratory
NUTS	Nomenclature of territorial units for statistics
O&M	Operating and maintenance
OS	Oil shale
OSPP	Oil shale power plant
OXY	Oxy-fuel combustion capture
PCC	Post-combustion capture
PSTR	Panel Smooth Transition Regression
R&D	Research and Development
RBTC	Routine-biased technical change
RP	Reference plant
SBTC	Skill-biased technical change
SDG	Sustainable development goals
TRL	Technology readiness level
WHO	World Health Organization

Explanations of abbreviations used in the thesis – the table.

1 Overview of the Literature

1.1 Environmental Kuznets Curve: Decoupling economic development from carbon dioxide emissions

Below, the author offers a review of the general literature with main findings on the primary determinants and specific effects of the digitalization components on CO_2 emissions, concentrating on hypotheses associated with moderated and nonlinear impacts.

1.1.1 Digitalization and economic development

The early dispute around Solow's (1987) "productivity paradox" had been resolved as the related research confirms that a rise in productivity after 1995 was induced by the adoption and use of ICT technology (e.g., Jorgenson et al., 2008). The first wave of literature estimated the economic effect of ICT on growth of productivity and output at different levels of aggregation (Kohli and Grover, 2008; Lee et al., 2005). The outcomes and the strengths of these early contributions have been constructively reviewed, for instance in Draca et al. (2007). The research on "ICT value" shows that investments in ICT capital positively impact productivity growth for developed economies (Dewan and Kraemer, 2000; Ollo-Lopez and Aramendia-Muneta, 2012) as well as for higher-income developing economies (Dedrick et al., 2013). Further, digital technologies can improve economic development and productivity by automating processes, which leads to more efficient resource use and stimulates investments, including in green technologies (Evangelista et al., 2014; Antonioli et al., 2018; Tortorella and Fetterman, 2018).

Digital technologies have changed the types of services and goods available in the economy. For instance, digital goods generate considerable gains in welfare that are not represented in traditional measures of productivity and GDP (Brynjolfsson et al., 2019). Whereas, in most cases, GDP represents economic growth and is broadly used, its use as an indicator of the state of the economy is theoretically and practically controversial, particularly when used as a measure of well-being (van den Bergh, 2009; Vadén et al., 2020). Thus, the goods in the digital economy are not included in GDP, since each digital good's (e.g., smartphone applications, Wikipedia) copy created by a user often has a zero-market price and almost zero marginal cost (Brynjolfsson et al., 2019).

In the digital age, information flows are an element of the global economy (Sui and Rejeski, 2002). Economic development leads to increased consumption of digital goods, which results in higher electricity usage and carbon emissions. As per the Environmental Kuznets Curve (EKC) hypothesis, CO_2 emissions grow in the early stages of economic development until a threshold is reached but later, they decrease as economies advance further with a shift toward more environmentally friendly and cleaner technologies, as shown in Figure 1 (Grossman and Krueger, 1995; Stern, 2004; Ansuategi and Escapa, 2002).

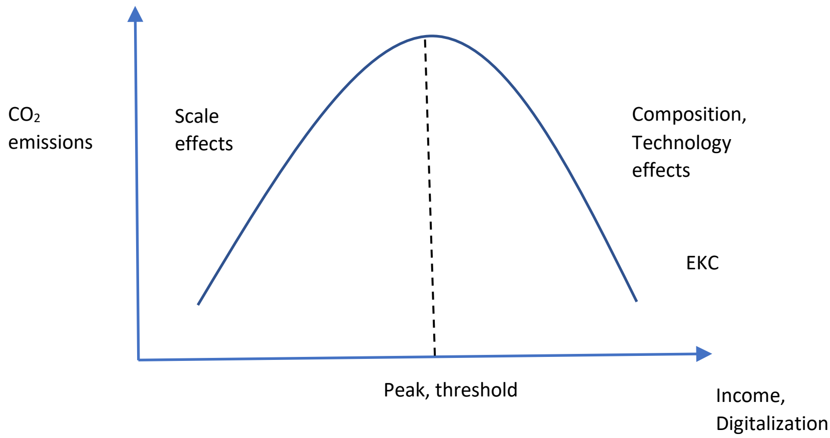

Figure 1. Environmental Kuznets curve (Grossman and Krueger, 1995; compiled by the author).

The EKC hypothesis defines the relationship between income inequality, level of income per capita, and environmental quality (Acemoglu and Robinson, 2002; Marco et al., 2022). This inverted U-shaped relationship is the result of scale, technology, and composition effects (Grossman and Krueger, 1995; Dinda, 2004; Aslanidis, 2009). The environmentally adverse scale effect dominates at lower levels of economic development, with positive composition and technology effects prevailing as the economy expands. A country's income level is also positively linked to environmental awareness and regulations that promote sustainability (Arrow et al., 1995; Aslanidis, 2009). However, the EKC nexus embraces not only income inequality and environmental sustainability but also economic complexity, forming the so-called trinity, which has three desired but incompatible goals (Marco et al., 2022). The environmental performance of CO_2 emissions is empirically shown to be highly path-dependent (Bianchini et al., 2023).

Dinda (2004) has reviewed the literature related to the EKC hypothesis, and recently Shahbaz and Sinha (2019) have overviewed the studies regarding concretely CO_2 emissions. However, empirical evidence on the EKC relationship regarding CO_2 emissions is mixed because this nexus varies across countries, which differ in their development trajectories and policies (Haini, 2021). For instance, while Grossman and Krueger (1995), Yandle et al. (2002), and Cheikh et al. (2021) find support for the EKC relationship, Arrow et al. (1995), Stern (2004), Hussain and Dogan (2021) find no such evidence. Some studies claim that the results supporting the EKC hypothesis apply to high-income but not low- and middle-income countries (Le and Quah, 2018). The complexity and nonlinearity of the EKC relationship requires a more advanced framework for estimation (Van Alstine and Neumayer, 2010), which must allow for non-linearity and heterogeneity in parameters (Higon et al., 2017; Cakar et al., 2021).

1.1.2 Environmental impacts of digitalization

Digital transformation has clear environmental impacts, but whether this influence is positive or negative is debated (Briglauer et al., 2023). Also, the paucity of research on the environmental outcomes of the digital transition adds to this ambiguity (Bianchini et al., 2023). Further, digital technologies are not a uniform entity, but they represent a collection of various, interconnected, and complementary areas of knowledge, the so-called digital ecosystem. Thus, distinct digital technologies induce heterogeneous impacts on environmental quality.

In general, digital technologies have specific common features, such as electricity consumption.[8] These technologies (primarily connected devices, data centers and transmission networks) are responsible for generating about 2% of total GHG emissions from energy use (IEA, 2023a). The proportion of electricity consumption of the digitalization and ICT main components are as follows (Banet et al., 2021): mobile and fixed broadband networks (incl. access and main networks) use 27% of total ICT-related electricity consumption; data centers use 31%, and end-user devices (incl. laptops, PCs, smartphones, TVs) use around 42% of overall ICT electricity demand. Despite the swiftly expanding use of digitalization, carbon emissions have increased modestly over the past decade due to a transition to renewable energy sources, improvements in energy efficiency, and general decarbonization of electric power grids. For instance, while Internet traffic and data centers' workloads have increased several times from 2010 to 2019, the data centers' energy use barely changed (IEA, 2020). However, to achieve the carbon-free target by 2050, emissions need to be halved by 2030.

Like connectivity technologies (e.g., gigabit, 5G, 6G), semiconductors are essential for a sustainable digital transition (European Commission, 2022a). The recent applications of AI, big data processing capacities, the transition to "edge computing" and the need for infrastructure to facilitate a distributed workforce, induced by the COVID-19, demand the increased computational capacity, extra security, and decreased energy consumption. The emerging quantum computing technologies can spur innovations in such complex areas of R&D as healthcare, climate change, sustainable energy, digital twins, and AI (European Commission, 2022b). Digital technologies (e.g., ML) have spillover effects on other inventions and technology progress at the sectoral and economy-wide levels (Cockburn et al., 2019; Wu et al., 2024).

Given digital technology's positive and negative environmental effects, what is the overall net impact of digitalization? The nexus of digitalization and electricity consumption is the key factor in determining whether digitalization is, in general, beneficial, or detrimental to a sustainable environment. Horner et al. (2016) provide a practical classification of the ambivalent environmental effects of digitalization. The direct effects can be categorized as follows: the consumption of electricity related to manufacturing (embodied energy), using (operational energy), and discarding elements (incl. obsolescence effect)[9]. The next level of indirect effects (in terms of a

[8] The digital ecosystem's structure elements are data related processes, computational power to process data, connected devices via IoT, industrial robots, peripheral devices – all use electricity.

[9] The obsolescence effects occur when the new technologies are introduced and still functioning digital equipment is disposed of before its useful life expires.

single service) can be related to efficiency (decreasing net electricity consumption), substitution (opposing effects), and direct rebound effects (increasing electricity use)[10].

The direct rebound effect, which is the elasticity effect of own price, can result when income and substitution effects lead to increased consumption while prices and operational costs decrease. The third level comprises the indirect rebound effect, resulting from the demand's cross-price elasticity for other goods because of higher real income. The fourth level refers to economy-wide structural effects, when digitalization originates macroeconomic changes, facilitating or restraining growth in other industries, which leads to modifications in energy use. The dynamic, long-term environmental impacts of digital technologies can transform economic structures and lifestyles (e.g., remote work, e-commerce platforms), changes that are not immediately obvious (Dedrick, 2010). Again, the impact of this effect is counteracting. Finally, transformational effects relate to the alteration of consumer preferences and social and economic institutions, induced *inter alia* by the growth of digitalization (Greening et al., 2000). Likewise, the sign of such effect is ambiguous.

Another substantial aspect that determines the EKC form is the interaction between GDP and tertiarization, which takes place when the proportion of intangible such as service sector in the overall GDP rises. In developed economies, structural change is supported by digitalization, which, in turn, contributes to tertiarization that creates environmental value (Lange et al., 2020). When digitalization exhibits tertiarization effects, energy consumption will decrease, as this results in a reduced energy intensity, more frugal electricity use, and growth in the use of renewable energy. Similarly, financialization or the increased share of economy's financial sector results in decoupling of economic growth from environmental degradation (Kovacic et al., 2018; Vadén et al., 2020).

The increase in financial intensity (financial assets per unit of gross value added) plays a crucial role in the reduction of energy intensity (per unit of GDP). Financialization gives rise to several rent-seeking practices that have enabled and stimulated the reorganization of production toward tertiarization and outsourcing (of industry to developing economies), which, in turn, lead to the relative decoupling of energy intensity and GDP (Kovacic et al., 2018).

Trade may also drive CO_2 emissions with heterogeneous and opposing effects that relate to various groups of countries. Although increased trade volumes may heighten emissions due to growth in manufacturing and transport, it can also have positive environmental effects via income growth, resulting in stricter regulations and lower domestic production of pollution-intensive goods (Briglauer et al., 2023). Nevertheless, the hypothesis of "pollution haven" implies that developing economies may be involved in the production of the most emission-intensive products because of dissimilarities in the environmental norms and regulations of developing and advanced countries. Although the ability to manufacture complex, eco-friendly goods is linked to decreased CO_2 emissions per person, green complexity also involves R&D, human capital and institutions, so this cannot be entirely attributed to the trade effect (Mealy and Teytelboym, 2022).

Regarding trade in ICT technologies, the emission-intensive large-scale manufacturing of digital devices, ICT-related waste disposal (digital devices' materials are not always

[10] The rebound effects occur when energy efficiency gains (due to technological innovations) result in decreased operating costs, causing consumers to save less energy than originally expected (Sui and Rejeski, 2002; Gillingham et al., 2016).

recyclable), and the mining of rare earth metals are located in large developing economies, such as China, India, and East Asian countries (Kunkel and Matthess, 2020). However, the extent of diffusion of digital technologies remains lower in developing economies, and thus, these do not fully experience the favorable enabling effects of digitalization's use (Lange et al., 2020). Although the obvious impact of population growth on the environment, since each person requires an energy to meet their primary needs, the related effects of urbanization and density of population are often contradictory and non-linear (Higon et al., 2017).

Recent and scarce empirical studies examine the influence of different ICT elements concerning their electricity consumption on CO_2 emissions. Most studies detect a negative relationship, meaning that the higher the intensity of digitalization use, the lower the overall CO_2 emissions. Remarkably, almost all studies employing data for developed economies reveal a negative relationship between the digitalization components and CO_2 emissions. However, the evidence for this nexus in less developed countries is mixed. These outcomes support the "pollution haven" hypothesis and demand further investigation.

Existing studies separately examine the relationship between digitalization and carbon dioxide emissions (Gong et al., 2020; Lange et al., 2020) and the nexus of technological inventions and CO_2 emissions (Churchill et al., 2019; Du et al., 2019). Dwivedi et al. (2022) combine the digitalization elements and technological innovation and investigate their joint impact on CO_2 emissions. Wang et al. (2021) find that technological innovation in the digital sector intensifies CO_2 emissions, while spillovers of digital technologies across industries and borders decreases carbon footprint.

Díaz et al. (2019) examine the mechanisms of energy intensity transformation and green-energy conversion that affect energy consumption and GDP growth using data for 134 countries for the period 1960 to 2010. The scholars detect a connection between higher energy intensity and lower growth of GDP per capita, and this relationship is valid for developed and developing economies. Hence, a reduction in energy intensity leads to higher economic growth globally. The transition from fossil fuels to renewable energy sources, that is conditioned by level of energy intensity, is positively associated with GDP growth. Further mechanisms influencing a country's energy composition and intensity can be detected, considering the degree of digitalization's penetration and its enabling effects (reducing energy intensity, promoting economic growth).

Lee and Brahmasrene (2014) use panel data of the ASEAN countries from 1991 to 2009 to show that ICT positively affects economic growth and CO_2 emissions. Using panel data of 142 developing and developed countries over the period 1995–2010, Higon et al. (2017) find a nonlinear inverted U-shaped relationship underlying ICT and CO_2 emissions, thus supporting the EKC hypothesis. Edquist and Bergmark (2024) explore the impact of mobile broadband on CO_2 emissions using panel data of 181 countries for the years 2002 to 2020, finding that a 10-percentage point increase in mobile broadband adoption caused an 8% reduction in CO_2 emissions per capita. However, this relationship was only significant for high-income countries.

The existing literature does not sufficiently address the digitalization effects on environmental sustainability despite appeals for research. There is thus a need for further exploration of the positive and negative environmental impacts of digitalization in differently developed countries globally, as environmental challenges are international in scope. In its recent policy, the EC (2020a, 2020b) focuses on the interaction between green and digital transitions, with an emphasis on digital technologies' beneficial effects that can address social and environmental issues.

Based on the above discussion, this thesis explores whether those countries with greater overall and environmental technologies' endowments benefit both directly and through the symbiosis of green and digital technologies. More precisely, the study contributes by estimating the nonlinear digitalization – CO_2 emission relationship as dependent on the time- and country-varying technological (incl. green-tech) R&D output level and by testing whether the positive environmental effects of digitalization outweigh the negative ones.

1.2 Techno-economic perspectives of carbon capture

1.2.1 Economic feasibility of carbon capture

CO_2 emissions, a major contributor to GHG emissions, are still growing globally despite countries' agreements and commitments to mitigate climate change (Crippa et al., 2023). For the EU27, CO_2 emissions are projected to decrease to 2.6 billion tons in 2023, 7.4% lower than in 2022 (GCP, 2023). Estonia is one of the few countries that has relied on oil shale (OS) in terms of electricity generation. On the positive side, the high OS consumption as a domestic fuel enhances the country's energy security. However, OS is a carbon-intensive fossil fuel, and OS-based electricity generation emits substantial CO_2 (Augutis et al., 2020), about 1 ton of CO_2 per MWh_e of electricity produced.

In 2018, when OS electricity production was high, Estonia was one of the three largest GHG producers in Europe, with 15.3 tons of GHG emissions per capita. From 2019 to 2021, Estonia's OS electricity generation decreased, as evidenced by its per capita GHG emissions of 9.6 tons in 2021, which decreased by a further 6% in 2022 (Crippa et al., 2023). In 2020, Estonia transitioned from being an electricity exporter to being an importer, and, on some days, it registered zero electricity generation using OS. Nonetheless, the 2021 global energy crisis, exacerbated by increased energy demand and elevated electricity prices, right after the COVID-19 pandemic peak, and Estonia's energy security concerns, has resulted in an increase of OS electricity generation and, in turn, growth in CO_2 emissions. Despite Estonia reduced its overall CO_2 emissions by 6.8% to 10.9 Mt CO_2 in 2022 (compared to 2021), the country's power industry increased CO_2 emissions by 5.2% (net GHG emissions in equivalent of CO_2) to 4.1 Mt CO_2, which is 37% of all emissions in Estonia (Crippa et al., 2023). For comparison, the same industry's share of CO_2 emissions was 51% of the country's emissions in 2018. Thus, to reduce GHG emissions in Estonia, it should focus on reducing CO_2 emissions from energy production.

The amount of electricity produced by the OSPPs largely depends on electricity prices on the Nord Pool market and the price of the European CO_2 allowance set for the EU Emissions Trading System (ETS). The ETS is one of the EU's main mechanisms to gain cost-efficient reductions in GHG emissions and achieve its goals under various commitments (e.g., Kyoto Protocol), with the ETS acting like a structure that internalizes negative externalities.

The energy transition is not only technological but also social and political, as practices and concepts developed within the fossil fuel-based energy system must be reconsidered from a low-carbon perspective (Höysniemi, 2022). Also, the integration of EU power markets faces challenges in terms of energy-supply security, the promotion of renewable energy, the reduction of emissions, and the decentralization of the production–consumption link, as they all demand improved national policies (Pepermans, 2019).

The EC introduced the REPowerEU plan in response to economic uncertainty and the turmoil in global energy markets provoked by Russia’s 2022 invasion of Ukraine and the sanctions imposed on Russian energy imports into the EU (European Commission, 2022c). The plan’s measures are focused on accelerating the introduction of green energy, enlarging EU energy supplies, and energy conservation. In response to high energy prices, in 2022, the EC (2019, 2022d, 2022e) adopted the “action plan on digitalizing the energy system”, to facilitate the EU’s energy policy objectives and the EGD by promoting transparent, cyber-secure, sustainable, and competitive market for digitalized energy services, ensuring data privacy, sovereignty and supporting investment in energy infrastructure (Benedetti et al., 2023). This plan indicates the considerable environmental, economic, and social benefits of the energy sector’s digitalization.

Since energy prices recently skyrocketed to record levels again (Nord Pool, 2024), the economic motivation for diffusing green and low-carbon technologies increased keeping in mind the environmental challenges. For instance, such high electricity prices and decreasing prices for photovoltaic (PV) panels motivate consumers to increase demand for PV panels (Paiho et al., 2023). Existing large heterogeneities across EU member states and high electricity prices remain the EU’s main challenges (European Commission, 2021). As a result, understanding the paths of price convergence and how national regulations impact the electricity prices’ harmonization is essential to design the EU energy, environmental, and climate policies (Saez et al., 2019).

1.2.2 Carbon capture possibilities in oil shale power plants

CC refers to the capture of CO_2 from a large source, such as an electricity production plant that uses fossil fuels (e.g., OS) as an input. There are approximately 40 operating commercial installations that already apply CC in electricity generation and other industrial processes (IEA, 2023b). The introduction of CC has occurred on a much smaller scale than initially expected, but its adoption has recently gained momentum. In the case of Estonia CC facilities can be installed on existing OSPPs, which can be modernized or retrofitted.

CC systems involve an extremely nonlinear and complex interaction of mass and heat transfer, chemical reactions, and thermodynamics (Lawal et al., 2009). Precise modeling of their behavior is computationally intensive, time-consuming, and demands progressive capabilities in process systems development. Digital and data-driven modeling employing ML, which is easier to perform, can accurately model and predict the utterly sophisticated underlying interrelations in CC systems with a decreased computational load (Wu et al., 2024).

Although considerable technological developments in the Estonian energy sector have recently led to decreased CO_2 emissions, further reductions are necessary under current EU policies. The EU strategy requires the development of CO_2 capture technologies, which can be technologically implemented in Estonian OSPPs. However, adding CC capacity to existing power plants will raise the cost of generated electricity and decrease efficiency. Introducing CC in OS energy generation would be financially feasible as long as the electricity produced remains competitive with that generated from other sources (and imported electricity via the EU’s Nord Pool power exchange).

Thus, a techno-economic analysis is necessary to identify the most effective CC technologies and estimate their implementation cost and competitiveness. The question to be answered is whether it would be technologically and financially feasible for Estonia to implement the relevant and effective CC technologies and to reduce carbon emissions in existing power generation facilities without compromising its reliable electricity supply. Doing so might facilitate keeping the electricity prices stable and decreasing CO_2 emissions while using the existing local advantages (accumulated knowledge, complexity, path-dependence, domestic energy) of OS based power generation.

The technical and economic assessment of retrofitting Estonia's OSPPs with CC is based on the introduction of two promising CC technologies: post-combustion capture (PCC) and oxy-fuel combustion (OXY). OXY and PCC have comparatively high technology readiness level (TRL) and can potentially be used in OSPPs. The study proposes an assessment of the deployment of CC technologies for the OS power generation units and conducts a comparative analysis of capture costs. This case study represents the first extensive evaluation of the integration of CC technologies into Estonia's OS energy industry. The study does not provide quantitative estimates of the comprehensive economic feasibility of integrating CC, but it addresses some crucial externalities.

1.3 Human-centered digital transformation

1.3.1 Digital divide

As the digital economy has developed, the digital divide has become an important and constantly evolving issue for organizations, policymakers, and scholars (Van Dijk, 2020)[11]. Manifestations of the digital divide can increase social inequality since they can damage the economic and social capital of individuals (Ragnedda, 2017); the ongoing digital transformation introduces social inequality as it does not offer everyone the same opportunities. The effective use of digital technologies is also considered a powerful tool for achieving the UN's Sustainable Development Goals (SDGs), particularly "Reducing Inequalities" (Goal 10) (United Nations, 2020). Thus, clear understanding of the digital divide phenomenon and its different perspectives is essential in identifying technological needs that can stimulate the development of more coherent policies. Presumably, Goal 10 of the SDGs is most impacted by digital technologies, as their skillful use can promote equality by providing access to important information (e.g., on education, training, and employment opportunities) and ensuring citizens' active participation in the economy and society (Lythreatis et al., 2022).

The digital divide is defined by level. The level-1 digital divide (digital access) refers to inequality in terms of access due to infrastructure and costs (Dewan and Riggins, 2005). Level-2 (digital capability) refers to inequality due to an individual's skills and knowledge (digital literacy) and technological capabilities (Hargittai, 2002; DiMaggio et al., 2004). Within this level of the digital divide, Van Dijk (2006) includes the inequalities in motivational access (associated with low self-efficacy, computer anxiety, or other psychological factors) that prevent people from using specific technologies. The level-3 digital divide (digital outcome) refers to outcomes, such as productivity and learning, that result from utilizing ICT and emerge from the digital capability divide (level-2) as well as additional contextual aspects (Wei et al., 2011).

[11] The digital divide is defined as inequalities in the access to and exploitation of digital devices and the Internet (Castells, 2002), in respect of the following: 1) material access to the Internet and personal computer (PC), 2) motivational access, an aspiration to have access, 3) skills access, or essential skills to exploit the Internet and PC, 4) usage access, or the length, variety and effectiveness of use (van Dijk, 2006).

Due to proliferation of digitalization, the digital literacy and skills[12] are now fundamental for labor market participation in practically all industries (Martin, 2006) and are twenty-first-century skills for communication, cooperation, citizenship, critical thinking, problem solving, productivity and creativity (Voogt and Roblin, 2012). Individuals' unequal living conditions improve moderately with economic development, but inequalities continue to affect their skills and performance even in countries with equitable conditions (van Deursen and van Dijk, 2019).

The nexus between inequality and digital technology advancement has been debated. For instance, technological innovation (incl. the Internet and e-commerce) can decrease economic and social inequality by introducing new employment opportunities, engaging marginalized communities in the global economy, and increasing productivity (Ambrogio et al., 2022; Suhrab et al., 2024). However, technological development can exacerbate socio-economic disparities, including access to technology (Bordot, 2022). Thus, individuals with better access to digital technologies have an advantage in acquiring new information and skills, which increases their employability and income. However, this transition has also reduced job opportunities for low-skilled workers due to automation and digitalization, leading to their displacement and rising unemployment.

The digitalization's effects on inequality and the digital divide are largely explained by government regulations, socio-demographic and socio-economic determinants (such as income, age, gender, educational attainment level, ethnicity, and level of urbanization). These factors are influential not only in technology adoption (Niehaves and Plattfaut, 2014) but also in determining the level-2 (skills) (Hargittai, 2002) and level-3 (outcomes) digital divide (Scheerder et al., 2019; Hidalgo et al., 2020). However, research does not consistently disclose the contextual relationships implicated in this divide (Scheerder et al., 2019). The level of educational attainment of individuals and that of their parents positively impacts their ability to tackle complex digital-related issues, controlling for age (Gui, 2007).

Studying the factors that determine the digital divide may help resolve this inequality. For example, studies find that the relationship between digitalization and agility is essential. One of the main factors determining agility is the level of digitalization of a country or industry (Škare and Soriano, 2021); also relevant are digital competencies at the individual (Seale et al., 2010) and the workplace level (Breu et al., 2002).

The COVID-19 outbreak brought the digital divide to the forefront, with emergence of a new order, in which humans without adequate Internet access and digital skills faced isolation and suffered other disadvantages (De' et al., 2020). During the pandemic, government agencies and organizations expressed concern regarding the deteriorating digital divide, which became life-threatening as many people were forced to work, study, access services, and communicate from home (United Nations, 2020).

The rates of adoption of basic fixed broadband connections reached almost 100% at the EU household level (European Commission, 2022a), meaning that coverage and adoption rates are now largely equal. However, a substantial gap remains between the rates of coverage and adoption for more advanced fiber-based broadband connections, with the share of adopted to accessible connections (i.e., adoption rate) remaining below 50% in many developed economies (European Commission, 2022a).

[12] Digital skills are defined broadly as the ability to solve ICT issues (Claro et al., 2018), or to utilize and take advantage of digital technologies (Aydin, 2021).

Existing research on the digital divide addresses the impact of digitalization on employment in different ways, with particular attention to the development of economic and social inequalities that disadvantage older and less digitally educated people (Codagnone, 2009). Therefore, it is essential to better understand the trajectories of the adoption and use of digital technologies in society and organizations to better identify their effect on inequality, productivity, and labor market outcomes (Ciarli et al., 2021).

1.3.2 Digital transformation of the labor markets

In response to COVID-19-induced restrictions, organizations and labor have been advanced further towards digital forms (Baptista et al., 2020). The evolution of digital and workplace technologies recently has led to the hybridization of their use with human activities, forming complex human-in-the-cycle or meta-human structures as new forms of sociotechnical systems. This challenges researchers to identify the profound impacts of workplace technology and the emerging human–technology configurations and understand their strategic implications.

As with earlier technological advances, analyzing the long-term and aggregate impacts of digitalization on employment is a challenging endeavor. Today digitalization is an even more complex phenomenon in terms of its measurement and conceptualization (Calvino et al., 2018). It also affects employment in different ways depending on the institutional and industrial context: firms and sectors differ by various organizational and technological aspects; economies are distinguished by disparate labor market policies, structures, and macroeconomic conditions (Calvino and Virgillito, 2018; Evangelista et al., 2014). Because modern digital devices are more technologically advanced and "smarter" than their forerunners, it raises concerns that this technology will cause mass unemployment. Digital technologies allow machines to perform assigned tasks, which are cognitively complicated for humans, increasing the likelihood that the latter will be displaced in a growing range of positions and tasks. For employees, the danger posed by digital technologies is far-reaching, enabling to automate the entire stages of manufacturing processes or to disintegrate them into sub-tasks (Cirillo et al., 2021).

Data-intensive technologies advance rapidly due to increased computing power and can be integrated in ways that facilitate new applications (Henfridsson et al., 2018). Such re-combinations and the evolution of task-specific software and devices make it possible to employ digital technologies to innovate further (Zittrain, 2008). An employee's individual tasks are essentially separate fundamental units that can be modified or replaced using digital devices, and a job can be defined as a set or "bundle of tasks" (Autor et al., 2003). The switch in research focus from skills to tasks has led to a shift from skill-biased to the routine-biased technical change (from SBTC to RBTC; Acemoglu and Autor, 2011)[13]. Occupations that contain tasks requiring a greater degree of complex thinking and creativity encounter much lower risk.

More recent literature shifted the focus to digitalization's long-term impacts on economic growth. Following Brynjolfsson and McAfee's (2014) prominent work, the scholars have considered the features of current technological shift, referring to the potentially large-scale impact of digitalization on employment (Balsmeier and Woerter, 2019). The main difference from earlier technological advances is the number of tasks

[13] The RBTC hypothesis states that professions that exhibit a high proportion of repetitive and programmable tasks (a series of instructions that a machine can understand and execute) face a greater risk and opportunity of being fully automated (Acemoglu and Autor, 2011).

that digitally enabled devices can now perform, some of which were formerly the exclusive domain of humans. In investigating the influence and relevance of digitalization, a key empirical issue is how digitalization is defined and measured.

The SBTC hypothesis (Acemoglu, 2002) claims that technologies (incl. digital ones) and machines compete with humans as performers of tasks or factors of production. SBTC suggests that digital technologies have differentiated impacts on marginal labor productivity depending on the qualifications and skill level of the workforce. Recent (digital) technologies are expected to complement high-skill jobs (due to the cognitive skills associated with the use of digital devices) but are assumed to displace those in mid- and low-skilled jobs. Also, skilled (i.e., more educated) employees are expected to be more flexible when job assignments change and better able to master digital technologies, resulting in increased productivity. For such workers, digital technologies free up time from repetitive tasks and provide additional resources for completing abstract and creative tasks. Hence, workers in medium- and low-skilled jobs face a greater risk of being replaced, as their skills are less complementary to digital technologies. This hypothesis (e.g., Michaels et al., 2014) explains the long-term changes in the structure of employment observed in most industrialized countries since the 1980s, and the increase in the proportion of highly skilled workers in the labor force.

Unable to fully explain the dynamics of employment (and wage) polarization, SBTC has recently been replaced by an RBTC approach that focuses on the tasks of workers, a target of the technology-based labor-saving process. This approach ranks positions according to their relative proportion of routine tasks rather than in terms of overall skill requirements. In proposed RBTC hypothesis Autor et al. (2003) argue that ICT development is biased towards substituting routine tasks (both cognitive and manual) that are repetitive, standardized, easily codified, and at greater risk of being replaced by labor-saving technological changes.

The empirical evidence on the impact of digitalization on employment is mixed. This is mostly the result of heterogeneity in the level of aggregation and the type of digitalization indicator employed. However, most investigations agree that digitalization exhibits beneficial effects on employment. Early studies examine the impact of broadband Internet access on employment and find that broadband access is positively linked to employment dynamics (e.g., Atasoy, 2013; based on US data). Biagi and Falk (2017), addressing a resembling question, find that overall ICT growth did not result in jobs decline, and the use of enterprise resource planning (ERP) applications and websites (as a digitalization proxy) has a positive effect on employment in Europe. Balsmeier and Woerter (2019) employ Swiss firm-level data on investment in digital technologies (e.g., ERP, robots, 3D printing, IoT) and detect that digitalization leads to an increase in high-skilled jobs and a decrease in low-skilled employment. Autor and Salomons (2018) explore the technological innovation's impact on employment and productivity in various industries of advanced economies. The authors emphasize the innovation's (automation) negative direct impact in own-industry (where it originates) and the positive and compensating indirect effect on employment in other industries. Cirillo et al. (2021) find (based on Italian data) that the digitalization's influence on employment is mediated by the extent of routineness that characterizes the tasks concentrated in each occupation. Specifically, they detect that the digital technology use is more intensive among those in high-skilled professions (e.g., software developers, scientists, technicians) and markedly less so among those in low-skilled occupations (e.g., waiters, construction and delivery workers). Therefore, the extant empirical evidence appears to support the proposition that digitalization has a beneficial effect on employment, at least at the macro level.

1.4 Green and digital twin transition: Challenges and policy implications

1.4.1 Challenges of decoupling economic growth from carbon emissions

The concept of "production capabilities" appears in the development and growth literature. In terms of development, capabilities are often regarded in relation to the technologies, infrastructure, productive knowledge, and institutions that allow an economy to increase productivity and growth rates (Sutton and Trefler, 2016). Production capabilities can be treated similarly, but with a specific focus on the capabilities linked to the green economy (Mealy and Teytelboym, 2022). A country tends to expand into economic activities where it has existing production capabilities and is already proficient (Hidalgo et al., 2018). A country will struggle to instantly diversify from producing an established product to an unrelated new product as it would have to accumulate novel production know-how and invest in entirely new production factors. This then suggests the "relatedness" and path-dependent nature of development (Aghion et al., 2016).

Evidence confirming this dependence in the process of knowledge acquisition is reported for different activities. Studies have considered the relatedness underpinning various technologies by researching patent citations (Rigby, 2015) and the classification of technology patents (Kogler et al., 2017) and by investigating the flow of employees between industries (Neffke et al., 2017). However, despite requests from policymakers to identify more sustainable and greener development programs, only a few studies apply the concepts of economic complexity and relatedness to advance the transformation to a green economy.

Technology adoption and innovations' output are lower in regions and countries, where economic knowledge is scarce, since new knowledge, even if reflected in patents, has a vital tacit element. The externalities of this knowledge are limited by space. Although the cost of information transfer has decreased substantially as digital technologies have advanced, the marginal costs of transferring new technological knowledge are lower when the social interactions between producers and users are frequent (Audretsch and Feldman, 2004).

Pre-existing regional knowledge base and specialization in green technologies is suggested to impact existing and future specialization in green technologies, a process that is defined as incremental and path-dependent (Montresor and Quatraro, 2020). However, green-tech development relies on previous green and non-green technologies. Existing studies imply that firm-level technological capacity can facilitate the reduction in emissions. Sectors that generate more green-technology-related inventions also reveal better environmental efficiency (Ghisetti and Quatraro, 2017).

Considering the accelerated transformation to an energy-efficient and carbon-free economy, research examines both aspects of the twin transition. These include factors facilitating the impact of technology (Reichardt et al., 2016), and policy instruments impacting technological advancement (Stevens et al., 2023) and the energy industry's innovations (Costantini et al., 2017). Also, renewable energy policies contribute to green innovations, and show greater effectiveness in economies with stronger green innovation capabilities (Yang et al., 2022).

The twin transitions embodied in the EC (2023b) strategies like the EGD, and the Digital Decade help to boost growth and innovate the EU economy. Over the past two decades, the EU's economy has grown by more than 61%, while CO_2 emissions have decreased by 28%, indicating an evident decoupling of growth from emissions. The introduction of digitalization in industries will make an even greater contribution to more efficient, sustainable, and eco-friendly production. For instance, firms that already invest in big data-driven innovations increase productivity about 5% to 10% faster than those that do not. Many EC programs (e.g., the Recovery and Resilience Facility) support the twin transition, with 35% of total EU expenditures dedicated to achieving climate goals.

Keeping in mind the ecological sustainability goals, the empirical evidence on environmental decoupling is scarce (Vadén et al., 2020). Also, the notion of decoupling requires specification and precision when employed in policy development. Decoupling as a principal strategy to integrate environmental and economic goals should be considered with a high degree of risk regarding the common future of humanity (Antal and Van Den Bergh, 2016). Furthermore, it is necessary to develop those conceptualizations of the economy that are not based on economic growth as the main path to human well-being and environmental sustainability. The evidence suggests that decoupling regarding environmental sustainability does not occur on a global level. There is evidence of the environmental impact decoupling regarding GHG emissions in developed countries for specific periods, but no evidence on continuous economy-wide decoupling. In many cases even re-coupling can be observed (Vadén et al., 2020).

The rise in global CO_2 emissions must be reversed (not just slowed) to ensure climate conditions remain at a safe level for human activity (Vadén et al., 2020). Therefore, global and continuous absolute economy-wide environmental decoupling is required[14]. Even if it is difficult to attain this type of decoupling (compared to, e.g., sectoral or product environmental decoupling) immediately, it should still be a goal, since its achievement truly reflects the SDGs, including ecological development. Also, fast climate change mitigation measures, such as replacing existing fossil fuel energy facilities with a renewable energy system, can lead to environmental imbalances (threat to ecosystems).

1.4.2 Social challenges of digital and technology transformation

Policymakers aim to increase per capita income while eliminating inequality and ensuring environmental sustainability (Marco et al., 2022). With the focus of EU policy on synergies between the digital and green transitions, digital technologies will contribute to solving social and environmental issues. A successful digital and green, or twin, transition requires a workforce with the necessary skills (where the EU is already facing skilled labor shortage) for companies to enter advanced industries (European Commission, 2023b). It is, therefore, crucial to provide needs-based learning opportunities and for firms and government agents to recognize those skills and qualifications acquired and create an environment that is attractive to employees to apply their skills to high-quality work.

Also, complex products (incl. digital goods) involve highly skilled workers, principally located in the wealthiest regions, with high wages (Marco et al., 2022). On the other hand, generally, people with advanced skills value the opportunity to earn a high income

[14] Absolute decoupling indicates improved environmental quality (CO_2 emissions reduced), while the economy is growing.

over an equal income distribution and tend to pay for a clean environment. However, despite the positive association between economic complexity and income equality at the country level (Hartmann et al., 2017), the inverse relationship can occur across regions (Balland et al., 2019).

Progress in digital technologies and infrastructure of the Internet provide an opportunity to collect data in large volumes and in real time. Organizations and firms are developing “digital twin” technology, which allows for a precise digital modeling of an object or system (Bauer et al., 2021). This technology allows for more effective planning and forecasting necessities, downtime, and disasters. Also, digital twins can considerably improve the efficiency of CC processes (e.g., R&D, optimization, integration with renewable energy). The EC (2023b) is elaborating a digital twin model of the Earth (Destination Earth) to simulate natural phenomena.

In a study of the coronavirus and climate change crises, Markard and Rosenbloom (2020) claim that the disruption of the COVID-19 and related recovery policies should be seized as a unique possibility to speed up the transition to sustainable, low-carbon economies and lifestyles. However, it takes time for the full impact of socio-technical transformation to manifest.

Ongoing investments related to intelligent technologies (incl. AI) and automation are mostly motivated by opportunity to reduce the costs, and the employers are attracted by the prospects of income growth without the need to raise wages and employ more people (De Cremer et al., 2022). If these cost-cutting attempts are not coupled with investments in human upskilling and retraining, where people’s actions, capabilities, and interests are nurtured and enhanced with the support of technology, then intelligent technologies may entail the harm. The obsessive search for technological solutions to optimize efficiency and maximize productivity will prioritize investments in innovations that mainly serve the interests of those designing and disseminating intelligent technologies. Following such a path will lead to a technologically regulated society that serves the interests of machines and their developers rather than humankind at large. Another vital consideration is the impact of technological development on wealth distribution. The concentration of wealth among a few individuals who control and exploit new technologies contributes to widening wealth and income inequality (Suhrab et al., 2024).

2 Research Questions and Hypotheses

Today, digitalization encompasses nearly all economic and social fields, with diverse countervailing effects at the macroeconomic, sector, and consumer levels on electricity consumption (immediate impact) and then on CO_2 emissions (Danish et al., 2018). As of 2020, the CO_2 emissions from the ICT sector represent as high as 2.1–3.9% of total global emissions and are projected to increase without intervention (e.g., policy-related, industrial efforts; Freitag et al., 2021). This proportion can be compared to that of the aviation industry, which accounts for around 2.5% of global annual CO_2 emissions and has been heavily criticized for its adverse environmental impact (Klöwer et al., 2021).

Despite the numerous favorable environmental impacts, digitalization also has counteracting effects, for example, efficiency gains obtained via technological development might be offset by increased electricity demands and corresponding growth in CO_2 emissions with the increased manufacture, exploitation, and disposal of digital equipment.

Thus, based on the reasoning above, **Article I** addresses the following research questions: (1) what effect does digitalization have on CO_2 emissions? and (2) does the degree of this effect depend on the level of technological development as an R&D output? The author answers these questions employing a panel-based non-linear PSTR approach at the macroeconomic level to provide a robust estimate of the relationship of digitalization, human capital, economic development, and CO_2 emissions, moderated by technological patent progress, based on a sample of diverse high- and middle-income economies.

Therefore, the following hypothesis is proposed to test this non-linear, inverted U-shaped nexus between digitalization and CO_2 emissions as moderated by R&D output level:

Hypothesis 1: Progress in digital inclusion has crucial socioeconomic significance and an important environmental effect; that is, in a low R&D output regime digitalization entails an increase in CO_2 emissions, but in high R&D regime, digitalization decreases CO_2 emissions.

The development and adoption of digitalization through stimulating R&D activities and technological structural change in the economy can abate CO_2 emissions (Lahouel et al., 2021). R&D expenditures (R&D inputs) positively correlate with innovative technological patents (R&D outputs) and are crucial for reducing energy intensity and increasing renewable energy supplies (Fernandez et al., 2018; Alam et al., 2021). Technological patents have heterogeneous and direct reducing effect on CO_2 emissions and moderating effect, lowering carbon emissions by impacting economic development (Cheng et al., 2021). Existing studies pay little attention to R&D output (measured in technology patents), which serves as a transmission instrument driving the heterogeneous impacts of digitalization on CO_2 emissions globally in a nonlinear PSTR setup. Only Ma et al. (2022) examines the mediating effect of R&D investment in the nexus between the digital economy and environment, based on Chinese provinces from 2006 to 2017. While Ma et al. (2022) assess the moderating role of R&D as an interaction term, this study estimates a smooth shift in R&D regimes that drives digitalization's impact on carbon emissions. This leads to the second hypothesis of the study:

Hypothesis 2: The level of R&D, measured by the number of technological patents per country inhabitant, drives the countries' transition from environmentally polluting and economically advancing regime to sustainable and innovative economic regime.

Article II considers the need to transition from fossil fuels to low-carbon energy systems to address the intensified climate crisis. As demand for electricity continues to grow over the coming decades, CO_2 emissions from power plants will remain a major challenge to the sustainability of the electricity industry (Vu et al., 2020). Carbon capture technologies (including those related to OS power plants) and their implementation are thus essential to achieving sustainable development.

Retrofitting OS power plants by integrating CC technologies will be financially feasible until the electricity generated by those CC-equipped OSPPs is competitive with electricity produced from alternative sources (including imported electricity). Thus, a techno-economic evaluation is necessary to identify and estimate the cost of the technologically most promising CC alternatives in OS electricity generation. This assessment is helpful in considering electricity's competitiveness when produced by OSPPs utilizing CC technology. Based on the discussion related to CO_2 capturing possibilities in OS power plants, the following hypothesis is proposed:

Hypothesis 3. Implementing the most efficient and technologically feasible post-combustion and oxy-fuel combustion CC technologies in retrofitting existing OS power plants in Estonia is more cost-effective compared to the combined CO_2 emission allowance and environmental charges.

With respect to **Article III,** the literature on the digital divide offers a different perspective on the impact of digitalization on employment, focusing on the development of new types of social and economic exclusion that disadvantage older people and the digitally uneducated workforce (Codagnone, 2009). This literature reveals that access to digital technologies and skills in their use influence employment outcomes throughout the life cycle, affecting a range of decisions related to the labor market. These include, for example, the assessment of opportunity to participate in the labor market, the probability of getting employed (Codagnone, 2009), the probability of losing a job (Aubert et al., 2006), early retirement opportunity (Schleife, 2006), the duration of employment (Silva and Lima, 2017) and the employment contract (Aubert-Tarby et al., 2018). Therefore, it is necessary to determine whether individuals with higher digital skills, better access to digital technologies (Internet) and higher education are more likely to be employed and whether the COVID-19 adjusted these relationships.

The interactions of the key variables with the coronavirus infection rates and governmental containment stringency are expected to reflect the digital skills–employment nexus moderated by the COVID-19. More advanced digital skills and greater broadband Internet access as well as higher level of educational attainment are expected to improve individual's employment outcomes. Therefore, the following hypotheses are proposed:

Hypothesis 4. The interaction of digital skills (broadband Internet access) with the regions' COVID-19 infection rate and containment measures increases the probability of employment.

Hypothesis 5. The onset of the COVID-19 pandemic reshaped the digitalization–employment nexus, improving employment outcomes resulting from broadband Internet access, especially the likelihood of individuals' retaining non-manual work.

Hypothesis 6. Digital skills positively impact non-manual employment outcomes at the higher levels of education, as the more advanced digital skills provide the greatest probability of employment and of getting a more skill-intensive occupation.

Hypothesis 7. The COVID-19 outbreak induced the greatest relative improvement in employment outcomes among individuals with entry-level digital skills compared to those who are digitally illiterate, and a reduction in the advantage of those with higher level of digital skills.

Hypothesis 8. The within-household spillover effects resulting from members with tertiary education enhance employment outcomes in the post-COVID-19 period.

3 Data and Methodology

Article I investigates the relationship between digitalization and CO_2 emissions at the country level. This relationship assumes the involvement of moderating R&D output, or knowledge creation and technology development (Audretsch and Feldman, 2004), and its implications for environmental quality.

In addition to economic and political determinants, technology is widely regarded as the key factor in the anthropogenic impact on environmental quality (Higon et al., 2017; Briglauer et al., 2023). Other environmental drivers include income level, human capital, renewable energy consumption, R&D (incl. technology patents), the structure of the economy, and the quality of institutions (Bianchini et al., 2023). With some exceptions, most of these exogenous variables reveal nonlinear and ambiguous effects on CO_2 emissions. The EKC relationship reflects the considerable effect of technological advancement after a specific turning point or threshold in income growth, explaining the decoupling of economic development from environmental degradation. Further investigations reveal that for specific pollutants and industries, this relationship can be N-shaped; however, these cases reinforce the contributing effect of technology (Pata et al., 2023). The study applies PSTR estimator, with the nonlinear effects expressed via the transition function that includes R&D output-driven interactions.

However, the studies addressing the EKC nexus have mixed outcomes, which may also be due to measurement issues. Some studies employ linear quadratic polynomial models, which cannot identify more complex nonlinearity forms and are not flexible (Aslanidis, 2009; Aydin et al., 2019). Standard estimators for panel data (e.g., fixed, or random effects) cannot cope with biases from cross-sectional or dynamic heterogeneity in coefficient estimates (González et al., 2017). To treat these issues, Article I uses a nonlinear PSTR estimator (González et al., 2005).

Applying the flexible PSTR estimator to the complex nexus of R&D, digitalization and CO_2 emission necessitates a large and fairly long panel of country-level data that control for human capital, GDP, green energy use, manufacturing value added, and government efficiency to avoid omitted variables bias in CO_2 impact estimates (Aslanidis and Xepapadeas, 2006). The specification of the model is based on particular assumptions tested and confirmed on a balanced panel of 18 middle-income and 37 high-income economies from 1996 to 2019. This period starts with the explosive expansion of the commercial Internet and ends before the disruption of the COVID-19. Also, the incorporation of middle-income economies that have achieved rapid economic progress and productivity growth in recent years due to ICT (Dedrick et al., 2013) and their concomitant increase in the use of fossil fuels, helps test the EKC nexus. Countries in the sample are selected based on data availability and their universities being ranked (by Quacquarelli Symonds University Rankings) among the world's top 1,000, which reflects a country's R&D development potential. Some studies address the ICT implications for abating CO_2 emissions on a regional level, but the comparative analysis of environmental impact must be performed at the global level (Vadén et al., 2020).

The dependent variable is CO_2 emissions from fossil fuels and the cement industry expressed in tons per capita (Friedlingstein et al., 2022); it acts as a proxy for sustainability and captures major environmental effects that are of prime concern to policymakers. The R&D output measured in technological patents per million inhabitants is selected as a transition variable, which should also be time-varying and continuous (Colletaz and Hurlin, 2006). This variable allows the more extensive assessment of countries' technological innovations and public policies (Yii and Geetha, 2017) and has sharper linearity test results (part of the PSTR framework). Since the error term in the PSTR model specification is not correlated with the selected transition variable, the exogeneity condition is satisfied. Primarily, the empirical studies, including at the macro-level, confirm the value of technology and innovations in reducing carbon emissions, (Du et al., 2019; Ganda, 2019; Hashmi and Alam, 2019; Salman et al., 2019; Töbelmann and Wendler, 2020). Many of these investigations measure technology development through patent applications, suggesting that, despite their limitations, they are a reliable indicator of the inventions' production and dissemination (Hall et al., 2001; Acs et al., 2002).

Existing empirical studies mostly measure only one or very few elements of the digitalization ecosystem, and these are insufficient to properly capture the effects of this complex ecosystem. A more comprehensive measure of digitalization is employed to address the research question. More specifically, the underlying heterogeneity of digitalization is specified as an index reflecting the principal stages of technology advancement and consists of five major elements (Lee and Brahmasrene, 2014): (1) fixed telephone, fixed broadband, and mobile cellular subscriptions; (2) individuals using the Internet (incl. data centers, content provision); and (3) personal computers (consumer devices and equipment). Digitalization effects rely on human capital, which is the driving force of technological progress (Cakar et al., 2021). An educational level index captures this and partially digital literacy and includes two indicators – average and expected years of education (Higon et al., 2017; Haini, 2021). The estimation model also contains GDP per capita in real terms to test the EKC relationship and renewable energy consumption as a share of total energy use; the use of renewables does not directly cause pollution, unlike the exploitation of fossil fuels in power plants (Lange et al., 2020). The model also includes manufacturing value added (as a share of GDP) to address the "composition effect" of the EKC nexus (Chen et al., 2019) and the government efficiency index to reflect the policies implemented that can improve environmental sustainability (Tamazian and Rao, 2010). According to the model specification (González et al., 2017), all control and exogenous variables are included with their lagged values ($t-1$).

PSTR models (González et al., 2005) are elaborated as an extension of Hansen's (1999) threshold time series regression (PTR) that enables only a small number of regimes, between which the estimated parameters shift sharply (Aydin et al., 2022). This is not consistent with evidence of the nexus between digitalization and CO_2 emissions, which advances smoothly. In contrast, PSTR models treat heterogeneous panels, allowing regressor coefficients to vary over time and across observations in several regimes that shift smoothly, thus providing more flexibility (González et al., 2017). PSTR estimates the threshold level endogenously without subjectively (and in advance) determining the regime switch (Aydin et al., 2019). The balanced panel data structure allows the use of fixed effects to detect unobserved heterogeneity at the country level. The PSTR estimation framework includes three stages: model specification, estimation, and evaluation. The Lagrange Multiplier linearity test (Colletaz and Hurlin, 2006; González et al., 2005) is based on the transition variable, has heteroskedasticity and autocorrelation consistent (HAC) versions and determines whether to continue with the linear model (null hypothesis) or to apply PSTR (alternative hypothesis) when testing for two regimes. The sign of the regression coefficients is essential and reflects increasing or decreasing CO_2 emissions' effect driven by the transition variable since these coefficients cannot be explained in a conventional way (Colletaz and Hurlin, 2006). The PSTR model is estimated using heteroscedasticity and a cluster-robust covariance estimator that accounts for heteroskedasticity in standard errors (Cameron et al., 2011). The nonlinear least squares method estimates the PSTR model parameters, utilizing the within-transformed form that tests for unobserved heterogeneity.

Article II estimates the financial cost of implementing CC technologies in existing Estonian OS power generating plants. An estimate of the average incremental cost per ton of CO_2 captured at each OSPP retrofitted with CC technology is compared with the same plant without implementing CC. CO_2 capture becomes financially feasible when the cost of integrating CC is less than the CO_2 emission allowance and environmental fees incurred without CC. The average incremental cost per MWh of electricity generated by an OSPP integrated with CC technology is then contrasted with the electricity cost of the same CC-free power plant to clearly identify the increase in electricity unit cost caused by integrating the CC technology.

Substantial differences are identified and examined in various studies concerning the cost estimating aspects for CC deployment: cost constituents, assumptions, scope and scale of CC projects, characteristics of definite CC technologies and power plants, geographical and time-related conditions, and terminology (Rubin, 2012). This study presents cost estimates (in 2021 euros) for retrofitting Estonian power generating units with CC using the two technologically feasible alternatives – PCC and OXY.

The methodology used for these assessments relies on the concepts underlying the prevalent levelized cost of electricity (LCOE; Rubin et al., 2013) as a time value of investment, operating and maintenance (O&M) as well as fuel costs per unit (ton of CO_2 captured or MWh of electricity generated). In addition to CC costs, the estimation of LCOE demands reliable data on production costs (not publicly available), electricity sales volumes, and CO_2 emission allowance prices in the future. Thus, to avoid uncertainty (and unfounded assumptions), this study compares the average incremental cost per ton of CO_2 captured (and per MWh of net electricity generated) from an OSPP integrated with CC technology with the same plant without CC technology rather than estimating the LCOE. Unlike an LCOE assessment, this methodology only requires a cost estimate for the initial year of operation. This method enables relevant and consistent estimates of the financial costs of implementing CC in OSPP because it is evidence-based.

The average annual cost of one captured ton of CO_2 (2021 €/tCO_2) (cost per MWh of net electricity generated in 2021 €/MWh) includes investment-related, O&M, and fuel-related costs and is assessed using 2021 as a base year. The investment cost of retrofitting covers the technical parameters and scale of the power units considered. Investment costs are then converted to capital costs by calculating annuity payments over the useful life of the CC installations once a proper discount rate is determined. O&M costs include chemicals, labor, and maintenance costs. The fuel cost represents the energy required for the CC process, i.e., the revenue lost from the unsold electricity due to energy use in the CC process. The tons of CO_2 captured annually by CC technology in the OSPP (and the annual net electricity produced in MWh) are then obtained.

The estimation of the capital costs assumes that the installation of CC technology would take around one year (Jilvero et al., 2014), and the CC equipment's maximum useful life is 24 years (Kuramochi et al., 2013). CC investment costs (with installation) at a comparable reference plant (RP) are calculated based on data from the Department of Energy (DOE)/National Energy Technology Laboratory (NETL) reference cases (S22A, S22F, L22A, and L22B; Black, 2011; Matuszewski, 2010), which are adjusted for the technical parameters of the Estonian PP units. These costs are then scaled to correct for the production capacity of the regarded PP (based on the production capacity of the RP) using the exponent (with the range of 0.61–0.69 for OXY technology and 0.43–0.77 for PCC technology) and depending on the equipment type, as proposed in Guandalini et al. (2019) and the DOE/NETL reference cases (Matuszewski, 2010; Spek et al., 2017). The cost of CC equipment corresponding to the technical parameters of the existing PP units reported in 2007 U.S. dollars for the DOE/NETL reference cases (Black, 2011; Matuszewski, 2010) is converted into euros based on the exchange rate from the European Central Bank (ECB, 2023). These costs are then adjusted to 2021 values (from the RP values of 2007) based on Eurostat (2022) price indices for comparable industrial equipment and its installation.

The discount rate, *r*, is selected as the unleveraged cost of equity (due to the specificity of local income tax system). This study uses an *r* valuation model based on an incremental approach (Butler and Pinkerton, 2006) that includes the risk-free rate of return, market risk premium, Estonian risk premium, beta multiplier representing systemic risk, liquidity premium, and project-based risk premium. Since the company potentially integrating the CC technologies (the state-owned Eesti Energia AS) is relatively large, the risk premium for a small company is omitted. Based on the values from existing literature, the discount rate averaged approximately 9% (pre-tax discount rate; Climate, 2021).

As for the O&M costs, the labor, maintenance, and chemicals costs are estimated, whereas cooling water and additional costs are considered relatively minor. The DOE/NETL reference cases S22A, S22F, L22A, and L22B (Black, 2011; Matuszewski, 2010), all of which involve coal-fired power plants (RPs) in the US, are used to model labor, maintenance, and chemical costs (in 2007 U.S. dollars). Adjustments are then made to technology and scaling, e.g., for labor costs, a scaling factor of 0.65 (Guandalini et al., 2019) is used for both technologies. The costs are then converted to 2021 euros using the corresponding labor costs, chemical production, and equipment-repair price indices from Eurostat (2022), the U.S. Bureau of Labor Statistics (2019), and Statistics Estonia (2019, 2022).

Since all CC equipment will potentially be installed into existing OSPPs, the electricity cost of CC equipment reflects the loss of production efficiency (electricity sales) due to the addition of CC and is assessed to be about 0.3 MWh/tCO_2, depending on the OSPP unit and CC technology installed with an assumed capacity factor of 85% (i.e., operating at full power for 85% of the total number of hours per year). The average Nord Pool electricity price of 86.7 €/MWh for the Estonian price region in 2021 is used (Nord Pool, 2022). The high volatility of Nord Pool's electricity prices is addressed in the sensitivity analysis.

The study examines two scenarios. The base case (1) assumes that the OSPPs operate at full capacity for 85% of the hours annually, accounting for scheduled maintenance and the CC technology's expected 24-year lifespan. The alternative scenario (2) suggests that CC technology is applied to electricity production at full capacity for 42.5% of annual hours (half of the 85% capacity). Scenario 2 is elaborated to show what happens when OS electricity is competitive in the market only half of the time, following real historical patterns (Climate, 2021). The estimation results are sensitive to changes in input values, including the use of CC technology at partial capacity (fewer than 24 years), which would result in a substantial increase in the cost of capturing each ton of CO_2.

The literature related to **Article III** primarily defines digitalization as the simple implementation or acquisition of particular ICT technologies (software, hardware). For instance, Autor and Dorn (2013) consider the effect of investment in ICT capital, while Acemoglu and Restrepo (2018) assess the impact of robots' use on employment. However, the use of these digitalization proxies is, in most cases, driven by data limitations. Detecting a consistent and comprehensive indicator that can capture the main characteristics of phenomenon as complex as digitalization remains a difficult task. Organizations are nevertheless addressing this issue. For instance, in recent years, Eurostat has surveyed ICT use and collected data on a wide range of ICT-related activities performed by individuals and households. Such data represent an extensive source of information for assessing the economic effect and relevance of digitalization, even at a very granular level.

Article III that investigates digital skills effects on employment dynamics, utilizes a unique micro-data set from the Community Statistics on Information Society (CSIS) provided by Eurostat in the form of pre- and post-COVID-19 survey rounds (for 2017, 2019, and 2021). This dataset covers the 26 EU member states and Norway. CSIS categorizes those aged 16 to 74 years old into households that provide household-level data on size, Internet access, and location, which are supplied at the nomenclature of territorial units for statistics (NUTS), or country level for 14 countries and the NUTS1 (region) level for the remaining 13 states, or 56 regions. At the individual level, the survey covers data on gender, age, level of educational attainment[15], employment state, and occupation groups[16]. Skills constitute the basic dimension for the ISCO classification, and this allows to examine a single distribution function of occupational statuses as depending on skill specialization (digital skill level), skill level (education level), and work preferences (individual and family characteristics) in four segments. Occupational status is treated as an ordinal variable that ranks individuals into four categories: (1) not participating in the labor market (lowest); (2) manual workers (ISCO levels 6–9); (3) non-manual employees (ISCO levels 0–5; non-ICT professionals); (4) ICT experts (by ISCO subcategories).

The CSIS microdata are then merged with Eurostat statistics at a more granular (NUTS1) regional level on the digitalization infrastructure (Internet's broadband coverage rate), tertiary education and the rate of unemployment. The data on cumulative coronavirus infection rates are obtained from the COVID-19 European Regional Tracker, which is subnational data for 26 European states (Naqvi, 2021). The pandemic data are then merged with the CSIS dataset at the regional NUTS1 level[17]. Comparative statistics on governments' efforts to contain the COVID-19 pandemic, aggregated at the country level, are obtained from the Oxford COVID-19 Government Response Tracker (OxCGRT) database (Hale et al., 2021). The estimations consider the impact on employment of national policy measures to contain the spread of COVID-19 using the 2021 Stringency Index and the Economic Support Index (as a control). The nexus between digitalization and employment dynamics is examined in Article III by focusing on individuals aged 25 to 54 who are either employed, self-employed, unemployed, or inactive, excluding non-working students. The total sample consists of 262,277 individual observations, which are equally distributed across three rounds of the survey (2017, 2019, 2021). In terms of occupational categories and based on all observations, 21.1% of participants are engaged in manual labor, 2.7% are employed in ICT related occupations, and 55.8% are engaged in other non-manual occupations, together amounting to 79.7% of employed

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[15] According to the International Standard Classification of Education (ISCED) categories.

[16] As per the International Standard Classification of Occupations (ISCO).

[17] For Germany (no NUTS1 level data in CSIS) and small countries (do not have regional data) the national-level data on cumulative COVID-19 cases are obtained from the 'Our World in Data' (WHO, 2020).

persons. The digital divide is measured using two variables: the presence of broadband Internet access at home and the digital skills level, which are derived from the CSIS waves used. The CSIS rounds offer an extensive measure of digital skills such as communication, problem-solving, information retrieval, and software skills. This division corresponds to the core twenty-first-century digital skills identified in the literature (van Laar et al., 2020). The survey maps the digital skills' level of individuals who have used the Internet at least once in the past three months (categorized as "Internet users"). For the ordinal digital skills variable, individuals are categorized as having (1) "no digital skills" (reference category), (2) "low skills", (3) "basic skills" and (4) "above basic skills".

The main relationships of interest are reflected in the estimates of Internet access, digital skills, formal education, and spillover effects in households from members with higher education. For empirical estimation, a random utility approach is used (McFadden, 1974). Individuals derive utility from using their skills in employment, and improved job-skill matching leads to higher utility. As such, high skill levels increase the likelihood of labor market participation and employment that utilizes more skills. Some substantial simplifications are introduced to allow a more direct empirical approach. First, the study supposes a single ordinal scale for the increase in utility from labor supply at the intensive (profession-skill ladder) and extensive (participation/non-participation) margins. Second, it does not disentangle utility effects from voluntary and involuntary nonparticipation in the labor market, an issue that is moderated by selecting individuals aged 25–54 (prime working age) when the utility of employment is highest. Third, the estimation procedure does not clearly dissociate labor supply and demand, but the latter is indirectly controlled for in the equation on occupational outcome by the rate of unemployment (ages 20–64) at the NUTS1 level.

The relationship among digital skills, Internet access and employment status on the individual level is estimated using a univariate and bivariate model. A univariate ordered probit model estimates a single equation treating all independent variables as exogenous to employment status. The extended bivariate regression framework estimates the employment outcome and digital skills equations separately, handling the latter as likely endogenous. The joint estimate enables the use of different regressors in the employment and digital skills equations, instrumenting digital skills with exogenous digitalization parameters aggregated at the regional level and individual's household composition indicators.

Intra-household spillover effects from members with tertiary education are measured using a dummy variable[18]. The interaction of major determinants with COVID-19 cases and government countermeasures is expected to provide insight into the relationship between digital skills and employment mediated by the COVID-19. The ordinal scale of the key variables under consideration suggests a non-linear estimation. Treating digital skills as exogenous (an assumption that can be violated) makes an ordered probit estimation of employment outcome possible. Relaxing this assumption entails a joint estimation of two ordered variables (digital skills and employment) and results in a bivariate ordered probit model. This generalized conditional likelihood setup processes two separate equations for employment and digital skills concurrently, enabling their stochastic (error) components to covary while establishing a triangular relationship between digital skills and employment outcome. The joint recursive estimation occurs

[18] Takes the value 1 if the individual has at least one household member (other than herself) aged 25–54 who has a higher education.

using full information maximum likelihood (FIML) approach. Parameters' identification should be based on exclusion restrictions rather than functional form and nonlinearity alone (Maddala and Lee 1976; Sajaia, 2008). For instance, Falck et al. (2021) use regional differences in broadband Internet availability to examine the impact of ICT skills on wages. This study uses a similar strategy in selecting the instruments to identify variation in digital skills at the individual level. This identification strategy involves the assumption that regional digitalization variables and household demographic factors can adequately measure individuals' supply of digital skills. Thus, the equation for digital skills has several region- and household-level covariates, such as NUTS1-level high-speed Internet access and the extensiveness of use, family size, the share of the population with a higher education, country-age group mean digital skills and gender-age composition of households; these are not included in the employment equation. This empirical setting allows for the coronavirus pandemic to exhibit a moderating effect on the relationship among digital skills, Internet access, and employment outcome. The employment equation's interaction terms allow the skill parameters to vary in the pre- and post-COVID-19 periods, conditional on the cumulative infection cases in NUTS1 regions or countries' containment efforts, respectively. In contrast, the development of individuals' digital skills as a function of aggregate regional indicators of digitalization, education, and family composition variables, is not considered fundamentally altered by the pandemic.

4 Key Findings and Discussion

Emerging forms of digitalization, such as AI, impact equality, productivity, and environmental quality (Acemoglu and Restrepo, 2018; Vinuesa et al., 2020). Moreover, AI technology can potentially impact all components of the internationally agreed 17 SDGs (UNGA, 2015). The fast development and increased mainstream application of AI technologies recently may lead to a reduction of not only numerous presently in demand jobs, but also of the need for people to learn the skills that allowed them to reach the level of advanced civilization today. Hence, humans must take care in adopting these technologies to avoid becoming over-reliant on AI, which, although can expand our capabilities, should be regarded as a tool to achieve humanity's desired goals, and not as something to which society must be subjugated. Also, the overall effect of digitalization on the labor market can be positive and there are still areas where humans cope better (e.g., communication, health care, social relationships).

Policies related to climate change can be broadly divided into two categories: policies that focus on reducing the mitigation costs and policies aimed at increasing R&D investments into technologies related to energy generation and efficiency (Husain et al., 2022). Innovation demands investment in R&D and knowledge, as well as conducting additional experiments with knowledge (Teece, 2010; Audretsch and Belitski, 2022).

While green complexity reveals the countries, which are presently competitive in green technologies, successfully transitioning to a green economy will necessitate countries to reorient existing structures of production and develop novel green industries (Mealy and Teytelboym, 2022). Clearly, if economies could identify green diversification opportunities that are tightly linked to their present productive capabilities, these can benefit from the existing skills, technological knowledge, and infrastructure.

In **Article I**, the main research question on the digitalization – CO_2 nexus is answered using panel data from 55 high- and middle-income economies for the period of 1996 to 2019 and applying the PSTR estimator. The study involves a comprehensive measure of digitalization as a prime variable of interest, alongside related control variables. The results confirm the validity of the EKC hypothesis, proving that the link of CO_2 emissions with digitalization and income level takes an inverted U-shape. This nonlinear nexus is driven by exogenous R&D output (technology patents) level that determines the smooth transition. The digitalization indicator in the lower R&D regime has a positive estimate, which is smaller than the negative estimate in the higher regime; therefore, the R&D-moderated effect of digitalization that decrease CO_2 emissions exceed the direct effect increasing carbon emissions. The transition function governed by R&D output shifts between the two regimes at the threshold of 39.9 technology patents per million inhabitants.

The model is first tested for nonlinearity to determine whether it should incorporate at least one transition variable. The linearity test results reveal a model with two regimes and show that the nonlinear PSTR model is preferred to the linear form. The successive evaluation tests for residual nonlinearity do not reject the two-regime model. The results of a sequence of homogeneity tests (HAC version) show that $m = 1$ (number of location parameters) is the best fit for the transition variable "technological patents". Thus, the best choice for estimating the PSTR model is a transition variable that captures R&D output, represented by technological patents, in support of Hypothesis 2. The results of the parameter constancy test (robust versions) to verify the adequacy of the estimated model indicate that parameter constancy can be rejected, meaning that there is variation in the parameters over time.

The estimated parameters of the two-regime PSTR model are presented for the first regime (low R&D output), for the nonlinear part, and for the second regime (high R&D output) that combines the estimates from nonlinear and linear sections. The estimated slope parameter of the transition function (main specification), γ, equals 1.28, suggesting a smooth transition from the R&D output's lower regime to the higher regime. The transition function's location (threshold) parameter has a turning point estimate of 39.9 technological patents per million inhabitants. In the model with two regimes (related to low and high values of technological patents), the estimated coefficients smoothly shift from the first extreme regime to the second, while the technological patents increase, and the change is centered at 39.9.

The parameter estimates are mainly interpretable by their signs (Colletaz and Hurlin, 2006). This study strongly supports the EKC hypothesis of the nexus between GDP per capita and CO_2 emissions per capita, with parameter point estimates equal to −0.43 in the nonlinear part and 0.59 in the linear part. These results support the findings of Aydin et al. (2019), who uses a similar methodological design but with different dependent (ecological footprint) and transition variables, reporting that the positive effect of income in the linear part exceeded income's negative effect (reducing footprint) in the non-linear part, with worldwide pollution the likely explanation.

The digitalization in the lower R&D output regime exhibits a positive estimate of 0.07, while in the higher R&D regime and in the nonlinear part, all estimates are negative at −0.14 and −0.21, respectively. Thus, in support of Hypothesis 1, an inverted U-shaped nexus is detected for the transition of CO_2 emissions in the R&D output level in relation to digitalization as well. The digitalization's high level may also reflect better digital environmental management, more efficient energy consumption (Aydin and Esen, 2018), wider information dissemination, and higher environmental awareness, reducing CO_2 emissions (Chen et al., 2019) in economies with higher level of technological inventions. Advanced countries generate higher levels of R&D output, leading to the adoption of cutting-edge technologies, resulting in lower CO_2 emissions (Churchill et al., 2019). The digitalization – CO_2 emissions relationship has not previously been studied using the nonlinear PSTR estimator and estimating the R&D threshold. Only Lahouel et al. (2021) used smooth transition regression (STR) (based on one country) with a threshold variable of ICT, concluding that ICT contributes to the reduction of CO_2 emissions when the level of ICT is high.

The estimate of human capital is at −0.53 in the higher R&D regime, revealing that additional human capital supported by higher levels of technological inventions decreases CO_2 emissions. Cakar et al. (2021) comes to a similar conclusion using the PSTR framework and human capital as a transition variable, regarding a bell-shaped EKC curve. The renewable energy consumption indicator has a point estimate of −0.16 in the nonlinear part and −0.15 in the high R&D regime, supporting the view that higher levels of technology invention and human capital contribute to renewable energy R&D output and the adoption of energy-saving and green technologies (Aydin and Cetintas, 2022). From a market perspective, the introduction of green and low-carbon technologies depends on the level of economic development and involves a cost-benefit assessment (Du et al., 2019). Thus, the effects of green technology innovations on CO_2 emissions are more tangible in high-income countries, with better government support for these innovations and their adoption to improve living standards.

The change in manufacturing value added negatively affects the pollution variable, for which the point estimates are −0.15 and −0.19 in the first and second extreme regimes, respectively. This result confirms the EKC's theorized "composition effect", suggesting that the change in value added of manufacturing results in reduced CO_2 emissions, especially in the higher R&D output regime.

The robustness of the results is checked using the alternative transition variable of R&D expenditures as a share of GDP. As discussed above, R&D investments (inputs) correlate with technological patents and innovations (outputs; Alam et al., 2021). The outcomes of the specification and evaluation tests suggest that a two-regime nonlinear model is also appropriate in this case. The results of the PSTR model estimation with transition variable of R&D expenditures indicate it is robust and comparable by sign and magnitude with the estimated parameters of the model using technological patents as a transition variable.

Article II indicates that deploying CC can substantially decrease the CO_2 emission intensity in power production by 90% or more. The results of total estimated costs of retrofitting Estonian OSPPs with CC technology in two scenarios indicate that OXY technology (42–47 €/tCO_2 depending on PP unit) appears to be more financially beneficial than PCC (48–56 €/tCO_2 depending on PP unit). The costs are estimated for CO_2 capture and purification up to 99.98% and do not contain storage, use, or transportation costs. This finding is generally consistent with existing literature regarding PCC technology for coal-fired power plants (Sreedhar et al., 2017). In a rough comparison at coal power plants in 2011, the CC implementation cost per ton of CO_2 captured was estimated at approximately €37.9 (€62.0 in 2021 values) for OXY (Iyengar et al., 2017) and €41.8 (€67.3 in 2021 values) for PCC in the DOE/NETL reference case B12B (Zoelle et al., 2015).

Scenario 1 reveals the full potential of CC deployment in OSPPs, assuming that electricity generation will operate at full capacity (85% of all hours per year). Scenario 2 exemplifies working only half that time (42.5% of the hours per year). However, the actual long-term market conditions (e.g., Nord Pool electricity and European CO_2 emission allowance prices) can substantially lower generation, which would also mean less CO_2 captured and a considerably higher unit cost of capture than in Scenario 2. Capital and electricity costs are the most substantial components of CC costs in OSPPs, regardless of the capture technology selected. While the capital cost per ton of CO_2 captured represents investment as an annuity spread over the expected life of the CC technology, significant upfront investment and appropriate financing are required.

The CC costs per captured ton of CO_2 (per MWh of electricity generated) depend on the amount of investment, electricity prices, and the useful lifespan and intensity of CC use. The functioning of power units and their components is important for the operation of CC technology. When power units reach the end of their useful life, CC technology is unavoidably phased out, regardless of its ability to operate. The effect is comparable to temporary closures or deliberate decisions to shut down power units (the intention of Eesti Energia, the company that operates all these OSPPs, to stop producing OS electricity by 2030 (IEA, 2023c)), which limit the useful life or capacity of CC investments.

However, recent concerns around national energy security may delay the cessation of OS power generation, creating further ambiguity related to the outcomes of this analysis. Moreover, since the CC technologies considered have not previously been used in the OS industry and have not yet reached their final TRLs, the estimates obtained involve technology risk that may imply additional costs. Since CC technologies are expected to be about 90% efficient, the residual uncaptured CO_2 will be released into the atmosphere. The potential for regulatory changes makes it difficult to evaluate the prospective payments for these emissions.

Capturing CO_2 emitted by Estonian OSPPs is technologically feasible, but, in the long run, may prove to be more financially costly than the prices of European CO_2 emission allowances and environmental taxes. Thus, in an uncertain market, the OS industry may have no incentive to deploy CC without public commitment or support to make doing so economically viable. The cost of capture will, in any event, be passed on to producers or taxpayers, which could deteriorate the competitiveness of the Estonian economy.

The existing power generation capacities in Estonia that can be managed (i.e., not variable generation from solar or wind and required to ensure the power grid's frequency) are insufficient to cover local demand and are almost completely deteriorated. Therefore, the creation of such new capacities is just vital. Since further development of OS electricity production (where Estonia has the knowledge, capabilities, and experience) and its greening is most likely not viable, a possible path forward remains the introduction and assimilation of new green technologies, such as, e.g., nuclear energy (where mastering the full process will take several years, considering diversification principles; IEA, 2023c). In this case, Estonia can achieve electricity independence, being able to produce all electricity needed to meet local demand, and thus ensure the energy system's stability and broader climate objectives.

Article III shows that the coronavirus pandemic disrupted and rapidly transformed the labor market. Educational attainment, digital skills, and broadband Internet connectivity jointly determine individuals' employment outcomes. Also, positive spillover effects appear if household members have completed tertiary education. Article III revises the relationship between skills and employment and explores how four key capabilities that empower people in the labor world have become more vital since the onset of COVID-19: (1) level of education; (2) access to broadband Internet; (3) digital skills; and (4) effects of family members having higher education.

The results are presented as marginal effects of bivariate ordered probit and ordered probit model estimates for the pre- and post-COVID-19 periods for the variables of digital skills, educational level, and broadband access. The difference is minimal between the conditional marginal effects estimated separately for the pre- and post-COVID-19 samples and the unconditional marginal effects estimated for the total sample (allowing comparison of parameter estimates before and after COVID-19). The interaction terms for the COVID-19 allow the educational attainment, digital skills, and access parameters to change in the employment status equation before and after the outbreak. Because COVID-19 is measured using two alternative continuous variables, changes in the parameters in the employment status equation are proportional to the two dimensions. Alternative specifications of the model suggest that COVID-19-related changes in the impact of broadband connectivity and individuals' skills on employment status are stronger when they are driven by cumulative cases rather than the stringency of countermeasures. A cross-model Wald test (Clogg et al., 1995) shows the strongest statistical evidence of differences between the parameter estimates for higher education and "above-average" digital skills, followed by the effect of within-family spillover and broadband Internet access. This implies that the change in demand for digital capabilities and human skills caused by the COVID-19 was restrained by government responses to mitigate the effects of the economic downturn.

Broadband Internet access enhanced employment outcomes, particularly the probability of individuals retaining non-manual work; this effect is stronger in the post-COVID-19 period, and for residents of regions with higher rates of the coronavirus infection. When controlling for the rate of cumulative cases, stricter containment measures result in a slightly smaller increase in marginal effects, indicating that government policies have at least partially decreased labor market disadvantage for individuals living in households without a broadband connection. Greater digital competence and formal education have a stronger impact on non-manual employment than on the likelihood of being unemployed. Therefore, skill levels are more relevant to type of employment than labor market participation. The marginal effects for higher level of digital skills and tertiary education show comparable magnitude, and both are important for labor market outcome, although the absolute values of the marginal effects vary considerably across educational attainment and digital skill levels. The marginal effects of higher education are roughly twice those of secondary education. Likewise, the marginal effects of the "above basic" digital skills are two to three times the size of the effects of "low" digital skills. At absolute levels, these effects did not differ qualitatively between the pre- and post-COVID-19 assessments. While educational attainment has become more valuable since the pandemic and gaps between educational levels have expanded, the changes in digital skills have been non-homogeneous. Depending on educational level, COVID-19 has disparately fostered "newcomer-level" digital skills at the bottom of the skills distribution.

As for the marginal effects of digital skills on non-manual employment outcomes at the higher levels of education, digital skills have a monotonic utility-enhancing nexus with employment status, as the highest digital skills provide the greatest likelihood of employment and of entering a more skill-intensive occupation. Across educational and occupational levels, COVID-19 has advantaged the employment outcomes of individuals with entry-level digital skills over digitally illiterate persons. However, the individuals' gains from more advanced digital skills have diminished compared to those with only beginner skills. Since the COVID-19 outbreak, the intra-household spillover effects from tertiary education on employment outcome and labor market participation have grown considerably, from about 1 to 2–3 percentage points.

Unsurprisingly, access to broadband Internet at home has gained significance for employment outcomes as the COVID-19 progressed. According to the estimates, the relationship between broadband Internet and getting or retaining non-manual employment is stronger than the association with the exit from unemployment. This result is consistent with Akerman et al. (2015) assertion on complementarity between broadband Internet and job skills. The rewards of Internet access are greater for non-manual and skilled workers, for whom access helps retain or even enhance their status in the labor market. The findings indicate that educational attainment has gained importance in the post-pandemic period, with the employment gap between, e.g., secondary and tertiary education expanding. This is in line with Soh et al. (2022), who find a positive individual-level impact of tertiary education in digital occupations on employment in the U.S. Since the COVID-19 outbreak, there has been a tripling of the spillover effects of higher education within households. This highlights the value of non-monetary benefits of tertiary education and externalities of household production, the role of which has been especially increased due to the COVID-19 lockdown and containment measures.

Digital skills preserved a positive and strong effect on employment, but with heterogeneous results for different levels of digital skills before and after the pandemic. The COVID-19 disparately benefitted those with entry-level digital skills, and this reduced the gap between those with basic and those with above-basic digital skills. This provides evidence that digitally and skill-wise segmented labor markets have experienced asymmetric labor supply disturbance. COVID-19 has caused a surge in demand for entry-level digital skills in professions thus far characterized by low levels of digitalization and workers with missing or low digital skills. These findings are consistent with Zimpelmann et al. (2021), who claim that COVID-19-driven disruptions in labor supply have impacted mid- and low-skilled employees differently. These employees typically have little or no ability to work remotely and have little digital literacy. The abrupt shift in demand for workers with at least some digital skill appears to have improved employment opportunities for people able to facilitate the adoption of advanced digital tools in areas of work with low digitalization levels in the pre-pandemic period. Thus, asymmetric labor supply disturbances have had a greater impact at the lower end of the digital skills distribution.

Comparing outcomes based on regional statistics on cumulative coronavirus infections with public containment and support efforts shows that the latter mitigated the impact of the economic downturn for households and individuals and restrained some of the COVID-19-induced demand for digital capabilities and education. The spillover effects of higher education within households have increased substantially in the post-COVID-19 period, with lockdowns restricting people to their homes and making them more reliant on family resources. The containment efforts may thus have exacerbated the role of socioeconomic inequality in labor market outcomes.

5 Conclusions

The COVID-19 outbreak highlighted the ongoing need for technology and sustainable development, forcing organizations to accelerate their twin transition implementation (Rehman et al., 2023). Given the large-scale environmental challenges that currently exist, economies are looking to decouple economic development from rising carbon emissions. **Article I** investigates the relationship between digitalization and reducing CO_2 emissions through a comparative analysis and new empirical evidence on the role of R&D output in the transition toward decreased environmental pollution. The study confirms the nonlinear relationship among digitalization, economic advancement indicators, and CO_2 emissions for the large sample of high- and middle-income economies over the period 1996 to 2019 (ending immediately before the COVID-19 outbreak). The results also indicate that the effect of digitalization, unmitigated by R&D output, leads to an increase in carbon dioxide emissions. In contrast, if digitalization is moderated by intensive R&D output, it entails lower CO_2 emissions. This means that the digitalization use in a regime with relatively high levels of R&D contributes to environmental sustainability. The transition function shifts between the two R&D output regimes at a point estimated at 39.9 technological patents per million inhabitants.

The empirical results suggest directions for policy actions to improve environmental quality. Given the renewed rise in global CO_2 emissions since the COVID-19 pandemic was declared over, and countries' SDG commitments, governments should implement policies that promote R&D's role in digitalization to mitigate the environmental effects. R&D should receive enhanced support, with a focus on the generic, green, and digital technologies underpinning the twin transition, in a way that supports environmental sustainability. The study's outcomes suggest that governments should consider enhancing the use, intensity, and readiness for digitalization to achieve the SDG-13 goal by increasing environmental awareness, improving education, and strengthening institutions.

Digital solutions proved indispensable during the period of COVID-19 restrictions, and this momentum can be harnessed to drive further progress in digital and green transition. Policymakers should pay particular attention to promoting greater access to the Internet (e.g., fiber-based broadband connections) and digital technologies (SDG-9), and improvements in infrastructure while introducing green technologies and supporting R&D to improve energy efficiency and reduce pollution. Public policies should promote the simultaneous development of R&D inputs and outputs, technological innovations, and digitalization in the form of twin transitions as their interactions contribute to environmental sustainability. The introduction of green, energy-efficient, and low-carbon technologies while simultaneously promoting digitalization should be a priority in frontier economies and those that have not yet achieved the turning point of the R&D output regime.

The caveat to the study is that there may be alternative candidates for the variable driving the transition between development and pollution regimes; these alternatives may reflect technological implementation rather than development. Furthermore, while data on technology patents offers valuable insights into the capability of countries to innovate, directly linking patents with the production of green (or more general) technologies or their dissemination and tracking of how a country's patent count affects its overall economy remains challenging. Likewise, alternative indicators of digitalization can improve knowledge of environmental effects and influence some outcomes.

Article II presents a technological and economic assessment of the CC deployment in OSPPs. From a technological point of view, it is possible to retrofit existing OSPPs with PCC and OXY technologies. The implementation of CC can reduce the CO_2 emission intensity of electricity production by up to 90%; OXY technology is expected to marginally outperform PCC.

Financially, installing CC in Estonian OSPPs may not be feasible in an unstable market: the cost of CC plus storage was at least €89 per ton in 2021 when operating at full capacity over the expected 24-year life of the CC, which may exceed the CO_2 emission allowance and environmental fees. In addition, OSPPs equipped with CC may be at a competitive disadvantage in the electricity market compared to companies using non-fossil energy sources in electricity generation. Potentially, CC commitments or support measures could make this process economically feasible. However, the cost of CC would then be transferred to producers or taxpayers, which could negatively impact the competitiveness of the economy.

Although any CO_2 capture process reduces the net power generation capacity of the OSPPs (due to their own electricity consumption), the OSPPs operation guarantees stable production capacity (from domestic resources), which is important for the sustainable operation of the power grid. An instant and complete transition to renewable energy is not feasible in Estonia, given the necessity to ensure energy security and grid stability (Metcalf, 2014) and considering path dependence in technology development, the level of current energy storage technologies, and the duration of investments in the energy sector. Also, the influence of increased interest rates on the cost of low-carbon and transition-oriented projects has recently become a major concern. Moreover, to promote the implementation of renewable energy sources, the possibility of accumulating and storing any excess electricity produced must be ensured (Bareschino et al., 2020). OS-generated energy will likely continue to co-exist with cleaner technologies. However, introducing CC into the existing fossil fuel energy system can ensure a smooth transition toward climate neutrality targets. Also, the use of CC in fossil-fuels energy production is one way to prevent potential energy crises and balance the energy system if renewable resources fail to deliver the capacity required (Climate, 2021).

Because CC can decrease GHG emissions, there is a need for public interest in the adoption of these technologies in addition to the private sector's economic motives. The adoption of CC technologies may have considerable positive externalities; that is, if CC integration is not cost-effective for companies in market conditions, the public sector may still have the motivation to encourage to make them attractive or obligatory for the industry. When developing regulations and support measures, it is critical to consider the competitiveness of the OS industry in the international market.

A strategy is needed for the Estonian energy sector based on comprehensive and evidence-based comparative analysis (including potential CC) to ensure clarity and confidence for private companies and public institutions in terms of investment decisions and policy formulation (including R&D priorities, regulations, and environmental and energy measures). The country's energy strategy must include realistic solutions to guarantee consumers the required electricity at any time and at an affordable price. This requires new and green manageable electricity production capacities (involving private investors) in addition to the accelerated construction of renewable energy capacity (e.g., wind farms). The development of domestic grids, external connections (e.g., the creation of a third Estonian-Finnish electrical cable connection), electricity storage capacities, and compensated conscious reduction in energy consumption by end-users (IEA, 2023c) is also required. If, over the next few years, the country does not create sufficient electricity production capacity, electricity prices may rise to a level that worsens consumers' welfare, which will hinder economic development.

The necessity for stable power generation cannot be ignored. Currently, in Estonia this need is met by existing OSPPs. Hence, until non-fossil fuel alternatives can provide a stable electricity supply, the CC of Estonian OSPPs remains an option. Ensuring that OSPP capacities meet the EU's strategy of a "carbon neutral economy" may require CC integrating into their operations and accepting high private and public costs; the alternative is to depend on imported electricity and face potential energy insecurity and market fluctuations.

Article III offers a comparative analysis and augments existing evidence that high-speed Internet access, digital skills, and educational attainment collectively improve employment outcomes. The study shows how COVID-19 has substantially reshaped these associations. Educational level and digital skills are identified as strong complementary factors that together enhance an individual's employment prospects. The level of education of household members also positively affects the labor-market outlook. One likely interpretation of this result is that more highly educated individuals may be better able to encourage family members to get or maintain a job when this increasingly demands digital interaction.

Depending on their digital skills and Internet access, the COVID-19 pandemic has disparately enhanced the employment outcomes of individuals with entry-level ("low") digital skills compared to digitally illiterate persons. In contrast, individuals' gains from having more advanced digital skills decreased relative to those with low-level digital skills. The sharp disruptions in the labor market induced by COVID-19 responses necessitated a rapid transition to online work modes. This transition occurred primarily with respect to the extensive margin, with increasing demand for remote work hours, as opposed to the intensive margin, which would imply an increased demand for more complex digital skills. The shift to remote work happened more easily among highly skilled employees, a substantial proportion of whom are digitally savvy and already work remotely. The rapid digitalization trend in some mid- and low-skill occupations, where physical contact has been replaced by digital solutions following COVID-19 and accompanying social distancing requirements, has collided with the insufficient supply of digitally literate workers at the bottom of the pay-skill distribution; this may explain the disproportionate improvement in employment outcomes for mid- and low-skilled workers with minimal digital skills.

Overall, the results indicate that COVID-19 likely expanded the employment gap between advantaged individuals with high skills, from educated households and who are digitally literate, and those who are less advantaged. These findings highlight that efforts to ensure equal access to education and digital empowerment must be intensified. Future research could explore whether changes in the rewards for digital skills in the labor market prompted by the COVID-19 will permanently alter the distribution of digital skills supply and reshape work more universally to greater digitalization.

Governments and decision-making institutions should implement appropriate policies to address the challenges of the digital divide by, for example, equipping homes and schools with the infrastructure and technological needs (Aydin, 2021), supporting ongoing professional training of digital-skills educators, harmonizing the education system with the rapidly evolving labor markets' needs, conducting courses to transmit digital skills, and making these accessible to those experiencing digital inequalities.

The contribution of this dissertation is its identification of the necessity of digital and green transition. This twin transition should be more thoroughly considered and implemented to ensure one technology supports the other (e.g., via policies that influence technological outcomes) or mitigates adverse externalities (associated with the diffusion of the first technology). For instance, the adoption of digital technologies (that have positive effects) may also lead to negative consequences (direct effects) and electricity consumption that can be mitigated by the simultaneous integration of green technologies. In addition, the implementation of CC technologies to reduce CO_2 emissions is cost-ineffective (at least currently) and leads to uncompetitive prices for electricity generation. Again, this high CC cost can be reduced via the adoption of digital technologies (AI, ML, digital twins), improved CC technologies, or policy (e.g., EU support measures) that internalize the negative externalities caused by some features of one of the technologies in the twin transition. Likewise, access to digital technologies and skills in their use are essential. However, the proliferation of digital technologies creates a digital divide (also in terms of employment) that must be mitigated using other technologies (e.g., generative AI) or regulatory tools (upskilling, learning, increasing access).

Estimating changes in living standards and developing accurate policies affecting these requires properly measuring the welfare gains from all goods, including goods without positive market prices, such as digital, public, and environmental goods (Brynjolfsson et al., 2019). Zero-priced digital goods offer considerable value to customers even though they do not contribute to GDP. However, these free digital goods produce a consumer surplus, which can be estimated by applying the prices (quality-adjusted) and data consumption intensity of digital devices (Byrne and Corrado, 2019). In the same vein, alternative measures (regarding the techno-economic assessment of CC with market prices) can be used to estimate welfare gains for nonmarket goods (environmental and public goods) delivered by the government. This will help address an essential gap in comprehension of development of green and digital economy, since GDP measures production and not well-being.

Future studies could evaluate how to underpin twin transition's further integration and realization to create an even more sustainable society. Further, future studies on the decoupling of electricity consumption (and thus CO_2 emissions) and economic development alongside the deployment of digital and green technologies, should consider the energy embedded in imports and the effects of sectoral changes (e.g., tertiarization) (Moreau and Vuille, 2018; Vadén et al., 2020). Thus, deindustrialization that shifts electricity use abroad and structural changes in trade can lead to increased embodied national electricity consumption (which is not in official statistics). Also, the registered decoupling should be sufficiently extensive to infer if it represents an established pattern or interim stabilization (Palm et al., 2019). The claim that decoupling actually happens should be supported by policymakers through specific and detailed plans and actions for structural change that will clearly define differences for the future.

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Abstract

Economic Perspectives of Twin-transition: Low-carbon Production and Inclusive Digitalization

Attaining inclusive green development requires that economies consider the multiplicity of economic, environmental, and social factors. Complex green production should be regarded as contributing to the reduction of greenhouse gas (GHG) emissions. This study examines the nexus between digital and green transformations – the "twin" transition, which is underpinned by the development of contemporary technologies to determine the impact of digital and green technologies on CO_2 emissions. Advanced digital technologies (e.g., machine learning) help reduce the harmful effects of other carbon-intensive technologies but contribute to CO_2 emissions due to their own energy use. Whether digitalization is associated with an increase or decrease in carbon emissions may depend on the complexity of a country's research and development (R&D) output, represented by its technology patents. This study examines the transition in regime induced by R&D output that moderates the relationship between digitalization and CO_2 emissions. The study tests the environmental Kuznets curve (EKC) hypothesis using a panel smooth transition regression (PSTR) estimator with two regimes of R&D output to account for country- and year-varying impacts of digitalization, human capital, and income level on CO_2 emissions. The study includes data for 55 high- and middle-income countries between 1996 and 2019 and detects that the transition process is determined by a country's level of R&D output, measured in technological patents per inhabitant. The results confirm that CO_2 emissions have an inverted U-shaped relationship with digitalization and income levels and support the EKC hypothesis. This nonlinear association smoothly shifts with the level of exogenous R&D. The digitalization index in the lower R&D regime has a significant estimate of 0.07, whereas in the higher R&D regime the estimate is −0.14, meaning that the decreasing effect of digitalization on CO_2 emissions is greater than its increasing effect. The R&D output inflection point at which the transition function shifts between the two regimes is equal to 39.9 technological patents per million inhabitants. Policy actions promoting the twin transition must account for these findings, considering the benefits of digital transformation when underpinned by the promotion of contemporary and green technologies.

CO_2 is one of the main anthropogenic GHGs that contributes to global warming. Carbon capture (CC) – removing CO_2 before it is released into the atmosphere – is a key technology with the potential to reduce CO_2 emissions because its deployment can lead to decreased mitigation costs. R&D to create new or upgrade existing carbon capture technologies involves complex processes and demands digitalization tools (e.g., machine learning) to optimize big data modeling and reduce production time. The combustion of oil shale, a fossil fuel, in power plants results in high CO_2 emissions that need to be sharply reduced. This study provides a comparative techno-economic evaluation of the implementation of CO_2 capture technologies, specifically post- and oxy-fuel combustion technologies, by retrofitting existing oil shale power plants in Estonia.

The energy industry of Estonia is unique due to its heavy dependence on oil shale. The technical analysis in this study shows that oxy-fuel combustion capture will technically surpass post-combustion capture in oil shale power production. However, the implementation of CO_2 capture technologies will lead to a decrease in the generated energy of power units due to the energy requirements of carbon capture equipment.

The financial feasibility of CO_2 capture in Estonian oil shale power plants relies on the electricity market's long-term prospects and the emissions trading system. Operating at full capacity over an expected 24-year service life will cost at least €42 per ton of CO_2 captured and €89 per ton of CO_2 captured and stored at 2021 prices. Actual costs may surpass the payment of CO_2 emissions allowance fees and environmental taxes or lead to a decrease in competitiveness.

The outcomes of the sensitivity analysis for key inputs such as investment amount, electricity price, useful life and CC usage intensity indicate higher estimates of CC costs per ton of CO_2 captured. Therefore, only if the negative externalities arising from CO_2 emissions and domestic energy security concerns cannot be realistically alleviated by alternative, stable and manageable energy sources should government support the implementation of CO_2 capture technologies in the plants considered. All else being equal, introducing higher taxes to cover government aid or shifting the costs of CO_2 capture to the private sector may decrease the overall competitiveness of the Estonian economy.

Amid lockdowns and stay-at-home orders related to the COVID-19, the economy largely moved online, and digital technologies with Internet access became more critical than ever. The expanding use of digitalization in the workplace means that the employment market demands digital capabilities and skills, either in goods production or in workers with complementary skills. This study investigates the nexus between employment outcomes and access to broadband Internet, educational attainment, and digital skills deploying pre- and post-COVID-19 survey waves for 2017, 2019 and 2021 of the Eurostat Community Statistics on the Information Society in 27 European economies. The joint assessments of individuals' employment outcomes and digital skills include external controls using statistics from Eurostat and the European Regional COVID-19 Tracker at the NUTS1 level, as well as data from the Oxford COVID-19 Government Response Tracker on government restrictions and economic support measures. The pandemic increased the employment benefits of possessing at least some digital skills, while the relative advantages of more advanced digital skills have declined. Broadband Internet access, digital skills, and educational attainment combine to raise employment outcomes, but the COVID-19 transformed these relationships in disparate ways. It increased employment benefits from formal education and approximately tripled the labor market advantages from having household members with tertiary education.

Lühikokkuvõte

Rohe-digipöörde majanduslikud perspektiivid: Madala süsinikheitega tootmine ja kaasav digitaliseerimine

Kaasava rohelise majanduskasvu saavutamiseks peavad majandused arvestama majanduslike, keskkonna- ja sotsiaalsete tegurite mitmekesisusega. Ka kompleksset rohelist tootmist tuleks pidada kasvuhoonegaaside (KHG) heitkoguste vähendamisele kaasaaitavaks. Antud uuring keskendub rohepöörde ja digitaalsete arengute seosele – „rohe-digipöördele", mille aluseks on kaasaegsete tehnoloogiate areng, et teha kindlaks digitaalsete ja roheliste tehnoloogiate mõju CO_2 heitkogustele. Täiustatud digitaaltehnoloogiad, näiteks masinõpe, võivad vähendada teiste süsinikumahukate tehnoloogiate kahjulikke mõjusid, kuid nad ise aitavad kaasa CO_2 heitkogustele oma energiakasutuse tõttu. See, kas digitaliseerimine on seotud süsinikdioksiidi heitkoguste suurenemise või vähenemisega, võib sõltuda riigi teadus- ja arendustegevuse (T&A) väljundi keerukusest, mida esindavad tehnoloogiapatendid. Selles uuringus uuritakse üleminekut režiimis, mille põhjustab teadus- ja arendustegevuse väljund, mis modereerib digitaliseerimise ja CO_2-heite seost. Uuringus testitakse keskkonna Kuznetsi kõvera hüpoteesi, kasutades paneelandmete sujuva ülemineku regressiooni hindajat kahe teadus- ja arendustegevuse väljundi režiimiga, et arvestada digitaliseerimise, inimkapitali ja sissetulekute riigiti ja aasta lõikes muutuvat mõju CO_2 heitkogustele. Uuring hõlmab 55 kõrge ja keskmise sissetulekuga riiki aastatel 1996–2019. Uurimistöö tuvastab, et üleminekuprotsessi määrab teadus- ja arendustegevuse väljundi tase, mõõdetuna tehnoloogilistes patentides riigi elaniku kohta. Tulemused kinnitavad, et CO_2 emissioonidel on ümberpööratud U-kujuline seos digitaliseerimise ja sissetulekutasemega ning toetavad keskkonna Kuznetsi kõvera hüpoteesi. See mittelineaarne seos nihkub sujuvalt eksogeense teadus- ja arendustegevuse tasemes. Digitaliseerimise indeks madalamal T&A režiimil on oluliseks hinnanguks 0,07; kõrgemal T&A režiimil aga –0,14, mis tähendab, et digitaliseerimise mõju CO_2 heitkoguste vähendamisele on suurem kui selle suurendav mõju. Teadus- ja arendustegevuse väljundi pöördepunkt, mille juures üleminekufunktsioon kahe režiimi vahel nihkub, võrdub 39,9 tehnoloogilise patendiga miljoni elaniku kohta. Rohe-digipööret edendavates poliitikameetmetes tuleb neid järeldusi arvesse võtta, arvestades digitaalse ümberkujundamise eeliseid, kui seda toetavad kaasaegsete ja roheliste tehnoloogiate edendamine.

CO_2 on üks peamisi inimtekkelisi kasvuhoonegaase atmosfääris, mis aitab kaasa globaalsele soojenemisele. Süsinikdioksiidi püüdmine (CC) – CO_2 eemaldamine enne selle atmosfääri paiskamist on potentsiaalne võtmetehnoloogia CO_2 heitkoguste vähendamisel, kuna selle kasutuselevõtt võib vähendada leevenduskulusid. Teadus- ja arendustegevus uute või olemasolevate CC-tehnoloogiate loomiseks või täiustamiseks hõlmab keerulisi protsesse ja nõuab digitaliseerimistööriistu (nt masinõpet), et optimeerida suurandmete modelleerimist ja vähendada tootmisaega. Põlevkivi on fossiilkütus, mille põletamine elektrijaamades toob kaasa kõrge CO_2 emissiooni, mida tuleb järsult vähendada. Käesolev uuring annab võrdleva tehnilis-majandusliku hinnangu CO_2 püüdmistehnoloogiate, eelkõige järelpüüdmise- ja hapnikupõletamise tehnoloogiate rakendamisele Eestis olemasolevate põlevkivielektrijaamade moderniseerimise teel.

Eesti energeetika on ainulaadne oma suure põlevkivisõltuvuse tõttu. Tehniline analüüs näitab, et põlevkivienergia tootmisel ületab hapnikus põletamise püüdmistehnoloogia tehniliselt järelpüüdmise tehnoloogiat. Süsinikdioksiidi püüdmistehnoloogiate kasutuselevõtt toob aga kaasa CC-seadmete energiavajaduse tõttu energiaplokkides toodetava energia vähenemise. Eesti põlevkivielektrijaamade rahaline otstarbekus CO_2 püüdmiseks sõltub elektrituru pikaajalisest väljavaatest ja heitkogustega kauplemise süsteemist. Täisvõimsusel töötamine eeldatava 24-aastase kasutusea jooksul maksab 2021. aasta hindades vähemalt 42 eurot püütud CO_2 tonni kohta ja 89 eurot püütud ja ladustatud CO_2 tonni kohta. Tegelikud kulud võivad ületada CO_2 saastekvootide ja keskkonnamaksude maksmist või viia konkurentsivõime languseni.

Peamiste sisendite, nagu investeeringute summa, elektri hind, kasulik eluiga ja CC kasutamise intensiivsus, tundlikkusanalüüsi tulemused näitavad kõrgemaid hinnanguid CC kuludele püütud CO_2 tonni kohta. Seega peaks valitsus toetama CO_2 püüdmis-tehnoloogiate rakendamist asjaomastes tehastes vaid juhul, kui CO_2 heitkogustest ja riigisiseste energiajulgeolekuga seotud probleemidest tulenevaid negatiivseid välis-mõjusid ei ole võimalik reaalselt leevendada alternatiivsete, stabiilsete ja juhitavate energiaallikatega. Kõrgemate maksude kehtestamine, kui kõik muud asjaolud on võrdsed, riigiabi katteks või CO_2 püüdmise kulude suunamine erasektorisse võib vähendada Eesti majanduse üldist konkurentsivõimet.

COVID-19-ga seotud sulgemiste ja kojujäämise korralduste keskel on majandus liikunud suures osas võrku ja Interneti-juurdepääsuga digitaaltehnoloogiad on muutunud kriitilisemaks kui kunagi varem. Digitaliseerimise laienev kasutamine töökohal tähendab, et tööturg nõuab digitaalseid võimeid ja oskusi kas kaupade tootmisel või täiendavate oskustega töötajatel. Selles uuringus uuritakse seost tööhõivetulemuste ja lairiba-Internetile juurdepääsu, haridustaseme ja digioskuste vahel, kasutades Eurostati infoühiskonda käsitleva ühenduse statistika 2017., 2019. ja 2021. aasta COVID-19-eelseid ja -järgseid uuringulaineid 27 Euroopa majanduses. Üksikisikute tööhõiveväljundite ja digioskuste ühishinnangud hõlmavad väliseid kontrolltegureid, kasutades Eurostati ja Euroopa piirkondliku COVID-19 jälgija statistikat NUTS1 tasemel, samuti Oxfordi COVID-19 valitsuse reageerimise jälgimise andmeid valitsuse piirangute ja majanduslike toetusmeetmete kohta. Pandeemia on suurendanud vähemalt mõningate digioskuste omamisest saadavat kasu tööhõivele, samas kui arenenumate digioskuste suhtelised eelised on vähenenud. Lairiba Interneti-juurdepääs, digitaalsed oskused ja haridustase suurendavad üheskoos tööhõivetulemusi, kuid COVID-19 on neid suhteid erineval viisil muutnud. See on suurendanud formaalharidusest saadavat kasu tööhõivele ja ligikaudu kolmekordistanud kõrgharidusega leibkonnaliikmete tööhõive eeliseid.

Appendix 1. Publication I

DIGITALIZATION AND CO_2 EMISSIONS: DYNAMICS UNDER R&D AND TECHNOLOGY INNOVATION REGIMES

Publication I

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Digitalization and CO_2 emissions: Dynamics under R&D and technology innovation regimes

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ABSTRACT

New digital technologies help to curtail those that are carbon intensive but are accompanied by CO_2 emissions due to their own energy demand. Whether digitalization relates to increased or decreased carbon emissions may depend on the sophistication of an economy's research and development (R&D) output. This study explores the R&D-induced regime transition that governs the relationship between digitalization and CO_2 emissions. The study seeks evidence of the environmental Kuznets curve hypothesis and tests it with a panel smooth transition regression (PSTR). Employing this estimator with two R&D output regimes makes it possible to account for year- and country-varying effects of digitalization, human capital, and country income level on CO_2 emission. The research covers 55 high- and middle-income economies from 1996 to 2019. The paper finds that the transition process is driven by R&D output level – measured in technology patents per country inhabitants. The findings support the environmental Kuznets curve hypothesis and confirm that CO_2 emissions have an inverted U-shaped relationship with digitalization and income level. This nonlinear relationship transitions smoothly in the exogenous R&D output level. The digitalization indicator in the lower R&D regime has a significant point estimate of 0.07; in the higher regime, the estimate is −0.14. The R&D output threshold at which the transition function switches between the two regimes corresponds to a level of 39.9 technology patents per million inhabitants.

1. Introduction

One of the most alarming issues facing humanity in recent decades has been the growing volume of carbon dioxide (CO_2) emissions, which lead to global warming and environmental disequilibrium. The United Nations (UN) conference on climate change (COP27 [1]), urged states to take action to reach the global goals – established by the Paris Agreement and the United Nations Framework Convention on Climate Change (UNFCCC) – to cut greenhouse gas (GHG) emissions (including CO_2) and limit global warming to 1.5° Celsius above pre-industrial levels [2]. A major challenge in formulating environmental policy is that reducing CO_2 emissions may compromise people's economic well-being [3]. Therefore, environmental economics scholars have diligently investigated the connection between economic development and environmental policy and sought the most effective means of measuring this relationship. Environmental indicators have shown that income level growth below a certain threshold harms the environmental balance, and growth above that threshold improves environmental quality. Such an inverted U-shaped relationship between income and environmental pollution is defined by the environmental Kuznets curve (EKC), which was introduced by [4] and is based on [5] original hypothesis of an inverted U-shaped relationship between income level and inequality. The environmental economics literature has researched the EKC extensively within individual countries and among groups of countries [6–16].

Research on the EKC has, however, not delivered unanimous results; this may relate, in part, to measurement problems. The linear quadratic polynomial equations used in some investigations of the EKC relationship cannot detect more complex forms of nonlinearity and are inflexible [10,17]. Similarly, the standard panel data estimators, including time and fixed or random effects, cannot handle biases that arise from cross-sectional or dynamic heterogeneity in a panel's coefficient estimates [18]. Also, the issue of time inconstancy has not received sufficient attention in the literature [19]. To address these issues, this study employs Panel Smooth Transition Regression (PSTR) [20], a more flexible estimator that allows for nonlinear estimates that vary in cross-sections among countries and over time.

In studying the relationship between economic growth and

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decarbonization, a key element to consider is digitalization [21]. Digital technologies[1] have fundamentally changed how firms operate (e-commerce, business processes), how individuals communicate (social networks), and how governments disseminate policies and engage citizens (e-government services). Artificial intelligence and machine learning are fundamentally reshaping the distribution of tasks between labor and technology.

Digitalization entails countervailing effects upon achieving climate goals which require energy use to be reduced and the share of renewable energy increased [21,24]. Production and maintenance of digital infrastructure, such as cloud servers or data centers, increase energy consumption [25,26]. On the other hand, smart digital solutions enable the optimization of production processes [27], the development of energy-efficient infrastructures, buildings, and electrical grids, and reduce carbon emissions thus promoting sustainability of the economy [28,29]. So far, the research has not found consensus on the aggregate environmental impacts of digitalization [30,31]. According to the Global Enabling Sustainability Initiative (GeSI) and Deloitte [32], by 2030 digitalization could potentially decrease global CO_2 emissions by 9%. This reduction in carbon footprint would arise from the optimization of processes in energy networks and improvement of energy conservation. High-speed Internet and cloud solutions can contribute to achieving sustainable development. Internet of Things and artificial intelligence may facilitate increased use of renewable energy by enhancing efficiency in the power grid and increasing access to solar energy (GeSI and Deloitte, 2019; [33]). Digital knowledge sharing and transfer, and e-learning facilities generate educational benefits. The aggregate environmental and economic effects of digitalization warrant further investigation at the global level.

The combined application of green innovations and digital technologies offers promising avenues for achieving carbon neutral economic growth [2]. R&D has a central role in generating inventions and introducing technologies, not only applicable in the energy sector but throughout the economy, for attaining sustainable growth [31,34].

As the main contribution this study demonstrates the crucial role of R&D in reshaping the digitalization–CO_2 emissions' nexus. R&D in technological advances operates as a nonlinear transition function that makes digitalization a tool for combating climate change. Existing studies [35,36] suggest that advances in R&D accelerate renewable energy transition and improve energy efficiency. The current study adds the link between digitalization and R&D and addresses the research gap in two main aspects. Firstly, it assesses the significance of the R&D-induced regime transition that moderates the response of CO_2 emissions to digitalization, while controlling for the country income and human capital level, renewable energy consumption, manufacturing value added, and government effectiveness. Secondly, this study employs a nonlinear generalized PSTR estimator that allows for smooth transition governed by the R&D as transition variable and that provides heterogeneous estimates that vary across regimes. Digitalization – CO_2 emissions nexus under non-linear smooth regime change in R&D has not been studied before. Previous studies have investigated in separation the link between digitalization and carbon emission [37,38]; Higon, Gholami and Shirazi, 2017; [39,40]; Lange, Pohl and Santarius, 2020; [30,31,36,41,42]; and the link between technological innovation and CO_2 emissions (Fernandez, Lopez and Blanco, 2018; [9]; Du, Li and Yan 2019; [43]; Zeraibi, Balsalobre-Lorente and Murshed, 2021). Alternatively, Dwivedi et al. (2022) merge technology innovation and digitalization components and study their joint effect on carbon emission. [34] shows that technological innovation in digital industry increases CO_2 intensity, but digital technology cross-industry and cross-border spillovers reduce carbon footprint. Unlike previous studies, the current investigation disentangles the R&D-induced technological innovation and digitalization processes while examining their joint non-linear mechanism upon CO_2 emission. In this setting R&D operates as a transition force that changes the impact of digitalization to carbon footprint. Beyond addressing this nonlinear mechanism, the current study employs a global sample of middle- and high-income economies and applies PSTR as a generalized non-linear panel estimator that captures the smooth transition process governing the link between technological advancement and carbon emission. The PSTR estimator proposed by [20,44] has proved its value in environmental economic research [6,7,10,19,35,45–47]. Unlike sharp threshold estimators the PSTR permits units to change the regime in different timeframes with the threshold variable shifting smoothly over time.

Application of the PSTR model in the complex setup of R&D – digitalization and carbon emission triangle requires a large and sufficiently long panel of rich country data that allow for controls of human capital, income level, energy consumption and institutional data beyond the digitalization and carbon emission indicators. The model specification is subject to several assumptions that have been tested and validated on a balanced panel of 55 countries (Table A.1. in Annex A) from 1996 to 2019. The dataset includes 37 high-income and 18 middle-income countries, thus offering the necessary time and country variation. According to the EKC, CO_2 emissions have an inverted U-shaped relationship with the national level of economic and technological development. This study confirms the EKC hypothesis in R&D output and shows that carbon emissions grow with digitalization in countries with lower R&D output levels until reaching the R&D threshold, beyond which the CO_2 emissions begin to decrease as the economies advance in digitalization.

This study is structured as follows: Section 2 includes a review of the existing theoretical and empirical literature and develops hypotheses in three subsections: (1) evidence on the EKC, (2) the relationship between digitalization and CO_2 emissions, and (3) linkages between R&D and CO_2 emissions. Section 3 describes the data and sets out the methodology and transition-variable selection in three separate sub-sections. Section 4 presents and discusses the results, and Section 5 presents the study's conclusions and policy implications.

2. Literature review and hypotheses development

2.1. *Theoretical foundations and empirical evidence on the environmental Kuznets curve*

The relationship between economic growth and CO_2 emissions proposed by the EKC stems from three main effects [4,17,48]. The *scale effect* arises when the increased exploitation of natural resources and energy use, resulting from production growth, leads to the degradation of environmental quality. The *composition effect* has a positive, countervailing impact on the environment; as GDP grows, the economic structure shifts toward less polluting and cleaner activities that entail lower CO_2 emissions. Cleaner structure of production is associated with a decreasing role for manufacturing and other energy-intensive industries and an increasing role for services, knowledge, and information technology activities that have relatively low energy consumption. Finally, the *technological effect* appears in more advanced countries that increase their R&D expenditures during technological progress [9,49]. This entails replacing old and polluting technologies with new and cleaner ones, introducing more sustainable production processes, and thus preserving the environment [4].

The environmentally harmful scale effect dominates at lower levels of economic advancement, with the technology and composition effects strengthening as the economy expands. National income level is also positively associated with environmental awareness and regulations that promote sustainability [17]. Societies in which there is greater environmental awareness are more likely to demand a strengthening of environmental norms and regulations, including pollution charges and

[1] Digital technologies comprise of information and communication technologies (ICT) – communication equipment (PCs, mobile phones, network hardware), software, applications [22], and the Internet [23].

taxes, monitoring, strong regulatory institutions, and public environmental education [8,50–52]. Additionally, more effectively defining and enforcing property rights and removing environmentally harmful subsidies can improve environmental standards [53,54].

Empirical results concerning the EKC hypothesis are mixed [55] since the nexus between growth and CO_2 emissions differs across countries that have a distinct growth paths (incl. R&D and diffusion of technology) [56] and policies [41]. For example, support for the EKC hypothesis is found by [11,54,57,58] and [59]. By contrast [10,50,55, 60–63], find no robust evidence for the relationship. [64] suggest that the results are consistent with the EKC hypothesis only for high-income countries but not for low- and middle-income economies. The estimation of the relationship must incorporate nonlinearity and enable parameters' heterogeneity with controls for multiple variables such as education, energy consumption, and democracy [46,65].

2.2. Digitalization, economic growth, and CO_2 emissions

Digitalization and ICT's positive impact on economic growth and productivity is broadly recognized [66–68]. Existing literature on "ICT value" shows that investments into ICT capital have a positive influence on productivity for highly developed [69,70] and upper-middle-income [71] economies. Digital exchange of information strengthens R&D collaboration within and across organizations [72] and contributes to innovation [70]. [73] claim that education through non-excludable digital technology results in an equivalent allocation of educational capital, subject to the availability of an Internet connection. Furthermore, almost zero expenses on digital content sharing and distribution can facilitate an increase in global knowledge dissemination [74]. Extensive use of advanced digital technologies necessitates the availability and quality of human resources, as seen in the growing demand for advanced conceptual and technical skills in programming and engineering and, more generally, for problem-solving skills and creative thinking [75].

The positive impacts of digitalization on the environment have been referred to as the "three D's for the economy" – decarbonization (via reduced energy use), dematerialization (by switching from print to e-books), and demobilization (e-commerce reduces traffic) [37]. There are two ways of thinking about ICT and GHG emissions – "green ICT" and "ICT for green." The first concerns the environmental effects of ICT that must be mitigated (also known as *direct effects*) by making the production and use of ICT greener or more environmentally beneficial; this can be achieved by reducing the energy consumption of hardware, data centers, and data-intensive processes, utilizing renewable energy sources, virtualization, and recycling electronic waste [28,76,77]. The idea of "ICT for green" is that ICT and digitalization can act as mechanisms that improve environmental quality (so-called *indirect effects*). For instance, "smart grid" technology may utilize digitalization to improve performance of the transmission, consumption, and generation of electricity, which accounts for a major source of CO_2 emissions since many power plants globally utilize fossil fuels to produce electricity [23,78]. Thus, in addition to their positive externalities in respect of growth and productivity, digital technologies can reduce CO_2 emissions through the optimization of manufacturing processes [27], exploitation of smart devices, by inducing resource efficiency and reduced waste [79], promotion of pro-environmental behavior over the Internet [40], development of transport networks, construction of smart cities, and facilitation of teleworking [65,77].

Digitalization's *tertiary effects* derive from modification in economic structures or consumption patterns and individual behavior, which lead to an increase in green energy use and frugal consumption of energy, supported by heightened environmental awareness [70,76]. Therefore, digitalization can improve the environment by increasing energy efficiency directly and promoting structural change (tertiarization) while moderating the effects of manufacturing, use, and disposal of ICTs [21].

Past research has shown that economic development and energy consumption are interdependent [80,81], and whether digitalization development has a causal effect on economic growth, energy use, and CO_2 emissions has been investigated. [38] uses an autoregressive distributed lag (ARDL) bounds testing model for Japan and shows that long-run ICT investments lead to more efficient energy use. A recent study [33] shows that ICT goods trade (export and import) in South Asian countries can directly (via interaction effects) and indirectly abate CO_2 emissions via increased consumption of renewable energy and decreased intensity of energy use. [65] use a panel of 142 countries and claim that the nexus between ICT and CO_2 emissions can be described by an inverted U-shape, implying the presence of the EKC relationship. [30] employ digitally delivered services as a proxy for digitalization and, using an unbalanced panel of 190 countries, reveal a bell-shaped relationship between CO_2 emissions and digitalization, supporting the EKC relationship and implying that higher levels of digitalization lead to reduced emissions. By contrast, in their study of the relationship between ICT, economic growth, and CO_2 emissions for nine ASEAN countries from 1991 to 2009 [82], find that ICT positively influences growth and CO_2 emissions through increased consumption of ICT goods and electricity. [68] claim that ICT (Internet and mobile use) and economic growth stimulate energy consumption, increasing emissions.

Although the impact of digitalization on economic growth and environmental pollution has received attention in the academic literature, the evidence on the sign and magnitude of that effect is still inconclusive, as some studies imply that digital technologies reduce CO_2 emissions directly or indirectly [39,41,83], whereas others suggest that digitalization may damage the environment [77,82]. Consequently, examining the implications of digitalization for environmental performance is a natural direction for further research. Previous research [42] stresses that this relationship should be investigated in the nonlinear context.

This research thus contributes to the literature by testing the nonlinear, inverted U-shaped relationship between digitalization and CO_2 emissions as dependent on the time-varying and country-varying technological R&D output level, which leads to the main hypothesis of the study.

Hypothesis 1. Progress in digitalization has a crucial environmental impact – that in a low R&D output regime the digitalization induces an increase in CO_2 emissions, while in a high R&D regime, digitalization reduces CO_2 emissions.

2.3. Relationship between research and development and CO_2 emissions

According to endogenous growth theory, investments in R&D, human capital, and innovation prompt technological progress, which can trigger more efficient and sustainable production that saves energy and natural resources [9,84,85]. [86] stresses how technological advances complement knowledge and human capital. [87] study the joint impacts of R&D and ICT on productivity, finding that ICTs have been effective in increasing production efficiency and creating inter-industry spillovers, while R&D increased the extent of technical change and stimulated knowledge spillover effects within industries, with complementarity between the two to reduce inefficiencies. Economic growth, triggered by technological progress, enables countries to increase investment in R&D and adopt cutting-edge technologies that enhance economic performance and environmental sustainability [48,49].

CO_2 emissions can be abated by developing and utilizing digitalization via promoting R&D activities and technological structural change in the economy [42]. In addition, when countries endeavor to reduce the intensity of CO_2 emissions, they need to boost R&D activities and the implementation of intellectual property protection to facilitate the technological innovation of the digitalization industry [34]. Public R&D activities promote the development of renewable energy technologies that can accelerate the transition to green energy [88], thereby mitigating carbon emissions. R&D expenditures have been found to be positively correlated with innovative technological patents and are crucial for reducing energy intensity and increasing renewable energy supplies by advancing energy-saving and clean energy technologies [89]. Thus, the inputs of R&D activities are tightly related to outputs, for example, technological inventions that reduce CO_2 emissions [90,91]. Technology innovations can effectively increase energy efficiency [80] and, thus, abate CO_2 emissions [56]. [43] claim that technological innovation (measured by patents) has heterogeneous and decreasing direct impact on CO_2 emissions and a moderating effect, lowering carbon emissions via impacting economic growth.

The empirical literature on how R&D impacts CO_2 emissions, which is primarily focused on single-country evidence, shows that R&D expenditures reduce CO_2 emissions if the best available technologies are employed. Comparative country panel studies using observation periods ranging between 10 and 20 years show that R&D investments and innovations reduce CO_2 emissions [90]. [9] in their study on the impact of R&D intensity on CO_2 emissions, use panel data of G7 countries and a non-parametric estimation framework, finding that the relationship between R&D and CO_2 emissions is time-varying and is negative over most of the period 1870–2014, with a positive relationship in 1955–1990.

Digitalization alone may be insufficient to reduce CO_2 emissions since digital technologies are contingent on the degree of human capital development [41]. Human capital is decisive in the uptake and deployment of technology and in promoting the innovative potential that result in technological advancement [41] and new technology creation [71]. Therefore, human capital growth can improve the environment by facilitating R&D in green energy and low-carbon, energy-saving technologies [92]. Since human capital development also promotes economic growth, the relationship between human capital progress and CO_2 emissions may also be described by the EKC hypothesis.

The existing literature pays limited attention to R&D output (measured in technological inventions per capita) acting as a transmission mechanism that drives the heterogenous effects of digitalization on carbon emissions on the global level in a nonlinear framework of PSTR. Only the study by [36] considers the mediating role of R&D investments in reshaping the environmental effect of the digital economy. Their findings on 30 Chinese provinces over 2006–2017 showed long-run cointegrating relationships between R&D, digitalization, and carbon dioxide emissions. Unlike the current study they estimated the moderating effect of R&D as an interaction variable term, while the given research models the smoothly transitioning regime shift in the effects of digitalization and GDP upon CO_2 emission.

Fig. 1 presents the conceptual model employed in the current study. Growth in R&D intensity, measured in technological patents, determines the smoothly transitioning regime shift from environment polluting state towards non-polluting state. In the environment polluting regime that is featured by low R&D intensity both digitalization and GDP increase CO_2 emissions. In the non-polluting regime with high R&D intensity, digitalization and GDP reduce the carbon footprint.

Hypothesis 2. The R&D output level (measured in country's technology patents per inhabitants) governs the transition process that leads countries from an environmentally exploitative and expansive economic regime into an innovative and sustainable economic regime under digitalization.

3. Data and methodology

3.1. Data

The empirical analysis employs a balanced panel of 55 countries, including 37 high-income and 18 middle-income economies[2] over a 23-year period from 1996 to 2019. This period begins with the explosive diffusion of commercial Internet across the world and has been named the era of mass digitalization by [74] and concludes before the shocks of the COVID-19 pandemic. The countries in the sample were selected based, in part, on their universities being included in the world's top-thousand institutions disclosed by Quacquarelli Symonds (QS) University Rankings and data availability; this ranking is used as a proxy for a country's R&D output development potential. Additionally, inclusion the middle-income countries that have experienced rapid economic advancement and productivity increases from ICT [71] in recent decades and concomitant growth in fossil fuel consumption helps in testing the EKC hypothesis.

[6] stress that omitted variables may bias the estimated effects on CO_2 emissions. Therefore, this research controls for several variables, including economic growth per capita, renewable energy consumption, manufacturing value added, and government effectiveness. Doing so helps in identifying the dynamic relationship between digitalization and human capital-driven productivity growth and environmental pollution, conditioned by the regime-shifting R&D driver.

The measurement of CO_2 emissions requires consideration because there are multiple indicators and measurement frameworks available. The UNFCCC requires that countries report their CO_2 emissions using a production approach. Under this rule, carbon emissions are assigned to the country in which they originate during production [93]. The awareness-raising environmental indicators are typically expressed in mass units [94]. The measure "fossil fuels and cement production CO_2 emissions" was chosen as the dependent variable in this research [42, 95].

The R&D output indicator representing "all technological inventions (patents)" in numbers per million inhabitants is selected as the transition variable (the selection process is described in Section 3.2.). This measure of patents enables the assessment of countries' technological innovations and government policies, which also relate to the environment and innovation [96].

Following [82]; the digitalization indicator is defined as the constructed index reflecting a multi-dimensional perspective. This composite digitalization index includes several phases of technology development, namely: (1) readiness and (2) use, and intensity. Variables that reflect digital technology readiness include three indicators: personal computers, fixed telephone subscriptions, and mobile cellular subscriptions (all per 100 people). Indicators representing digitalization intensity and use include fixed broadband subscriptions (Internet) and individuals using the Internet (all per 100 people). The composite index weights all these five indicators equally (average scores of the subcomponents), an approach that relies on the existing literature [82].[3]

The effect of digitalization depends on the level of human capital, since human capital spurs technological progress, prompts innovations [46], and makes digital technologies more effective in an economy [41]. The index of educational attainment includes two indicators for human capital: mean years and expected years of schooling; this index also partly captures digital literacy [41,65].

[2] High-income, upper-middle income, and lower-middle income economies are included, following the World Bank classification. https://datahelpdesk.worldbank.org/knowledgebase/articles/906519.

[3] The composite digitalization index using the weights from the principal component analysis leads to qualitatively similar results to those obtained using the equal-weighted index. The results from this robustness check are available on request from the author.

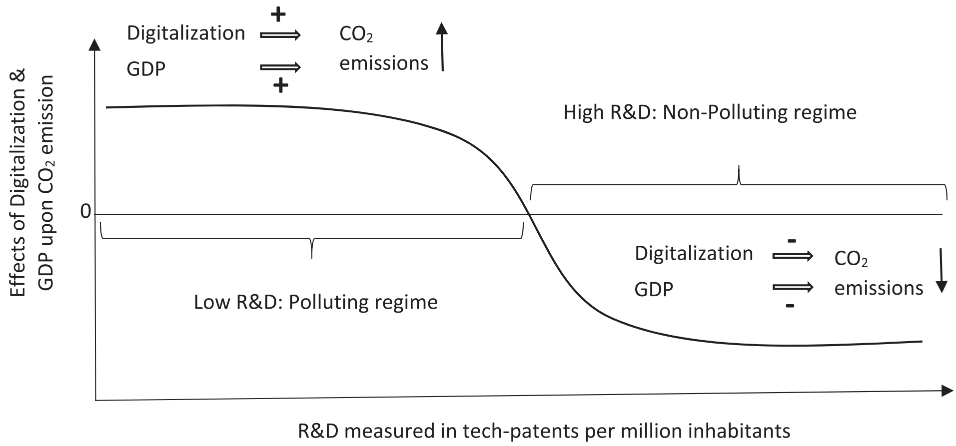

Fig. 1. Conceptual model.

The model includes real gross domestic product (GDP) per capita as a control variable [11] to test the EKC hypothesis. Another control variable included is renewable energy consumption as a percent of total energy consumption (energy demand); renewable energy use does not contribute to pollution directly, unlike fossil fuel utilization in power plants [21,56]. The share of value added in manufacturing is included to address the EKC's theoretical "composition effect" since, with economic growth, the share of manufacturing decreases, which entails lower CO_2 emission levels [8]. The effect of the institutional setting and development, which can improve environmental quality [97] is considered by including the government effectiveness index in the model. Table 1 presents the variable names, explanations, and data sources.

Table 2 presents the descriptive statistics of the key variables based on a sample of high-income and middle-income countries for the period 1996–2019. The average real GDP per capita for the sample of high-income countries for 1996–2018 (Panel A) was 41.09 (in thousands of international dollars). For upper-middle-income (Panel B) and lower-middle-income (Panel C) countries, it was 14.15 and 7.51 thousand international dollars, respectively. High-income countries produced higher CO_2 emissions per capita at 9.38 tons, compared to upper-middle-income and lower-middle-income countries with an average of 4.03 and 2.42 tons, respectively, in the period 1997–2019. In high-income countries, the digitalization index averaged 52.52% in the period 1996–2018, while for upper- and lower-middle-income economies, the index was 27.03% and 19.60%, respectively. The high-income countries produced more technological inventions per capita, 280.68, compared to the upper-middle-income and lower-middle-income countries that produced, on average, 10.62 and 1.56 inventions per capita, respectively, in the period 1996–2018. The statistics for technological inventions reveal that annual inventions have increased in practically all countries over the sampled period. Thus, the more relevant analysis is of regime shift induced by the increase in technological inventions and evidence that promoting technological development can also contribute to environmental improvement.

Similar to previous studies [18], all the exogenous and control variables enter the model with their lagged values (t−1) for the period 1996–2018. Table A2 in Annex A provides the correlations between the variables from 1996 to 2019.

Table 1
Variables, description, and data source.

Variable	Description	Source
CO_2	Fossil fuels and cement production CO_2 emissions, territorial, in tons per capita	UNFCCC, Global carbon project [95]
ATI	Patents for inventions in all technologies, in numbers per million inhabitants	Patents – Technology development [98]
DIG	Digitalization index (five components): individuals using the Internet, personal computers, fixed telephone subscriptions, mobile cellular subscriptions, and fixed broadband subscriptions (all per 100 inhabitants)	World Development Indicators [99], ICT Indicators [100]
EIX	Human capital: education index includes mean of years of schooling for adults (25 and above) and expected years of schooling for children	Human Development Data [101]
GDP	Real GDP per capita, PPP (purchasing power parity), constant 2017 international dollars, in thousands	World Development Indicators [102]
REN	Renewable energy consumption: nuclear, renewables, and other primary energy consumption, percentage of total energy consumption	U.S. Energy Information Administration data [108]
IVA	Value added from manufacturing, proportion of GDP	National accounts data [103]
GOV	Government effectiveness index: shows capacity to carry out and communicate prudent policies, commitment to policies, independence from political oppression; varies from −2.5 (weak institutions) to 2.5 (strong institutions), normalized from 0 to 100.	Worldwide Governance Indicators [104]

3.2. *Choice of the transition variable*

Economic considerations and the exogeneity condition should guide the selection of the transition variable, which must also be continuous and time-varying [105]. The transition variable should capture the regime effect of digitalization on CO_2 emissions according to its time-varying pattern. According to [9]; the relationship between R&D and CO_2 emissions is time-varying and negative over most of the sample period. Thus, in general, R&D output can serve as the transition variable to capture the nonlinear, time-varying relationship between CO_2 emissions and R&D output. The transition variable also accounts for country heterogeneity in R&D output and CO_2 emissions levels and in the strength of the relationship between them.

Two R&D output indicators were considered in selection of the most suitable transition variable: "patents for all technological inventions" and "scholarly output on environmental science," both per million inhabitants. Data for the first indicator of technological development were obtained from the "innovation in technologies" section of the [98]

Table 2
Descriptive statistics of the variables.

Variable	$CO_{2\,it}$	ATI_{it-1}	DIG_{it-1}	EIX_{it-1}	GDP_{it-1}	REN_{it-1}	IVA_{it-1}	GOV_{it-1}
Panel A: High-income economies								
Mean	9.38	280.68	52.52	81.21	41.09	20.30	15.04	76.47
Median	8.61	184.99	59.30	82.40	39.81	17.54	14.84	79.35
Standard deviation	4.35	354.95	21.65	7.86	17.67	16.70	5.27	11.68
Minimum	2.99	0.74	2.88	52.90	9.96	0.39	0.97	42.50
Maximum	25.98	2725.43	105.89	94.30	120.65	69.82	34.90	98.74
No. of countries	37	37	37	37	37	37	37	37
Observations	851	851	851	851	851	851	851	851
Panel B: Upper-middle-income economies								
Mean	4.03	10.62	27.03	62.97	14.15	14.90	19.09	51.82
Median	3.73	5.86	26.02	63.30	13.84	11.35	16.60	51.12
Standard deviation	2.32	12.97	18.44	8.25	5.30	11.86	6.40	8.90
Minimum	0.96	0.39	1.06	43.50	2.60	1.88	10.34	30.06
Maximum	9.95	73.99	64.68	84.20	28.32	41.83	33.10	75.34
No. of countries	11	11	11	11	11	11	11	11
Observations	253	253	253	253	253	253	253	253
Panel C: Lower-middle-income economies								
Mean	2.42	1.56	19.60	55.85	7.51	7.87	18.22	46.15
Median	1.84	1.11	15.95	55.70	7.19	4.50	16.73	45.71
Standard deviation	2.04	1.53	17.08	8.44	3.15	6.89	4.24	6.23
Minimum	0.58	0.04	0.34	35.10	2.22	0.21	11.90	32.45
Maximum	8.84	7.38	60.50	75.00	14.54	25.50	31.95	62.87
No. of countries	7	7	7	7	7	7	7	7
Observations	161	161	161	161	161	161	161	161

Notes: Panel A: high-income countries; Panel B: upper-middle-income countries; Panel C: lower-middle-income countries. $CO_{2\,it}$ – CO_2 emissions per capita, 1997–2019; ATI_{it-1} – all technological inventions (patents), per million capita, in lagged values (−1 year), 1996–2018; DIG_{it-1} – digitalization index, percent of population; EIX_{it-1} – education index; REN_{it-1} – renewable energy consumption, percent of total energy consumption; GDP_{it-1} – GDP per thousand capita; IVA_{it-1} – manufacturing value added, percent of GDP; GOV_{it-1} – government effectiveness index, normalized from 0 to 100. All exogenous variables are in lagged values (−1 year), 1996–2018.

database (technology domain: all technologies, total patents; family size: all inventions; presented by inventor country). Only published applications for "patents of invention" are considered. Data are based on the concept of the "simple patent family" [106]. This indicator is appropriate for a broad assessment of countries' innovation and related government policies. The second indicator, "scholarly output on environmental science" [107], includes data for all publication types (articles, conference papers, reviews, books, and books chapters) and serves as a proxy for the country's prolificacy. It also serves as a measure of publishing activity and productivity, being a snowball metric.

Both variables were subsequently tested with time-lagged values to avoid potential endogeneity from contemporaneous associations. The "technological inventions" indicator is suggested as the better candidate for the transition variable as it evaluates a country's technological progress more broadly and has a smoother, more continuous data structure with less variance and clearer results of linearity tests. This reasoning is also supported by the EKC technological effect and by previous research' findings that technology patents reduce CO_2 emissions [91,96]. Additionally, technological innovation (patents) was previously used as a controlling variable in the PSTR framework [46]. The alternative, "expenditures on R&D," is a less appropriate candidate since it reflects the input for innovation activities but does not represent technological development, which is generally considered as an output of innovation [56]. Since in equation (4) (see Section 4), the error term does not correlate with selected transition variable of technological inventions, then the exogeneity condition for this variable is fulfilled (it is not endogenous). Figure A.3. in Annex A presents the transition variable "technological inventions" per million inhabitants with respect to CO_2 emissions per capita for all countries in the study.

Since the "technological inventions" variable changes across countries and over time, it also allows the regression estimates to vary for each country and over time, implying that any country can move from one regime into another (smooth transition). With two regimes, the regression coefficients gradually shift from the lower extreme regime to the higher one as the "technological inventions" variable increases.

3.3. Model specification and estimation

PSTR models were developed by Gonzalez et al. [20] and [44] as an extension of [109] univariate sharp threshold time-series models (PTR). A two-regime PTR model defines two equations for the dependent variable, with the threshold variable determining which equation applies to a particular observation [105]. However, the application of this econometric technique is not trivial. The limitations of the PTR estimator are that it only allows for a small number of regimes and that the estimated parameters change between the regimes abruptly [110]. The latter is inconsistent with the evidence on the digitalization–CO_2 relationship that progresses gradually and not abruptly. PSTR models handle heterogeneous panels, allowing the coefficients of regressors to fluctuate over time and across observational units in a certain number of regimes that switch smoothly [18]. A common feature of PTR and PSTR is that both estimate the threshold level endogenously without relying on a subjective assessment of the regime change [10]. This property is a major advantage since it allows for cross-country heterogeneity without the necessity of the researcher to categorize countries in advance of the estimation [105].

PSTR is intended for use with non-dynamic (no lagged endogenous variable included) panel specifications; the approach is similar to univariate time-series smooth transition auto-regressive (STAR) estimators [111,112]. Given its properties mentioned above the PSTR framework provides greater flexibility compared to more conventional panel data estimators.

The empirical model applied in this research regresses CO_2 emissions on measures of digitalization, human capital, economic growth, renewable energy consumption, manufacturing value added, and government effectiveness using the technological inventions' level as the transition variable in the PSTR estimation framework [20,44]. All the variables enter the model in log-transformed form. The data's balanced panel structure enables the use of fixed effects to control for country-level unobserved heterogeneity. Overall, the PSTR modelling approach has three phases, which are model specification, estimation, and evaluation.

The decision as to whether to use PSTR (alternative hypothesis) or to stay with the linear model (null hypothesis) is based on the test of linearity when controlling for two regimes, or the test of no remaining nonlinearity when controlling for more than two regimes. The failure to reject the null hypothesis of linearity would mean that the relationship between CO_2 emissions and economic-capacity variables is invariant across countries and over time. [105] and Gonzalez et al. [20] suggest a linearity test for the model specification to determine the presence and number of regimes in the PSTR.

Before estimating the PSTR model, it is necessary to test for cross-sectional dependency (CSD) and a unit root. Cross-sectional dependence in panel data implies that a shock in one cross-sectional unit or country can induce consequences for other countries regarding the CO_2 emissions. [113] has proposed a unit root test robust to CSD in the panels, and [114] provides a test for determining the presence of CSD in the panel. The panels unit root test proposed by [115] was also performed. [116] cointegration test in panels allows for CSD and can robustly detect a long-run cointegrating relationship between digitalization (with related control variables) and CO_2 emissions. For comparison, the panels cointegration tests proposed by [117–119] are also conducted.

The baseline PSTR model with two regimes is set in the form:

$$\ln y_{it} = \mu_i + \lambda_t + \beta_0^{'} \ln x_{it} + \beta_1^{'} \ln x_{it} g(q_{it}; \gamma, c) + u_{it} \tag{1}$$

where $i = 1, \ldots, N$ and $t = 1, \ldots, T$, with N and T representing 55 countries (cross-sectional) and 23 years of the panel, respectively. β_{0j} and β_{1j} denote parameters' estimates in the linear part and the nonlinear part of the model. The independent variables – x_{it} is a k-dimensional vector of variables that vary in time (e.g., $\ln DIG_{it}$ denotes the log values of the digitalization). The dependent variable $\ln y_{it}$ indicates the log value of CO_2 emissions. Further, q_{it} is the transition variable of the technology development level, μ_i is a vector of country fixed effects, and λ_t is time fixed effects, the inclusion of which takes account of the level of exogenous developments in carbon mitigating technologies available to all countries [65]. The nonlinear transition function is denoted by $g(q_{it}; \gamma, c)$, which is continuous and bounded between 0 and 1, and u_{it} is the error term. This transition function depends on the transition variable q_{it}, the slope argument γ (which conditions the smoothness of the transition between regimes), and the threshold parameter c_j.

In accordance with [120] in terms of time-series modeling, as well as the elaborations by [44] and [20] in the panel data domain, the following logistic specification of the transition function is applied:

$$g(q_{it}; \gamma, c) = \left(1 + \exp\left(-\gamma \prod_{j=1}^{m} (q_{it} - c_j)\right)\right)^{-1} \tag{2}$$

where $\gamma > 0, c_1 < c_2 < \ldots < c_m$, $c = (c_1, \ldots, c_m)^{'}$ denotes the m-dimensional vector of location parameters. The conditions imposed on the slope and location parameters γ and c_j in equation (2) are determined for identification purposes. If $m = 1$ and the slope argument γ tends to infinity, this transition function $g(q_{it}; \gamma, c)$ becomes an indicator function that is equal to 1, if $q_{it} > c_1$, and 0 otherwise. If that is the case, the regression model defined in equation (1) is reduced to the threshold regression model for panel data (PTR) with two regimes, as proposed by [109]. For less extreme slope parameter value, the regression coefficients gradually shift from a lower regime into a higher one or from β_0 to $\beta_0 + \beta_1$, while the transition variable q_{it} increases and the change is centered at c_1. It is possible to obtain point estimates on location parameters.

Based on the reasoning presented in Section 3.2 and the results of the specification tests, it can be inferred that the sensitivity of CO_2 emissions to digitalization changes smoothly as a function of the countries' level of technological invention. Also important is the sign of the regression coefficients that may represent the growth or decline of CO_2 emissions as determined by the transition variable since the regression coefficients cannot be interpreted in the traditional way [105]. In current PSTR estimation, heteroskedasticity in standard errors is permitted and is estimated with the heteroskedasticity-consistent and cluster-robust covariance estimator [18,121].

Additionally, to address the issues of within-cluster dependence and heteroskedasticity, the wild bootstrap (WB) and wild cluster bootstrap (WCB) [122] evaluation tests were applied. Cluster-dependency means that the dependency may exist only within an individual and not across individuals [20].

In line with Gonzalez et al. [18], it is also possible to generalize the PSTR model with more than two regimes (additive model):

$$\ln y_{it} = \mu_i + \lambda_t + \beta_0^{'} \ln x_{it} + \sum_{j=1}^{r} \beta_j^{'} \ln x_{it} g_j\left(q_{it}^{(j)}; \gamma_j, c_j\right) + u_{it} \tag{3}$$

In this model, the transition functions $g_j(q_{it}^{(j)}; \gamma_j, c_j), j = 1, \ldots, r,$ are defined by the slope (γ_j) and location parameters (c_j), and the transition variable $q_{it}^{(j)}$. In terms of sources of endogeneity (unobserved heterogeneity), the PSTR estimator with multiple regimes defined by equation (3) represents an alternative hypothesis when testing for no remaining nonlinearity (heterogeneity) [18]. The null hypothesis of the linearity test ([105]; Gonzalez et al., 2005) is either $H_0 : \gamma = 0$ or $H_0^{'} : \beta_j = 0$. However, since the PSTR model has nuisance arguments that are not identified under either of the null hypotheses, the test statistics will obtain a non-standard distribution. The solution is developed for panel data and proposed by Gonzalez et al. [18], that suggests replacing the transition function $g(q_{it}, \gamma, c)$ in equation (1) with its first-order Taylor expansion around $\gamma = 0$ and performing the test of linearity, which is a Lagrange Multiplier (LM) test. These linearity LM tests are performed based on the transition variable: χ^2-version, F-version, χ^2-version heteroskedasticity and autocorrelation consistent (HAC), and F-version HAC tests.

Using the within-transformed form that controls for unobserved heterogeneity, the nonlinear least squares (NLS) estimate the PSTR model parameter. The initial values of the parameters c_j and γ_j are used in the estimation with subsequent application of the optimization method proposed by [123]. In this study, the PSTR modeling is performed applying the "PSTR" package in R software environment [124].

4. Results

This section reports and discusses the results from the analysis of the effect of the R&D-output regime driving the relationship between digitalization and CO_2 emissions. Before the PSTR was estimated, the baseline model was tested for the presence of nonlinearity to identify whether a model with at least one threshold variable ($r = 1$) should be estimated. The homogeneity test rejected the null hypothesis on linearity, based on p-value, which suggests that a threshold function must be incorporated to account for the coefficient heterogeneity across countries and over time. In other words, the results of the test suggested the use of two regimes and indicated that the nonlinear PSTR estimation is superior to a linear form. The subsequent evaluation tests for remaining nonlinearity did not reject the model with a single threshold function and two regimes.

Table A.4. in Annex A presents the results from the [114] test that does not reject the null hypothesis of no cross-sectional dependence in error terms. The results for the [113] panel unit root test (and the [115] panels unit root test) are presented in Table A.5., Annex A; the null hypothesis of non-stationarity is rejected for most variables except the manufacturing value added, a variable that is then integrated at its first difference values for inclusion in the model. The tests following [116,117]; and [118,119] reject the null hypothesis of no cointegration, suggesting that the variables in the model exhibit a stable long-run relationship (Table A.6. of Annex A).

Based on the reasoning presented in Section 3.2, two potential R&D output transition variables were proposed that can determine the nonlinearity between digitalization and carbon emissions. The tests results presented in Table 3 reveal that linearity is rejected for both prospective threshold variables (with $m = 1$ or $m = 2$). The p-values for all LM tests are almost equal to zero; thus, the specific threshold variable cannot be detected. However, the HAC versions of the linearity test return substantially lower p-values, implying that "technological inventions" is the most suited to the role of transition variable.

A sequence of homogeneity tests was conducted to determine the number of location parameters, m, (also transition function's order). Table 3 also presents the results of this specification test to select the order m of the PSTR model's transition function. Supported by the HAC version of the tests, the outcomes reveal that $m = 1$ is the most appropriate option for the transition variable "technological inventions." Therefore, the best choice for estimation of the PSTR model is the transition variable that captures R&D output in the form of technological inventions, in support of Hypothesis 2, with the number of switches (location parameters) equal to 1, which implies a two-regime model.

Table A.7. of Annex A reports the results for the tests of remaining nonlinearity or the possibility that the investigated relationships entail more than two regimes and that the parameters are not time-varying. The outcomes of the parameter constancy test and no remaining nonlinearity test (robust versions) to confirm the adequacy of the estimated model show that parameter constancy can be rejected (parameters time-variation is present), and heterogeneity in the coefficients across countries is entirely captured (no remaining nonlinearity). The results of these tests imply that the model with one transition is appropriate, as p-values are higher than 0.1, where the p-values of both the WB and WCB tests are equal to 1.00.

The specification tests of the PSTR model suggest a setup with a single transition function and a single location parameter. Hence, the model entails two regimes for the estimation of cross-country heterogeneity and time variability in the relationship between digitalization and CO_2 emissions.

The PSTR model specification is formulated as:

$$\begin{aligned} \ln CO_{2\ it} = {} & \mu_i + \lambda_t + \beta_{01} \ln DIG_{it-1} + \beta_{02} \ln EIX_{it-1} + \beta_{03} \ln \mathrm{GDP}_{it-1} \\ & + \beta_{04} \ln \mathrm{REN}_{it-1} + \beta_{05} \ln IVA_{it-1} + \beta_{06} \ln GOV_{it-1} + [\beta_{11} \ln DIG_{it-1} \\ & + \beta_{12} \ln EIX_{it-1} + \beta_{13} \ln GDP_{it-1} + \beta_{14} \ln REN_{it-1} + \beta_{15} \ln IVA_{it-1} \\ & + \beta_{16} \ln GOV_{it-1}] g(ATI_{it-1}; \gamma, c) + u_{it} \end{aligned} \tag{4}$$

where μ_i is country fixed effects, and λ_t is year fixed effects and the transition function is expressed as follows:

$$g(ATI_{i,t-1}; \gamma, c) = \left(1 + \exp\left(-\gamma\left(\ln ATI_{i,t-1} - c\right)\right)\right)^{-1}, \gamma > 0 \tag{5}$$

in the first part of the presented model (equation (4)), the independent variables impact carbon emissions directly and linearly, but in the second part, their nonlinear effects are moderated by transition variable of technological inventions. Table 5 presents the results of the final estimation of the PSTR model with one location parameter and one transition function.

Table 5 also presents the results of the estimated parameters from the linear part in the first regime (low R&D output), from the nonlinear part, and from the second regime (high R&D output), which is the result of the combined estimates from linear and nonlinear parts.

First, the simple model was estimated (Table 5, column 1) to investigate the heterogeneous impact of digitalization on CO_2 emissions and to control if the results are robust for the main exogenous variable of interest. The slope parameter γ of the transition function is 3.665, suggesting that the transition from the lower R&D regime to the higher regime is steeper compared to the main specification (Table 5, column 3). The location parameter is slightly higher for this specification at 3.897. Figure A.8. Annex A graphically presents the impact of digitalization (controlled for human capital) on CO_2 emissions conditioned by technological inventions. The estimates reveal that in the lower R&D output regime (primarily represented by lower-middle-income and upper-middle-income economies), the digitalization impact on CO_2 is positive and statistically significant: 0.18. Then, the transition function makes a shift at the value of 3.897 (log-scaled technological patents per million inhabitants) to the higher R&D regime (represented by high-income economies) where the digitalization effect on emissions is negative and significant: −0.144.

In the main specification of the PSTR model (Table 5, column 3), the estimated slope parameter γ of the transition function equals 1.277, implying the smooth transition from the lower R&D output regime to the higher regime. The location or threshold parameter specified in the transition function has a turning point estimate of 39.85 (antilog of 3.685) technological inventions per million inhabitants. In this model with two regimes, which are related to low and high values of q_{it} (technological inventions), the regression coefficients gradually shift from the first extreme regime to the second, while the technological inventions increase, and the change is centered at 39.85 (c_1).

The interpretation of the regression parameter estimates is primarily based on their signs. The baseline EKC hypothesis for the relationship between GDP per capita and CO_2 emissions per capita found firm support in the current study (main specification, Table 5, column 3), with significant parameter point estimates equal to 0.59 in the linear part and equal to −0.43 in the nonlinear part. These findings support previous research [19], where the estimates were: 0.51 and −0.55, respectively, for ASEAN countries and a different transition variable. The results

Table 3
Results of the linearity and sequence of homogeneity tests.

Linearity (homogeneity) tests					
LM tests: transition variable – scholarly output in Environmental Science					
m		LM_X	LM_F	HAC_X	HAC_F
1		482.3	65.14	19.19	2.59
	p-value	(0.00)	(0.00)	(0.008)	(0.012)
2		537.7	36.10	36.33	2.44
	p-value	(0.00)	(0.00)	(0.001)	(0.002)
LM tests: transition variable – technological inventions					
m		LM_X	LM_F	HAC_X	HAC_F
1		394.8	53.33	27.08	3.66
	p-value	(0.00)	(0.00)	(0.000)	(0.001)
2		453.4	30.44	34.79	2.34
	p-value	(0.00)	(0.00)	(0.002)	(0.003)
Sequence of homogeneity tests for choosing the number of "*m*"					
LM tests: transition variable – scholarly output in Environmental Science					
m		LM_X	LM_F	HAC_X	HAC_F
1		482.3	65.14	19.19	2.59
	p-value	(0.00)	(0.00)	(0.008)	(0.012)
2		89.61	12.03	12.80	1.72
	p-value	(0.00)	(0.00)	(0.077)	(0.101)
LM tests: transition variable – technological inventions					
m		LM_X	LM_F	HAC_X	HAC_F
1		394.8	53.33	27.08	3.66
	p-value	(0.00)	(0.00)	(0.000)	(0.001)
2		85.2	11.44	16.24	2.18
	p-value	(0.00)	(0.00)	(0.023)	(0.033)

Notes: m – number of location parameters/switches. Linearity LM tests considering two R&D output transition variables; χ^2-version, F-version, χ^2-version heteroskedasticity and autocorrelation consistent (HAC), and F-version HAC test. Model specification with $N = 55$; High-income and middle-income countries; 1210 observations.

Table 5
Estimated parameters of two-regime PSTR model.

Variables	Estimates, coefficients	(standard errors)	Estimates, coefficients	(standard errors)	Estimates, coefficients	(standard errors)
	(1)		(2)		(3)	
Low R&D level, β_{0j}, linear part, 1st extreme regime						
DIG_{it-1}	0.181	(0.029) ***	0.072	(0.037) *	0.070	(0.037) *
EIX_{it-1}	−0.389	(0.288)	−0.231	(0.297)	−0.245	(0.294)
GDP_{it-1}			0.591	(0.122) ***	0.588	(0.123) ***
REN_{it-1}			0.014	(0.042)	0.013	(0.042)
IVA_{it-1}					−0.150	(0.069) **
GOV_{it-1}			0.110	(0.128)	0.108	(0.127)
β_{1j}, nonlinear part						
DIG_{it-1}	−0.325	(0.056) ***	−0.211	(0.066) ***	−0.212	(0.065) ***
EIX_{it-1}	0.268	(0.055) ***	−0.326	(0.369)	−0.327	(0.364)
GDP_{it-1}			−0.431	(0.230) *	−0.430	(0.230) *
REN_{it-1}			−0.162	(0.068) **	−0.162	(0.068) **
IVA_{it-1}					−0.040	(0.139)
GOV_{it-1}			0.937	(0.301) ***	0.941	(0.298) ***
High R&D level, $\beta_{0j} + \beta_{1j}$, 2nd extreme regime						
DIG_{it-1}	−0.144	(0.060) **	−0.139	(0.055) **	−0.142	(0.055) ***
EIX_{it-1}	−0.122	(0.300)	−0.557	(0.290) *	−0.533	(0.290) *
GDP_{it-1}			0.159	(0.203)	0.158	(0.202)
REN_{it-1}			−0.149	(0.040) ***	−0.149	(0.039) ***
IVA_{it-1}					−0.190	(0.099) *
GOV_{it-1}			1.047	(0.258) ***	1.049	(0.255) ***
Slope parameter, γ	3.665	(1.332) ***	1.296	(0.568) **	1.277	(0.547) **
Location parameter, c_1, (antilog)	3.897 (49.25)	(0.244) ***	3.685, (39.85)	(0.490) ***	3.685, (39.85)	(0.484) ***

Notes: standard errors (in parentheses) are achieved by applying the heteroskedasticity-consistent and cluster-robust covariance estimator; dependent variable: $CO_{2\ it}$ – CO_2 emissions per capita; ATI_{it-1} – all technologies (patents) per million capita; DIG_{it-1} – digitalization index, percent of population; EIX_{it-1} – education index; GDP_{it-1} – GDP per thousand capita; REN_{it-1} – renewable energy consumption, percent of total energy consumption; IVA_{it-1} – value added from manufacturing, percent of GDP (first-differenced); GOV_{it-1} – government effectiveness index. The model includes dummy variables for OECD countries (= 1 for OECD, 0 otherwise) and global financial crisis (= 1 for 2007, 2008, 2009, 0 otherwise). All exogenous variables are in lagged values (−1 year), 1997–2018. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

confirm those in [10]; where in a similar methodological setup but with different transition (GDP) and dependent (ecological footprint) variables the income's positive impact in the linear part was greater than in the nonlinear part, with global pollution referenced as a probable explanation.

Moreover, the main variable of interest, digitalization in the lower

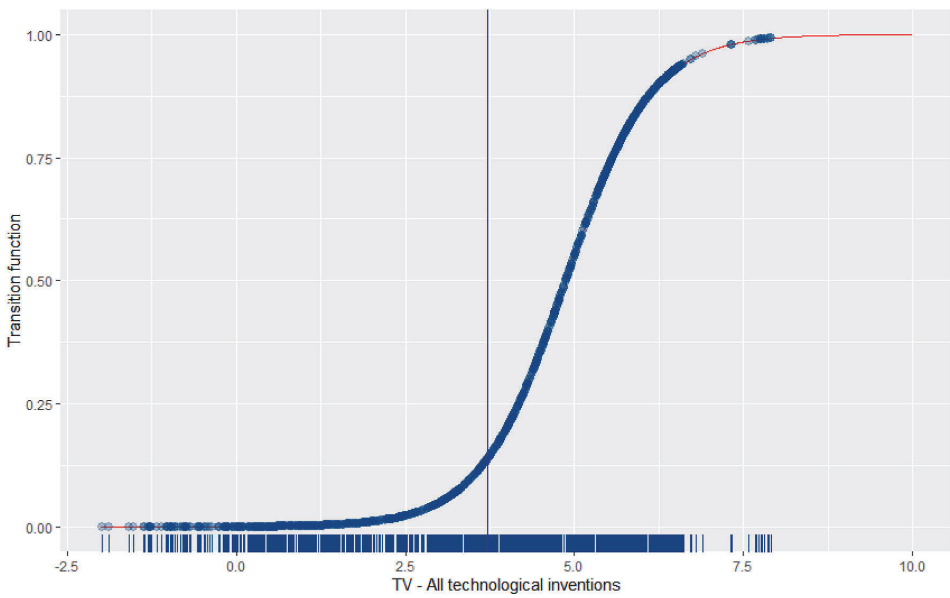

Fig. 2. PSTR model's estimated transition function based on technological inventions
Notes: Each dot indicates an observation. "All technological inventions (patents) per million inhabitants" is on the X axis in logarithmic scale. The turning point at the value of 3.685 is marked by a vertical line.

R&D output regime, had a positive and statistically significant point estimate of 0.070, whereas, in the higher regime, the estimate was negative at −0.142 and statistically significant. The estimate was also negative at −0.21 and statistically significant in the nonlinear part. Hence, in support of Hypothesis 1, an inverted U-shaped relationship was found for CO_2 emissions transitioning in the R&D output level with respect to digitalization as well. The high level of digitalization may also capture better digital environmental management (enhanced data collection and analysis), more efficient energy use [80], wider information spread, and a higher environmental-awareness effect that reduce CO_2 emissions [8,30] in advanced economies that have a high level of technological innovations. The results support Hypothesis 1: in the low R&D output regime, digitalization's impact on CO_2 emissions is positive; however, in a high R&D regime, digitalization's effect on carbon emissions is negative. At the same time, advanced economies produce higher levels of R&D output, which results in the deployment of the most innovative technologies (including digital technologies) that leads to lower CO_2 emissions' levels [9,49]. The relationship between digitalization and CO_2 emissions was not previously examined using a nonlinear PSTR estimator and testing the R&D threshold effect, with only [42] using STR estimator and ICT as a threshold variable and finding that ICT contributes to the mitigation of CO_2 emissions at a high level of ICT.

Fig. 2 presents the transition function $g(ATI_{i,t-1};\gamma,c)$ based on the log-scaled variable of technological inventions per million inhabitants. The turning point in the log scale is 3.685, which is represented in Fig. 2 by a vertical line.

The human capital estimate remained insignificant in the linear and nonlinear parts but was negative and statistically significant at the point estimate level of −0.53 in the higher R&D output regime. This indicates that incremental human capital supported by high technology innovation level reduces CO_2 emissions, a finding that at least partially supports the educational Kuznets curve hypothesis [125]. [46]; using the PSTR approach and human capital as a regime transition variable, show similar evidence on a hump-shaped Kuznets curve.

Additionally, the measure of renewable energy consumption had a significant negative point estimate of −0.16 in the nonlinear part and −0.15 in the high R&D output regime, which contributes to the evidence that human capital facilitates R&D in renewable energy and the introduction of energy-saving technologies [35,92]. Furthermore, the change in manufacturing value added negatively impacts the pollution variable; its estimates are −0.15 and −0.19 in the first and second extreme regimes, respectively, both are statistically significant. This result supports the EKC theoretical "composition effect", meaning that the change in manufacturing value added leads to decreased CO_2 emissions especially in the higher R&D regime. A somewhat surprising result appears in respect of the government effectiveness index, with a positive point estimate of 1.05 in the higher R&D regime. On the one hand, institutions play an important role in sustainability goals alongside economic and technological progress – institutions support the enforcement of regulations and enhance energy technology development [92]. However, efficient institutions can lead to economic advancement and increased energy use, which can, in turn, result in higher emission levels, with mixed findings revealed on this relationship in the extant literature [61].

Table 5, column (2), presents the results of a shorter version of the specification (without the indicator for manufacturing value added), which is compared to the main specification for robustness purposes. The estimations of this version are highly similar in terms of sign and magnitude. The slope parameter here is greater, indicating a steeper transition from the lower technological development regime to the higher one. The location parameter value remains similar at 3.69.

The robustness of the results is tested using the alternative transition variable of R&D expenditures as a percentage of GDP (obtained from World Development Indicators, with lagged values (−1 year) for 1996–2018; [126]. Based on the discussion in Section 2.3, R&D investments (inputs) correlate with innovative technologies (outputs) [89]. Table A.9. of Annex A shows the results of this estimation of the PSTR model (equation 6) with R&D expenditures as the transition variable and one location parameter (the results of the specification and evaluation tests imply a nonlinear model with one location parameter). The parameter estimates are indicated for low- and high-regime transitioned in the level of R&D investments. The findings reveal that the estimations with R&D input as the transition variable are robust and comparable (by sign and magnitude) with estimated parameters of the model with the transition variable of technological inventions, presented in Table 5. The slope parameter here 1.448 (main specification) is slightly higher, indicating a steeper transition from the lower to the higher R&D input regime. The transition function makes a shift between the two R&D regimes at a threshold of 0.58, which represents R&D expenditures taken as a share of GDP.

The model also includes a dummy variable for the global financial crisis (GFC) (equal to 1 for the years 2007, 2008, and 2009, and 0 otherwise) to control for the potential effect of GFC on the results. In the linear part (first extreme regime), the GFC impact was negative −0.030, while in the second extreme regime and nonlinear part, the coefficients were positive: 0.051 and 0.081, respectively (all statistically significant). This reveals that, in the higher R&D output regime, the impact of GFC on CO_2 emissions was positive.

5. Conclusions

In the face of massive environmental challenges, countries are seeking opportunities to decouple economic development from increasing carbon emissions. This study examines how digitalization links to abating of CO_2 emissions and provides new empirical evidence on the role of R&D output in driving the transition toward lower carbon emissions.

This study provides support for a nonlinear relationship between CO_2 emissions and economic advancement indicators for the broad sample of high-income and middle-income countries for the period 1996–2019. The study results support the EKC hypothesis, finding evidence of an inverted U-shaped relationship between CO_2 emissions per capita and GDP per capita. The facilitating role of R&D output in that nexus implies that policies focused on enhancing R&D output can contribute to the development of a carbon neutral economy. The findings in alignment with the EKC hypothesis show that economic development in low or moderate R&D and technology regime does not contribute to environmental quality, but the growth in later stages, supported by technological development, induces increased use of renewable energy resources and lower CO_2 emissions. An even stronger link is confirmed in the relationship between carbon dioxide emissions and digitalization. The findings also suggest that the digitalization effect not moderated by R&D output can trigger an increase in carbon emissions levels. By contrast, if digitalization is driven by intense R&D activities (especially those with favorable environmental effects), it leads to a decrease of CO_2 emissions. This implies that the use of digitalization in higher R&D regime promotes environmental sustainability. A partial EKC effect is found for human capital, as it has a negative relationship with CO_2 emissions in the high R&D output regime. The turning point at which the transition function shifts between the two R&D regimes is equal to 39.9, a metric that reflects the average number of technology patents per million inhabitants.

Considering the main goals of this study, the obtained empirical results suggest directions for policy recommendations to improve environmental sustainability. With resumed increase in global CO_2 emissions after the end of the COVID-19 pandemic and considering the obligations that countries have taken to achieve sustainable development goals (SDGs) [127], governments should preferably implement stringent policies that promote environmental as well as economic welfare. These policies should recognize the role of R&D in moderating the relationship between digitalization and CO_2 emissions. Hence, to sustain the environment, more R&D is needed in digital development that generates products and applications that serve human needs, either at a lower cost for the environment or, preferably, in an environmentally neutral or even improving way.

On these avenues digitalization explicitly addresses several of the SDGs set by the United Nations. In the context of decarbonization, digitalization plays a strong role in promoting industry, innovation and infrastructure, contributing to building of sustainable communities and cities and strengthening climate action while facilitating access to affordable and clean energy. The study findings reveal that governments should consider facilitating the increased use, intensity and readiness of digitalization that helps to achieve SDG-13 goals (targets 13.2 and 13.3) by raising environmental awareness, enhancing education and strengthening of institutions. Digital inventions that optimize processes and deploy artificial intelligence and smart technologies contribute to frugal energy use. Digital solutions already proved to be indispensable during the COVID-19 lockdowns, making remote work and e-learning pervasive, and the momentum could be used in striving for further progress in digitalization. Policymakers should put particular focus on promoting improved access to ICT technologies and the Internet (SDG-9 target 9.C) as well as more developed infrastructure (e.g., 4G, 5G networks), e-commerce and high-tech industries, with simultaneous introduction of green technologies (target 9.4) and facilitation of scientific R&D (targets 9.5 and 9.B) to improve efficiency of resource use and reduce pollution. It is also essential to implement policies that promote the tertiary effects of digitalization, such as environmental awareness in consumption habits and economic decision-making. Governments should consider digitalization, technological innovation, and R&D policies together as an interaction of these contributes to environmental sustainability. These policies and the ongoing transition to renewable energy sources pave the path to carbon neutral welfare growth.

The results of this study show that renewable energy consumption reduces CO_2 emissions when moderated by technological innovations. This means that the share of clean energy should be increased in total energy consumption by facilitating research into renewable energy solutions, adoption of advanced energy technology and development of energy infrastructure (SDG-7 targets 7.A and 7.B). However, the increased cost of manufacturing, transportation and installation of renewable energy equipment (e.g., wind turbines, solar panels) and recent energy crisis [14] will present additional challenges in shaping the policy. Governments should consider providing support to the public and private initiatives in pursuing R&D activities to lower the costs of renewable energy solutions. Furthermore, the study outcomes reveal that income growth moderated by technology inventions reduces pollution. Countries should therefore facilitate sustainable economic growth when recovering after the COVID-19 pandemic (SDG-8) so that digitalization supports increased productivity via introduction of technological upgrading and concentrating on high value-added industries (targets 8.2 and 8.3). Special attention should be paid to efficient resources use (incl. circular economy) and to the disconnection of economic growth from deterioration of environment (target 8.4).

The estimation outcomes imply that R&D output plays a crucial moderating role in environmental and economic sustainability. The results align with the findings of previous research [9,48] that high R&D output has a suppressing effect on CO_2 emissions as more efficient and green energy technologies are adopted that reduce waste, pollution, and energy use in the production processes and decrease the exploitation of non-renewable resources. Modern technologies, initially invented and introduced in advanced economies of the US, Europe, and Japan, also benefit the middle-income countries that are gradually adopting them, increasing production efficiency and sustainability, and reducing CO_2 emissions globally [128]. The adoption of energy-efficient technologies and the simultaneous deployment of digitalization should be prioritized in both frontier economies and those that have not yet reached the R&D regime turning point. Technological inventions can enable the middle-income economies to reach the technological threshold that has restrained the increase in their renewable energy generation capacity [129]. Furthermore, the implementation of these policies in high-income economies will generate spillovers for the middle-income countries that will help the latter to shape policies to increase energy efficiency, promote green digitalization and thus decrease emissions.

As for caveats to this study, there may be other candidates (beyond technological inventions, representing technological development, not adoption) for the transition variable governing the shift between the production-pollution regimes or an R&D variable other than technological inventions (patents) that may better capture the regime shift process. Similarly, alternative indicators for digitalization may deepen the knowledge of environmental impacts and affect some of the results. Finally, the results may be sensitive to the composition of the country-year panel.

Author statement

The submitted paper is an original research contribution and it has not been published previously neither in part nor in full and it is not under consideration for publication by any other journal. I am fully consent with the publication policy of the journal.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techsoc.2023.102323.

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Appendix 2. Publication II

TECHNO-ECONOMIC ASSESSMENT OF CO_2 CAPTURE POSSIBILITIES FOR OIL SHALE POWER PLANTS

Publication II

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Techno-economic assessment of CO_2 capture possibilities for oil shale power plants

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ABSTRACT

Oil shale is a calcium-rich fossil fuel, and its combustion in power plants generates high CO_2 emissions, which must be reduced drastically. Thus, this study conducts a comparative techno-economic analysis of adding CO_2 capture technologies, namely, post- and oxy-fuel combustion technologies, to existing oil shale power plants in Estonia. Estonia's energy sector is unique due to its heavy reliance on oil shale. The study's technical analysis indicates that oxy-fuel combustion capture would outperform post-combustion capture in oil shale power generation. However, integration of CO_2 capture technology would result in reductions in power units' heat rate performances by more than 10% points due its energy requirements. From a financial perspective, the feasibility of Estonian oil shale power plant CO_2 capture depends upon the long-term trends in the electricity market and CO_2 emissions trading system. Full-capacity operation over an assumed 24-year lifetime would cost at least 89 euros per ton of CO_2 captured and stored in 2021 values. The actual cost might exceed paying CO_2 emission allowance fees and environmental charges or result in a competitive disadvantage. Thus, only in the event that the negative externalities resulting from CO_2 emissions and national energy security concerns cannot be feasibly mitigated with alternative, stable, and controllable energy sources should state aid be used for CO_2 capture technologies for oil shale power plants. The need to impose higher taxes, *ceteris paribus*, to cover the state aid or transfer the CO_2 capture costs to the private sector might reduce the Estonian economy's overall competitiveness.

1. Introduction

The need to reduce greenhouse gas (GHG) emissions to combat climate change is evident [1,2]. The European Union (EU) has set targets of net-zero GHG emissions by 2050 and a 55% reduction in GHG emissions by 2030 compared to 1990 levels [3]. Oil shale (OS) is among the fossil fuels that generate relatively high CO_2 emissions in power plants—defined as at least 0.9–1.0 tons of CO_2 per MWh_e of electricity generated [4]—as CO_2 is created not only through the oxidation of carbon from organic material but also through the decomposition of carbonates in OS's mineral matrix [5,6].

OS is a fine-grained sedimentary rock that contains organic matter, more commonly known as kerogen [7]. The core difference between OS and coal is that the organic matter found in OS is mainly of algal origin [8,9]. Another distinctive feature of OS is that during the thermal decomposition of kerogen, a significant amount of shale oil and combustible gas is released, making it an unconventional oil resource. Generally, OS deposits are found on all continents and contain an estimated 6050 billion barrels of shale oil [10]. Despite its relative abundance, only a few countries consider OS to be a reliable source for power generation and shale oil production. As one of these countries, Estonia has a long-term knowledge base concerning, and industrial experience in, OS utilization. Estonian OS, called kukersite, belongs to a marine group of formations and is rich in carbonates. Its organic matter has a relatively high atomic ratio of hydrogen to carbon (H/C), typically exceeding 1.2 (comparable to that for conventional oil); a low oxygen-to-carbon ratio (O/C), typically falling below 0.12; a low nitrogen content of 0.33 %wt; and a chlorine presence of 0.75 %wt [9,11]. Due to the high hydrogen content in the organic matter, it can release up to 90% of its volatiles [9]. Minerals constitute 60–70% of this OS and typically consist of carbonate minerals (calcite and dolomite) and sandy clay [11,13]. This OS's average moisture content is around 10 %wt, and its average lower heating value is 8.5 MJ/kg [11,14].

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Abbreviations

BPP	Balti Power Plant
CC	CO_2 capture
CCUS	CO_2 capture, utilization, and storage
CFB	Circulating fluidized bed
DOE	U.S. Department of Energy
ECB	European Central Bank
EPP	Eesti Power Plant
ESP	Electrostatic precipitator
ETS	Emissions Trading System
EU	European Union
FF	Fabric filter
FW	Foster Wheeler
GHG	Greenhouse gas
H/C	Hydrogen-to-carbon atomic ratio
LCOE	Levelized cost of electricity
LHV	Lower heating value
MEA	Monoethanolamine
MWh/tCO_2	MWh per ton of CO_2 captured
NETL	National Energy Technology Laboratory
O/C	Oxygen-to-carbon atomic ratio
OS	Oil shale
OSPP	Oil shale power plant
OXY	Oxy-fuel combustion
PC	Pulverized combustion
PCC	Post-combustion capture
RP	Reference plant
TRL	Technology readiness level
WACC	Weighted average cost of capital
%ar	As-received basis percent
%wt	Weight percent

Estonia is unique in that a majority of its electricity is produced by oil shale power plants (OSPPs), a portion of which it exports. Therefore, Estonia's GHG emissions per capita have been among the highest in Europe. During the period 2013–2018, when OS electricity production volumes were high, Estonia, with its 13.8–16.7 tons of GHG emissions per capita, ranked among the top three GHG producers in Europe, along with Luxembourg and Iceland. During 2019–2020, OS electricity production declined in Estonia, as reflected in GHG emissions per capita of 11.2 tons in 2019 and 8.7 tons in 2020 [15]. The 2021 international energy crisis, amplified by Estonia's national energy security concerns following the 2022 invasion of Ukraine by Russia and imposed or planned sanctions regarding Russian fuel and energy imports to the EU, led to a sharp increase in OS electricity production and, inevitably, surging CO_2 emissions. No data are yet available for this period, but in 2018—the year likely to be most comparable with 2021 and 2022—Estonia's net GHG emissions, including international transport, reached the equivalent of 20.3 million tons of CO_2, of which 69% came from the energy sector [16]. Thus, to reduce GHG emissions in Estonia, the main focus should be on reducing CO_2 emissions from energy production.

Although significant technological improvements in the OS energy industry since the 1990s have significantly reduced CO_2 emissions, under the current climate change mitigation goals, further reductions in the industry's environmental footprint are necessary [5]. In line with the EU's strategy, CO_2 capture (CC) technologies must be developed and implemented to reduce CO_2 emissions [17]. CC could be used in the OSPPs [18,19], particularly if ways to store or utilize the captured CO_2 efficiently could be identified. However, adding CC capacity to existing production units would increase the cost of the electricity generated and reduce power generation efficiency. Implementing carbon capture, utilization, and storage (CCUS) in OS energy production would make financial sense if the electricity generated remained competitive with electricity generated from other energy sources. Estonian OS-based electricity must compete with fossil and renewable energy on the European market via the Nord Pool power exchange. Therefore, a techno-economic evaluation is needed to identify the technologically most promising CC methods for OS-based electricity generation and to assess their costs and competitiveness [5].

This study makes a novel contribution to an area that has received minimal attention in the literature. The paper's primary objective is to assess the suitability of available CC technologies for OS electricity generation in Estonia and to determine any additional associated costs. The techno-economic analysis of retrofitting CC into the OSPPs is based on the integration of two alternative CC technologies: post-combustion capture (PCC) and oxy-fuel combustion (OXY). PCC and OXY have relatively high technology readiness levels (TRLs $\geq$7) and can be used at OSPPs. The paper offers a comparative assessment of CC technologies for the OS energy industry, a comparative analysis of capture costs, and a discussion of the results, including policy implications. This paper represents the first comprehensive assessment of the integration of CC technologies into the OS-based power industry. To support and provide input for the OS specific analyses of CC technologies presented in this study (incl. in comparison with coal power plants), experiments have been carried out with the OXY technology on a pilot scale. These experiments build upon the authors' experiences in the field of OXY [20] and are transferable to other Ca-rich processes.

2. Material and methods

2.1. Oil shale as a fuel

The specifications for the two types of OS considered in this study are presented in Table 1. As these two OS compositions vary in terms of organic content, they are assigned different heating values. In this specification, carbonate CO_2 represents the CO_2 content in raw fuel bound with calcite and dolomite minerals.

2.2. Oil shale-based power generation

Over the last two decades, significant changes have occurred in the Estonian OS-based power generation industry, including the partial retrofitting of old pulverized combustion (PC) units with new circulating fluidized bed (CFB) boilers (Balti Power Plant (BPP) unit 11 and Eesti Power Plant (EPP) unit 8 in the period 2004–2005) [22] as well as the

Table 1
Specifications for the oil shales considered in this study.

Parameter	OS1	OS2
Carbon (organic), $\%_{ar}$	19.28	21.00
Hydrogen, $\%_{ar}$	2.37	2.48
Oxygen, $\%_{ar}$	3.62	2.46
Nitrogen, $\%_{ar}$	0.06	0.06
Sulfur (organic), $\%_{ar}$	0.39	0.37
Pyritic Sulfur, $\%_{ar}$	0.91	1.02
Sulphate Sulfur, $\%_{ar}$	0.03	
Chlorine, $\%_{ar}$	0.31	0.09
Carbonate CO_2, $\%_{ar}$	17.98	19.00
Corrected Ash Content, $\%_{ar}$	43.53	42.00
Crystallic Water Content, $\%_{ar}$	0.64	
Water Content, $\%_{ar}$	10.90	11.52
Lower Heating Value, MJ/kg	7.90	8.33

Sources: Measurements made during experiments by the authors and Enefit Power [12,21].

commissioning of a new 305 MW_e power unit at the Auvere Power Plant in 2016. An overview of current OS utilization in power generation is provided in Table 2. Only large-scale CFB units with rated capacities greater than 50 MW_e and using OS as their primary fuel are presented in this table.

Power generation volume at OSPPs greatly depends on electricity prices and the CO_2 European Emission Allowance price posted for the EU Emissions Trading System (ETS). As a result, OS power generation declined significantly in recent years. However, it has increased once more due to the sharp rise in electricity prices in 2021. Figs. 1 and 2 illustrate the recent dynamics of electricity generation and related CO_2 emissions in Estonia from OS firing power units. These figures show the unprecedented reversals in volume that occurred through 2020. On the one hand, these reversals significantly reduced absolute CO_2 emissions in the OS industry. On the other hand, CO_2 intensity per generated MWh decreased gradually due to the much higher heating rates of the remaining units. CO_2 emissions from the existing PC units exceeded 1200 kg/MWh_e [24], whereas for retrofitted and new CFB units, emissions were below 1000 kg/MWh_e. In 2020, Estonia switched from being a power exporter to a power importer and recorded several days with zero OS-based power generation; however, the energy deficit and high electricity prices in 2021 marked the comeback of the old PC units. This trend has been further escalated by the need to secure Estonian national power generation in light of regional security concerns.

Source: [25].

From a technical point of view, integrating CFB technology into OS

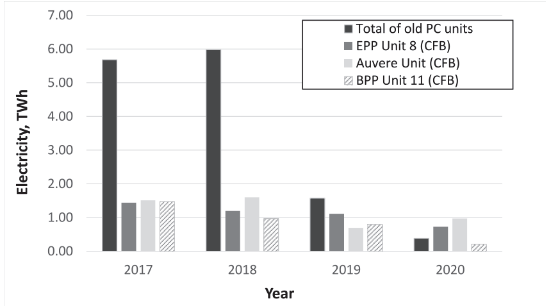

Fig. 1. Electricity generation during recent years.

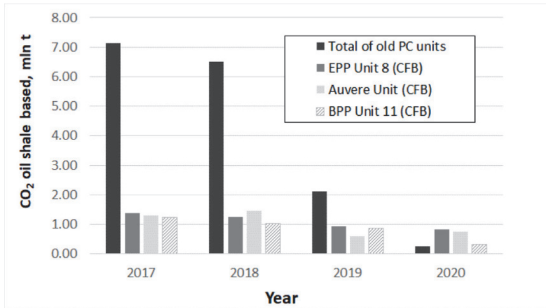

Fig. 2. CO_2 emissions based on the firing of shale oil.

power units results in radically different performance characteristics, such as technical availability, fuel flexibility, general thermal efficiency, and emissions of pollutants [22,26,27]. High carbonate mineral content—that is, a molar ratio of calcium to sulfur (Ca/S) of around eight, depending on OS quality—leads to the direct capture of almost all the sulfur in the CFB furnace. The relatively low nitrogen content in kukersite OS, combined with a lower combustion temperature, leads to lower NO_x formation, keeping it below its emission allowance of 200 mg/Nm^3. Another advantage of CFB boilers, especially in light of the recent decarbonized energy vector, is that they cause OS to decompose to a smaller extent, around 70–80% [28], resulting in lower specific CO_2 emissions compared with PC combustion, where carbonates decompose almost wholly. CFB boilers also offer fuel flexibility, making co-combustion with other types of fuels, including biomass fuel [26,29,30], which is regarded as carbon neutral under the current regulations, possible.

Considering these characteristics, the three CFB-based units were selected for this study's CC retrofit analysis. The power units BPP 11 and EPP 8 were deemed identical for this study's purposes. Thus, the results per unit (labeled as FW to refer to the Foster Wheeler-supplied technology used) apply to both BPP 11 and EPP 8. Additionally, in the technical analysis, a hypothetical power unit with a fixed net power output of 275 MW_e (making it the same size as the Auvere unit without CC) and powered by a CFB steam generator with supercritical parameters is included. This generator provides a net unit efficiency of 43% (LHV-based). It was assumed that the unit combusts OS2 fuel but can co-combust biomasses up to 50% via heat input.

Table 2
Overview of the main power generation units.

Parameter	BPP Unit 11 (FW)	EPP Unit 8 (FW)	Auvere Unit
Type	Two CFB boilers per single turbine	Two CFB boilers per single turbine	One CFB per single turbine
Rated Capacity (gross), MW_e	215[b]	215	305
Efficiency, % (net, LHV)	37[b]	37	40.27
Commissioning	Turbine 1970s, Boilers 2005	Turbine 1970s, Boilers 2004	2016–2018
Steam Parameters, MPa/°C/°C	12.7/535/535	12.7/535/535	17.2/540/565
Boiler Efficiency, %	~90	~90	~90
Fuel Type	Oil shale, biomass up to 50%	Oil shale, semi-coke gas	Oil shale, biomass up to 50%; semi-coke gas
Fuel Consumption, t/h	234.5[c]	234.5[d]	295.5[e]
Water Cooling System	Once-through	Once-through	Once-through
NOx Reduction Method	–	–	–
NOx, (mg/Nm^3 6% O_2)	<200	<200	<200
Sulfur Capture	Naturally, directly in CFB furnace	Naturally, directly in CFB furnace	Naturally, directly in CFB furnace
SO_2, (mg/Nm^3 6%O_2)	~3	~3	~3
Dust Control	ESP	ESP	ESP & FF
Particulate matter (i.e., dust), (mg/Nm^3 6%O_2)	<20–30	<20–30	<5
Flue Gas Flow, Nm^3/h	~767,455	~767,455	~1,034,514
Mt CO_2/y[a]	1.49	1.49	2.03

[a] Originating from combustion, based on 100% OS fuel and assuming 85% capacity factor.
[b] Without district heating load applied, can provide district heating load up to 110 MW_{th}.
[c] 100% OS firing with OS 7.9 MJ/kg, without district heating load.
[d] 100% OS firing with OS 7.9 MJ/kg.
[e] 100% OS firing with OS 8.33 MJ/kg.
Source: Authors' calculations based on [12,21,23].

2.3. Selection of potential CO_2 capture technologies for oil shale power plants

The techno-economic analysis of retrofitting CC into the FW and

Auvere power units in the present study is based on the integration of two alternative CC technologies: PCC and OXY that have relatively high technology readiness levels (TRLs ≥7) and can be used at OSPPs.

Various PCC methods have been described [17,31,32], but they all can be integrated into a power unit after the combustion section. These methods include CC via adsorption, absorption, membrane, chemical looping, and cryogenic processes. In this study, an amine solution absorption process was selected for studying CC deployment in OS power generation units [33] because it has been demonstrated on a commercial scale for power generation [34] and appears to be relatively cost-effective, at least among the PCC methods [35]. Furthermore, its characteristics have been well reported in the literature. This method absorbs CO_2 from flue gas via the amine solvent monoethanolamine (MEA).

OXY technology is another CC candidate for power plants. Compared to the amine process outlined above, OXY has the potential to be more energy and cost efficient [36]. The process is highly mature with a TRL of 7. Unlike the amine process, OXY has been considered in many research studies, including both modeling [37] and experimental studies. It has been explored in the laboratory [38–41] and pilot scales [20]. The pilot scale experiments [20] were extended to different O_2/CO_2 mixture ratios supplied to the combustion chamber, including the cold recirculation of flue gases and different operational parameters. These investigations have found that OS combustion in the oxy-fuel environment at CFB conditions is technically feasible. Furthermore, some positive effects have been observed; for example, it was demonstrated that the OS carbonate minerals (around 20% recalculating to CO_2) decompose to a lesser extent under oxy-fuel conditions than during combustion in air due to the higher CO_2 partial pressure under the former set-up [42]. Thus, each OS unit can produce a positive energy gain [43], leading not only to reduced specific CO_2 emissions and reduced specific fuel consumption but also to a significant reduction in NO_x emissions due to the lower conversion of fuel nitrogen to NO_x. At the same time, there is a nearly complete capture of sulfur in-situ (the SO_2 concentration in flue gases will be only a few ppm) due to the high Ca/S ratio in OS.

2.4. Methodology for estimating the cost of CO_2 capture at oil shale power plants

To assess the financial cost of CC, the estimate of the average additional cost per ton of CO_2 captured at each OSPP equipped with CC technology is compared to the same plant without CC technology. Capturing CO_2 becomes financially feasible when the cost of CC is less than the CO_2 emission allowance and applicable environmental charges incurred without CC. In addition, the average additional cost per MWh of the net electricity produced by an OSPP equipped with CC technology is compared with the cost of electricity from the same plant without CC technology to illustrate the increase in the unit cost of electricity brought about by the introduction of CC. The study does not quantitatively assess the broader economic feasibility of CC, but it does address some key externalities in the discussion section.

When specifying the methodology for this study, significant differences in the extant literature regarding the CC cost assessment methodology, cost components, assumptions, scale, and scope of the CC projects; features of specific CC technologies and power plants (including a new plant with CC vs an existing plant retrofitted with CC); geographical and temporal conditions; and terminology needed to be carefully considered when comparing various studies [5,44]. This study presents the cost estimates for retrofitting the Estonian FW and Auvere CFB units with CC via the two technologically promising alternatives mentioned earlier, i.e., PCC and OXY, in 2021 euros.

The methodology used for these estimates departs from the concepts underlying the often-used levelized cost of electricity (LCOE; e.g. Refs. [45,46]), as the per unit (ton of CO_2 captured or MWh of net electricity produced) time value of the investment cost, operating and maintenance costs, and cost of fuel are considered. The cost of fuel covers the revenue lost from electricity sales due to the consumption of energy in the CC process. Note that estimating the LCOE would require the availability of reliable information on production costs in addition to CC costs. In the case of OSPPs, no reliable information on the actual production cost of electricity is publicly available. For example, it has been suggested that the actual production cost of electricity for the FW and Auvere power units ranges from 15 to 25 EUR/MWh [47] to over 50 EUR/MWh [48], reflecting high ambiguity. Moreover, LCOE estimation would require inputting CO_2 emission allowance fees for each year of CC technology operation, but future CO_2 emission allowance fees depend on yet-to-be-made political decisions. Also, estimating the LCOE would necessitate making assumptions about electricity sale volumes for each future year of operation. Given the market characteristics described above, any such assumptions would be highly subjective. To avoid including elements with such high uncertainty, instead of estimating the LCOE, this paper compares the average additional cost per ton of CO_2 captured and average additional cost per MWh of net electricity produced in an OSPP equipped with CC technology with the same plant without CC technology. Unlike in LCOE estimation, where cost estimates would be needed for each future year of operation, cost estimates are needed for the first year of operation only. However, these estimates reconcile with the LCOE approach when it is assumed that the annual discount rate is equal to annual inflation in all cost components. This approach provides meaningful and useful estimates of the financial cost of implementing CC in an OSPP because it relies on evidence-based input.

The cost per ton of CO_2 captured (Equation (1)) as well as the cost per MWh of net electricity produced (Equation (2)) comprise the investment-related cost component (I), operating and maintenance costs (M) and the fuel-related cost (F). The retrofitting investment cost (Equation (3)) reflects the technical parameters and scale of the FW and Auvere power units. The investment cost is then converted into the capital cost for calculating the annuity payments over the useful working life of the CC equipment after the identification of an appropriate discount rate. Operating and maintenance costs (Equation (4)) include, e.g., the costs of chemicals, labor, and maintenance [49]. The fuel cost (Equation (5)) represents the energy needed for the CC process, i.e., the revenue lost from electricity sales due to consumption of energy in the CC process. The annual average costs per ton of CO_2 captured, $c1_t$ (EUR_{2021}/tCO_2), and per MWh of net electricity produced, $c2_t$ (EUR_{2021}/MWh), are estimated for base year $t_0 = 2021$.

$$c1_{t_0(EUR_{2021}/tCO_2)} = \frac{I_{t_0} + M_{t_0} + F_{t_0}}{V(CO_2)} \tag{1}$$

$$c2_{t_0(EUR_{2021}/MWh)} = \frac{I_{t_0} + M_{t_0} + F_{t_0}}{E_{t_0}(MWh)} \tag{2}$$

$$I_{t_0} = \frac{C_{ref_t}\left(\frac{Q}{Q_{ref}}\right)^s \times \alpha_{f,t} \times \gamma_{g,t} \times (1+r)}{\left[\frac{1-\frac{1}{(1+r)^n}}{r}\right]} \tag{3}$$

$$M_{t_0} = \sum_{i=1}^{j} g_{i,t} \times \alpha_{f,t} \times \gamma_{g,t} \tag{4}$$

$$F_{t_0} = E_{CC} \times p_{t_0} \tag{5}$$

where C_{ref} is the investment cost of the CC technology at a comparable reference plant (RP) in year *t* (according to the relevant literature), *Q* is the production capacity of the considered plant, Q_{ref} is the production capacity of the reference plant, *s* is the scale adjustment factor [50], α_{ft} represents a currency index with which to translate the amount in the original currency *f* spent on the reference plant in year *t* into euros for the same year, and γ_{gt} is a price index for translating the euros spent on good *g* in year *t* of the RP study into the base year t_0 value. Additionally, *r* is the discount rate, n is the useful life of the implemented CC technology in years, E_{CC} is the annual amount of energy in MWh needed for operating the CC technology, and p_{t0} is the market price of electricity in the base year t_0. Other costs are denoted with $g_{i(1 \ldots j)}$. Similar to investment costs, these costs are translated from the original currency and historical values used in the study on the RP into euros for the base year. $V(CO_2)$ denotes the annual tons of CO_2 captured with the CC technology at the OSPP and $E_t(MWh)$ denotes the annual net amount of electricity produced at the OSPP in MWh.

3. Assumptions for calculations and scenarios

3.1. Technological assessment of post-combustion capture of CO_2 at oil shale power plants

In the present study, the technical characteristics and investment and operating costs for the post-combustion solution were determined based on the rigorous analysis presented in DOE/NETL reference cases S22A and S22F [51]. One distinctive feature of that analysis involves the baseline performance and cost estimates provided for a power plant that uses CFB for steam generation. Thus, one of the main reasons for the reference case selection was that it closely matches the concept considered here.

Generally, the composition of the flue gas formed during OS combustion is quite similar to that of low-quality coal (lignite) and has some favorable features when the amine process is utilized. Namely, due to the naturally high carbonate mineral content in OS (Ca/S ~8), sulfur is generally fully captured in the furnace when CFB technology is used, positively impacting the CC process.

The flue gas composition assumed in this study for pure OS is provided in Table 3. For comparison purposes, a typical coal flue gas composition and the subbituminous and lignite coal flue gas compositions from the DOE/NETL reference case [51] are included. For each OS, the flue gas composition was calculated based on the ultimate fuel analysis shown in Table 1 while assuming an 80% carbonate decomposition. Note that the OS flue gas compositions are quite similar to those for the coals considered in the DOE/NETL reference case [51].

A cornerstone of the post-combustion process' performance is the energy required for amine regeneration. According to an overview of several commercially available amine-based capture technologies [53], this parameter falls in the range 2.2–3.6 GJ/tCO_2, depending on fuel type and technology supplier. In the DOE/NETL reference case [51], the CO_2 removal system was based on applying the Econamine FG process with the highest reboiler steam duty reviewed in Ref. [53]. It was assumed that the steam extracted from the turbine was used as a heat source. The equivalent electrical energy reduction of 0.22 MWh_e/MWh_{th} was used in this study. The condenser heat duty reduction, which occurs due to the reduction in the steam mass flow rate coming into the condenser, was obtained by applying a simple heat mass balance around the steam cycle [50]. A 90% capture efficiency was assumed, while the captured CO_2 was compressed to 15.3 MPa (supercritical state). It should be noted that there are no studies in the available literature that include rate-based calculations for the amine process. The primary performance characteristics implemented in the present study are provided in Table 4.

Sources [50–52]: and authors' calculations.

Table 3
Flue gas compositions in oil shale CFB units compared with typical coal power units.

Parameter	NETL S/L[a] [51], % Mole	Typical Coal [52], % Mole	OS1, % Mole	OS2, % Mole
CO_2	14.12/13.59	7–15	13.19	13.33
H_2O	11.04/14.29	5–15	13.84	13.38
N_2	70.82/68.11	65–75	68.71	69.21
O_2	3.17/3.19	2–12	4.26	4.08

[a] S represents subbituminous coal (Powder River Basin coal from Montana), and L represents lignite coal from North Dakota [51].
Sources [51,52]: and authors' calculations based on [9].

3.2. Technological assessment of the oxy-fuel capture of CO_2 at oil shale power plants

The technical parameters and economic indicators for retrofitting the existing Estonian CFB units and the hypothetical new CFB power unit with OXY technology were determined based on DOE/NETL reference cases L22A and L22B [54]. In those cases, cost and technical performance assessments under OXY for CFB-powered units were performed assuming the types of coal used were the same as those used in the post-combustion reference case [51]. These circumstances, which facilitated the comparative analysis of the PCC and OXY cases, were the primary consideration in the selection of these reference cases. Yet, as the OXY inevitably changes the combustion conditions and heat and mass transfers, its impact on the flue gas composition—specifically on the sulfur and NO_x emissions, as well as the carbonate decomposition—has been studied on a pilot scale with OS as the fuel [55,56]. Those results were considered in the selection and analysis of CC capture possibilities in OSPPs.

The OXY system's main technical characteristics were established as follows. The energy requirement for oxygen separation from the air, assuming conventional (available on a large scale) cryogenic distillation producing 95%mol, was assumed to be 196 kWh/tO_2. To establish a basis on which to compare post-combustion capture, it was assumed that the CO_2 formed in the OXY flue gas stream was purified and compressed to a level similar to that in the post-combustion reference case. The energy requirement in the compression and purification system was assumed to be 0.22 kWh/Nm^3_{CO2}.

3.3. Estimating the cost of CO_2 capture in oil shale power plants

To estimate capital costs, installing the CC technology was assumed to take about one year (as in Refs. [57,58], among others), and the maximum useful life of the equipment was assumed to be 24 years [57,58]. CC investment costs (including installation) were calculated based on the data from DOE/NETL reference cases S22A, S22F, L22A, and L22B [51,54] regarding RP investment costs, which were adjusted to the technical parameters of the FW and Auvere units. These costs were then scaled, as per Equation (3), with the exponent s, which fell in the range 0.61–0.69 for the OXY technology and 0.43–0.77 for the PCC technology, depending on the type of equipment, as suggested in Ref. [50] and following the DOE/NETL reference cases [54,59]. The costs of the CC equipment meeting the technical parameters of the FW and Auvere units given in 2007 US dollars for the DOE/NETL reference cases [51,54] were converted into euros based on the exchange rate provided by the European Central Bank (ECB). These costs were then updated to 2021 values based on Eurostat price indices for similar industrial equipment and their installation costs.

Due to the Estonian income tax system's peculiarities, the use of

Table 4
The main technical characteristics of the CO_2 removal system used in the present study.

Parameter	Units	Value
Specific reboiler duty [51]	GJ/tCO_2	3.2
Equivalent specific electrical energy reduction (power-to-heat ratio), estimated based on [50]	MWh_e/MWh_{th}	0.22
Electricity consumption [51]	kWh/tCO_2	34
Amine (MEA) consumption [51,52]	kg/tCO_2 (captured)	0.1
Cooling duty during the capture process [51]	kW/tCO_2	1.08
Capture efficiency [51]	%	90
CO_2 compression [51]	kWh/tCO_2	80

capital from loans does not entail a tax advantage (i.e., produce a tax shield). Thus, raising capital via loans at market terms does not significantly reduce the discount rate, and the weighted average cost of capital (WACC) is approximately equal to the unleveraged cost of equity. Consequently, the discount rate *r* is chosen as the cost of equity without leverage, which can be estimated via several methods in practice. This study develops a model for estimating *r* based on the logic of the build-up approach [60] and comprising the risk-free rate of return (r_F), market risk premium (rp_M), Estonian risk premium (rp_{EE}), beta multiplier reflecting systemic risk (β_U), liquidity premium (rp_{ILQ}) and project-based risk premium (rp_{PRJ}). Because the company potentially implementing the CC technologies (the state-owned Eesti Energia AS) is a relatively large one, the risk premium for a small company is omitted. Thus, the model used in this study to estimate the discount rate is as follows:

$$r = r_F + \beta_U \times (rp_M + rp_{EE}) + rp_{ILQ} + rp_{PRJ} \tag{6}$$

The numerical values or ranges of the components of *r* for 2021 were assumed to be as follows: the risk-free rate of return (r_F) ranged from −0.37% to 0% [61,62]; the market risk premium (rp_M) was in the range 4.7–4.72% [63,64]; the country risk premium (rp_{EE}) was 0.68% [63]; the beta multiplier (β_U) was 1.07 [65], the liquidity premium (rp_{ILQ}) fell in the range 0.5–1% [5] and the project-based risk premium (rp_{PRJ}) was 3% [66,67]. Based on these values, the discount rate, calculated according to Equation (6), ranged from 8.17% to 9.78%, producing an average of about 9%, which was then used as the *r* (pre-tax discount rate) value in this study.

For the operating and maintenance costs g_i, the costs of labor, maintenance, and chemicals were estimated, while cooling water and additional costs were considered to be relatively insignificant. The starting points for modeling the labor, maintenance, and chemical costs were DOE/NETL reference cases S22A, S22F, L22A, and L22B [51,54], all concerning US-based coal power plants (the reference plants) and measuring costs in 2007 US dollars. As a next step, technology and scaling adjustments were made (e.g., for labor costs, a scaling factor of 0.65 was used for both technologies [50]), and the costs were then converted to 2021 euros using relevant labor, chemical production, and equipment repair price indices from Eurostat [68], the US Bureau of Labor Statistics [69], and Statistics Estonia [70,71].

As all CC equipment would be integrated into the existing OSPPs, the CC electricity cost (cf. fuel cost in LCOE) represents the loss in electricity sales and generation efficiency due to adding the CC and was estimated to be around 0.3 MWh/tCO_2, depending on the OSPP unit and CC technology used and assuming an 85% capacity factor (i.e., operating at full capacity for 85% of the total hours available per year). NordPool's 2021 average electricity price of 86.73 EUR/MWh_e for the Estonian price region [72] was used for p_{t0}. The high volatility of NordPool's electricity prices was reflected in the sensitivity analysis described in the following section.

Two scenarios are presented: the baseline scenario, Scenario 1, assumes that the OSPPs operate at full capacity for 85% of annual hours, taking into consideration routine maintenance and downtime, and that the CC technology will have the expected 24-year lifetime (with a year for installation added). The alternative scenario, Scenario 2, assumes that the CC technology is applied to electricity generation at half of the above 85% capacity factor (i.e., the CC operates at full capacity for 42.5% of the annual hours). Scenario 2 was created to illustrate what happens when OS electricity is competitive in the market only part of the time, following actual historical patterns [5]. The analysis results are sensitive to variations in the input values, including the use of CC technology at less than full capacity or for less than 24 years, either of which would significantly increase the cost of capturing each ton of CO_2. These sensitivities are discussed in the next section.

4. Results

The technical results for retrofitting the FW (assuming OS1 use) and Auvere (assuming OS2 use) CFB power units for CC are shown in Table 5. For comparison, this table includes a hypothetical CFB power unit with supercritical steam parameters (assuming OS2 use). The main drawback of CC implementation is the reduction of turbine net power and power unit net efficiency due to the additional energy required to run the CC process in the retrofitted power units. The table below shows that CC deployment can significantly reduce CO_2 intensity in power generation—up to 90% or even more. Under the specified assumptions, to achieve a 90% CO_2 reduction, the net efficiency of an FW unit can drop by up to 25.12% for PCC and 26.36% for OXY. The Auvere unit demonstrates a better performance, mainly due to its higher initial thermal efficiency. Further CO_2 reduction is possible but would require additional energy when using pure OS as the primary fuel. However, if biomass, which is currently regarded as a CO_2-neutral fuel under environmental regulations, is combusted in the power units, then even net negative CO_2 emissions can be achieved under nearly the same energy penalty. Depending on the biomass's share of the fuel blend supplied to a unit, the negative CO_2 emissions can be as low as −40% (−0.59 Mt CO_2/y for BPP Unit 11 and –0.8 Mt CO_2/y for the Auvere unit) of the initial level when the biomass is at 50% of the fuel blend.

The total estimated costs of implementing CC technology in Estonian OSPPs in the above two scenarios is outlined in Table 6. The costs are for CO_2 capture and purification to 99.98%, and do not include storage, use, or transport. When amine-based absorption is used, OXY appears to be financially more favorable than PCC. This finding is broadly in line with previous literature concerning PCC technology for coal power plants [19]. Using a rough comparison, in coal power plants, in 2011, CC cost per ton of CO_2 captured was estimated to be approximately 37.9 euros (62.0 euros in 2021 values) for OXY [73] and 41.8 euros (67.3 euros in 2021 values) for PCC in the DOE/NETL reference case B12B [74].

Scenario 1 illustrates the full potential of CC implementation at OSPPs, assuming that electricity production will run at full capacity for 85% of all annual hours. Scenario 2 illustrates operation at only a half that time (i.e., operating for 42.5% of annual hours). Still, in reality, long-term market conditions (e.g., NordPool's electricity prices, and CO_2 European Emission Allowances prices) may lead to significantly lower production, which also means a lower amount of CO_2 captured and a significantly higher unit cost of capture than illustrated by Scenario 2.

As outlined in Table 6, the most significant CC cost components in OSPPs are capital and electricity costs, regardless of the capture technology chosen. Although the capital cost per ton of captured CO_2 includes investment in the form of an annuity, allocated over the CC technology's expected lifetime, significant initial investments would be needed at the beginning of the project, necessitating appropriate funding.

The CC costs per ton of CO_2 captured and per MWh of net electricity produced are susceptible to the amount of investment, electricity prices, and useful lifetime and intensity of use of the CC. The results of the sensitivity analysis for some of the main inputs are shown in Figs. 3 and 4.

The operation of the power units and their components is essential for CC technology operation. When the power units reach the end of their useful lives, CC technology use inevitably ends, regardless of its viability. A temporary shutdown of electricity generation units has a similar effect; e.g., when the electricity produced is not competitive on the market, the CC technology is not fully utilized, and the unit cost per ton of CO_2 captured increases.

5. Discussion

The results of this study depend highly on the assumptions. For instance, the CC technology is assumed to have a useful lifespan of 24 years. However, the remaining lives of the FW power generation equipment (e.g., the 1970s turbines in the EPP 8 and BPP 11 units) may be shorter than 24 years, thereby increasing the cost per ton of CO_2

Table 5
Results on main technical parameters of the considered power units after CC integration.

Parameter	FW Retrofit		Auvere Retrofit		New Supercritical Power Unit	
Type	Oxy-fuel	Post-Com-bustion	Oxy-fuel	Post-Com-bustion	Oxy-fuel	Post-Com-bustion
Net Rated Power, MW_e	135.7	129.3	201.6	192.7	275	275
Efficiency, % (net, LHV)	26.36	25.12	29.46	28.17	33.26	28.77
Fuel Consumption, t/h	234.5^{+}	234.5^{+}	295.5^{++}	295.5^{++}	357^{++}	413^{++}
Specific CO_2 Emissions^{+++}, kg/MWh_e	146	155	141	135	120	139
DOE/NETL L22B/L22F CO_2, kg/MWh_e [54]					114**	130
Mt CO_2/y*	0.149	0.149	0.203	0.203	0.283	0.243

+ 100% OS firing with OS 7.90 MJ/kg (OS1), without district heating load.
++ 100% OS firing with OS 8.33 MJ/kg (OS2).
+++ Based on combustion and 90% capture efficiency.
* Originating from combustion, based on 100% OS fuel and assuming an 85% capacity factor.
**Recalculated to 90% capture efficiency.
Sources: authors' calculations, [54]

Table 6
The estimated cost of CO_2 capture (EUR/tCO_2) and initial investment (EUR in millions).

Parameter	FW		Auvere	
	Oxy-fuel	Post-Com-bustion	Oxy-fuel	Post-Com-bustion
Scenario 1				
Cost of CO_2 capture (EUR/tCO_2), i.e. $c1_t$ (EUR_{2021}/tCO_2) in Equation 1	47.1	56.2	41.7	48.2
incl. capital cost (%)	39.1%	41.6%	32.1%	33.3%
electricity cost (%)	56.0%	52.5%	62.7%	60.8%
labor costs (%)	3.1%	2.7%	2.9%	2.0%
maintenance costs (incl. materials) (%)	1.6%	0.7%	2.1%	1.0%
cost of chemicals (%)	0.2%	2.2%	0.2%	2.6%
Cost of cooling water (%)	<0.1%	0.4%	<0.1%	0.2%
CC cost per unit of electricity produced (EUR/MWh_e), i.e. $c2_t$ (EUR_{2021}/MWh) in Equation 2	62.5	78.2	50.8	61.3
CO_2 captured (max annual amount; Mt)	1.34/unit (2.68 total)	1.34/unit (2.68 total)	1.83	1.83
Scenario 2				
Cost of CO_2 capture (EUR/tCO_2), i.e. $c1_t$ (EUR_{2021}/tCO_2) in Equation 1	67.1	81.1	56.3	65.3
CC cost per unit of electricity produced (EUR/MWh_e), i.e. $c2_t$ (EUR_{2021}/MWh) in Equation 2	89.0	112.8	68.5	83.0
CO_2 captured (max annual amount; Mt)	0.67/unit (1.34 total)	0.67/unit (1.34 total)	0.91	0.91
Initial investment in CC technology (EUR in millions)	220.2	279.1	217.6	261.3

captured and per MWh of electricity produced over the actual economic life of the CC equipment. Furthermore, Eesti Energia, the energy company operating all the CFB OSPPs in Estonia, announced in June 2021 their intention to terminate OS-based electricity generation by 2030 at latest [75]. This decision is welcome in view of the GHG emission reduction goals and justified by the research reported in Ref. [5] and done under the applied research project "Climate Change Mitigation with CCS and CCU Technologies" (ClimMit), which supported the current study (see acknowledgements). In the context of CC implementation in Estonian OSPPs, this decision limits the useful lifetime or capacity of any CC investment made. However, recent national energy security concerns may postpone the termination of OS-based electricity generation, adding further ambiguity to this modeling exercise. Moreover, as the above two CC technologies have not been used in the OS industry before and have not yet reached their final TRLs, the estimates used herein involve significant technological risk and may result in additional installation costs (e.g., reduced electricity generation at the OSPP) and contingency costs. In short, the CC costs may differ from the modeled ones in practice.

Based on Ref. [5], a recent comprehensive study concerning CCUS implementation possibilities for the Estonian OS industry, the primary option for disposing of any captured CO_2 is piping it to storage under the North Sea off the coast of Norway, although this storage infrastructure remains under development, because there are no CO_2 storage facilities in Estonia or feasible options for utilizing the total CO_2 captured. The approximate cost for the onshore transportation, shipment to Norway and storage of the CO_2 in the North Sea has been estimated at 47–59 EUR/tCO_2 [5] in 2020/2021 values.

As no CC technology operates at full efficiency (e.g., both PCC and OXY are expected to be around 90% efficient; see, e.g. Ref. [76]), any CO_2 that is not captured would be emitted. The potential charges for these emissions are challenging to estimate for the future due to potential changes in the regulatory environment.

Although any CO_2 capture process reduces the useable electricity generation capacity of the OSPPs due to the increase in their self-consumption of electricity, their operation ensures stable production capacity, which is essential for the sustained operation of the electricity grid. Also, stable electricity is guaranteed with domestic resources when utilizing OSPPs in Estonia. Due to the need to ensure energy security and network stability [77] and considering technological path dependence, the level of development of energy storage technologies, and the long duration of investments in the energy sector, an immediate and complete transition to renewable energy is not possible in Estonia. Moreover, to advance the implementation of renewable energy, it must be feasible to amass and store any surplus electricity generated [78]. Energy generated from OS will probably continue to exist in the near future in parallel with cleaner technologies. However, CC implementation in the existing fossil fuel-based energy system may allow a smooth transition toward climate neutrality goals. Additionally, the use of CC in fossil fuel energy production is one way to avoid potential energy crises and balance the grid should the planned renewable resources fail to provide the necessary capacity, e.g., due to their variability [5,79].

Capturing and storing CO_2 emitted by Estonian OSPPs is technologically possible but might be financially in the longer term more expensive than the prices of CO_2 European Emission Allowances and applicable environmental charges. Thus, in an uncertain market, there may be no incentive for the OS industry to implement CCUS without a public obligation or support measures making the process economically viable. Regardless, the cost of capture would be passed on to producers or taxpayers, which could harm the Estonian economy's competitiveness.

Since CCUS can reduce GHG emissions, public interest in implementing these technologies is vital, in addition to the private sector's economic considerations. The deployment of CCUS technologies has

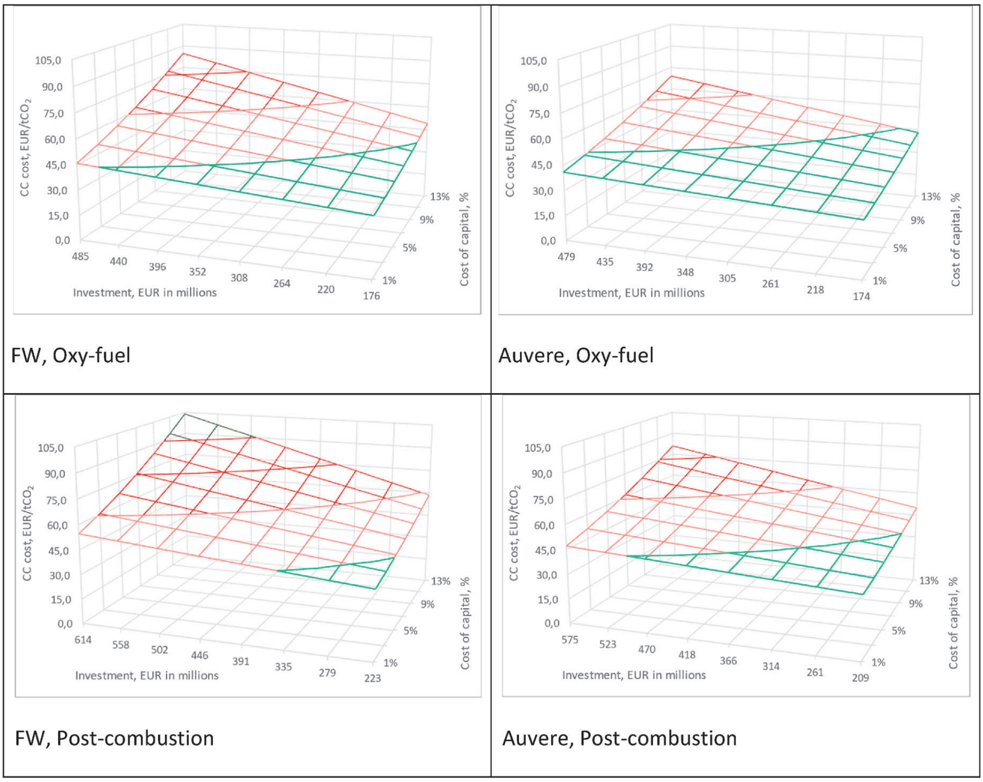

Fig. 3. Sensitivity of CC cost (EUR/tCO_2) to investment in CC technology and cost of capital.

potentially significant positive externalities; that is, if it is not cost-effective for companies under market conditions, the public sector may still be interested in encouraging the adoption of CCUS technologies through regulatory or supportive measures and making them attractive or mandatory for the industry. When designing regulations (including restrictions and obligations for the OS industry) and support measures, it is crucial to consider the competitiveness of the OS industry and related economic sectors on the international market. For example, in the long run, it may not make sense to support companies that meet environmental objectives (including fossil fuel-based industries adopting CCUS) but are not competitive in their core businesses, which might be the case for OS-fueled electricity. However, supporting internationally competitive core businesses in terms of adopting CCUS technologies to move toward environmental or sustainability goals may make sense even when such support is not cost-effective under market conditions.

An energy sector strategy for Estonia based on an integrated and evidence-based comparative analysis (including potential CCUS) is needed to provide clarity and certainty for both private companies and government agencies in terms of making investment decisions and informing policymaking (including the identification of related R&D priorities, development of appropriate regulations and legislation, and decision making on environmental and energy-related interventions), respectively. Such a strategy would contribute to the optimal use of public resources and ensure the security of the energy supply [5].

6. Conclusions

This study presents a technological and economic assessment of CC implementation in OSPPs. From a technological perspective, it is possible to retrofit existing OSPPs for the application of both PCC and OXY technologies. CC deployment can significantly reduce CO_2 intensity in power generation—up to 90% or even more. However, integration of CC technology would result in reductions in power units' heat rate performances by more than 10% points due its energy requirements. This reduction is smaller for OSPP units with higher base thermal performances. OXY is expected perform slightly better than PCC.

From a financial perspective, in an uncertain market, CC in the Estonian OSPPs might not be feasible, as the cost of CC plus storage was at least 89 euros per ton in 2021 under full capacity operation over the expected 24-year lifetime of the CC, which might exceed the CO_2 emission allowance fees and environmental charges. Furthermore, CC-equipped OSPPs could face a competitive disadvantage in the electricity market compared to companies employing non-fossil energy sources in power generation. Potentially, CC obligations or support measures (e.g., expanding biomass use in combination with OS in OSPPs or regarding the CC in biomass combustion as generating net negative emissions) could make the process economically feasible. However, the cost of CC would then be passed on to producers or taxpayers, which might negatively affect the economy's competitiveness.

The need for stable electricity generation cannot be overlooked. Currently, in Estonia, this need is fulfilled by existing OSPPs. Thus, until non-fossil-fuel-based alternatives can ensure a steady power supply, CCUS by Estonian OSPPs remains an option to consider. To ensure that OSPP capacity is in line with the EU's vision of a "carbon-neutral economy," it might be necessary to integrate CC into their operations and accept its high private and public costs, or rely on imported energy and face potential energy security issues and market fluctuations.

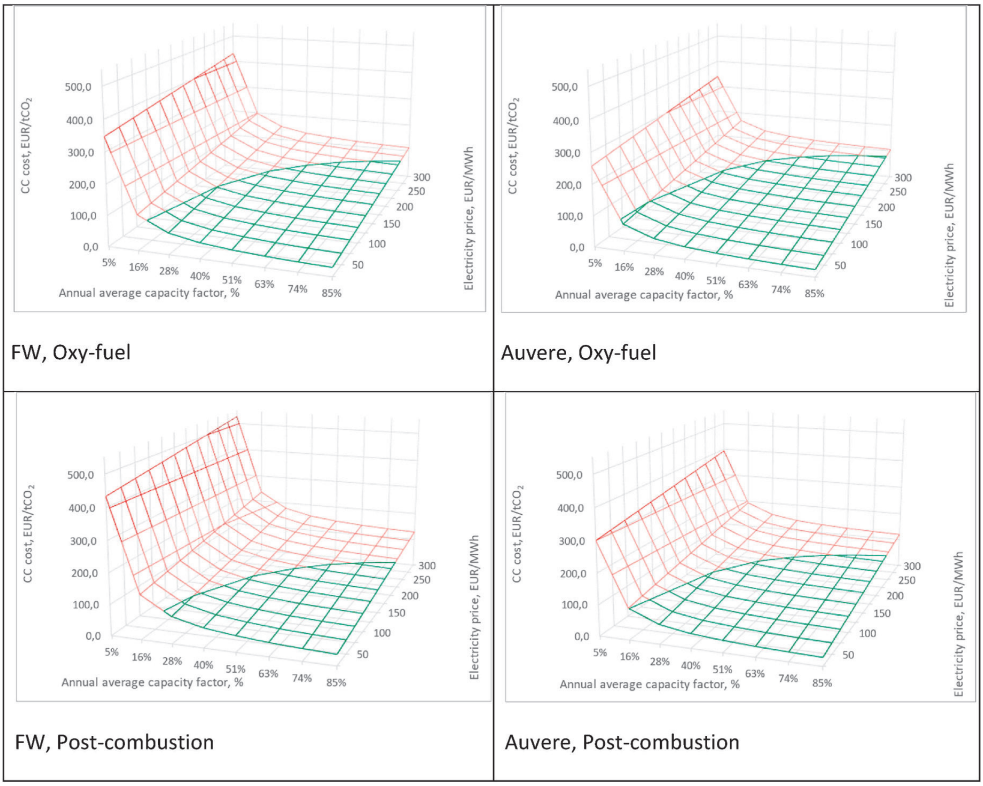

Fig. 4. Sensitivity of CC cost (EUR/tCO_2) to electricity price and average annual capacity factor.

Credit author statement

Artjom Saia: Formal analysis, Visualization, Writing - Original Draft, Dmitri Neshumayev: Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Aaro Hazak: Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Project administration, Priit Sander: Methodology, Formal analysis, Investigation, Oliver Järvik: Investigation, Writing - Review & Editing, Alar Konist: Conceptualization, Writing - Review & Editing, Funding acquisition, Project administration.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

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Appendix 3. Publication III

DIGITAL CAPACITY AND EMPLOYMENT OUTCOMES: MICRODATA EVIDENCE FROM PRE- AND POST-COVID-19 EUROPE

Publication III
This article “Digital Capacity and Employment Outcomes: Microdata Evidence from Pre- and Post-COVID-19 Europe” was published in *Telematics and Informatics*, Vol 83, Kadri Männasoo, Jon Kristian Pareliussen, Artjom Saia, pp. 1–21, Copyright Elsevier, (2023). DOI: https://doi.org/10.1016/j.tele.2023.102024. (ETIS 1.1).

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Digital capacity and employment outcomes: Microdata evidence from pre- and post-COVID-19 Europe

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ABSTRACT

This paper examines the relationship between employment outcomes and broadband Internet access, education and digital skills using the pre- and post-COVID-19 survey waves of the Eurostat Community Statistics on Information Society from 2017, 2019, and 2021 in 27 European countries. Joint estimates of individuals' employment status and skills employ external controls based on Eurostat and COVID-19 European Regional Tracker NUTS1-level regional statistics and Oxford COVID-19 Government Response Tracker information on governments' containment and economic support measures. Broadband access, digital skills and educational attainment combine to raise employment outcomes, but COVID-19 has changed these relationships in distinct ways. It has increased employment benefits from formal education and roughly tripled the labor market advantages from having household members with tertiary education. The pandemic has increased the employment value of having at least some digital skills, while the relative benefits of more advanced digital skills shrank.

1. Introduction

The digital transformation accelerated by COVID-19 has garnered academic interest in the fields of both the macro- and micro-economics. The macroeconomic line of research follows from Tinbergen's (1974) endogenous "race" between technology and skills supply. New technologies and digitalization processes generate skill-biased demand shifts (Goldin and Katz, 2008; Acemoglu and Autor, 2012, 2011). Microeconomic perspectives include firm-level studies with a focus on the effects of digital diffusion, digital skills and capacities on productivity (Gal et al., 2019; Heredia et al., 2022; Nicoletti et al., 2020; Pareliussen and Mosiashvili, 2020; Skog et al., 2018; Corrado et al., 2017), as well as individual-level studies concentrating on the socioeconomic and labor-market aspects of the digital divide (Akerman et al., 2015; Brynjolfsson and McAfee, 2011; Van Kessel et al., 2022).

The digital divide is a term used to describe disparities in, first, access to the Internet and frequency of use, and second, proficiency in Internet use or the level of digital skills. Scheerder et al (2017) and Aydin (2021) underline as a third dimension of the digital divide the interaction of digital skills with the contextual factors that shape the learning and productivity outcomes for the individual. The early literature on the digital divide investigated the inclusion and access of different social groups to the Internet and digital technologies. Most of this literature sought to determine which socio-demographic factors are associated with a higher (or lower) propensity to have access to or use the Internet (DiMaggio and Hargittai, 2001; Hargittai, 2002). This line of investigation has shown that

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individuals with higher socio-economic status in terms of income, education, and labor-market outcomes are more likely to have access and to use the Internet more frequently. This has raised concerns about the polarization and increasing inequality stemming from uneven digital access and Internet usage (Van Kessel et al., 2022).

The increasing affordability and use of information and communications technologies (ICT) have led to rapid digital diffusion in all spheres of human activity with considerable economic effects. Czernich et al. (2011) estimate a 0.9–1.5 percentage point increase in per capita economic growth in response to a 10% increase in broadband penetration. Nicoletti et al. (2020) assert that high-speed broadband connection and other digital technologies are highly complementary to technology adoption, emphasizing the necessity of ubiquitous broadband dissemination. Internet access has reached near full coverage in the economically advanced parts of the world, leaving only a small share of households with no connection to the Internet. Van Kessel et al. (2022) based on Eurostat's Community Statistics on Information Society (CSIS) 2019 survey, however, document large differences in Internet access between countries in North-Western and South-Eastern Europe. As of 2021, about 4% of households in Europe with a member aged 25–54 years reported having no broadband Internet access at home, according to CSIS. See Fig. C1 in the appendix.

Given that access to the Internet is more widespread than ever, the literature is shifting its focus away from digital access towards discrepancies in digital skills. Akerman et al. (2015) have noted that further gains from Internet accessibility in terms of labor-market inclusion and productivity might decrease unless there is a significant qualitative improvement in digital skills and patterns of digital use. DiMaggio and Hargittai (2001) and Hargittai (2002) refer to disparities in digital skills as a second-level digital divide.

The number of studies on digital skills is growing but has been restrained by the limited availability of reliable data. Krutova et al. (2022) admit that statistics on technology are in their infancy and highlight the need for more detailed data, for instance regarding the qualitative characteristics of technology, which would enable the study of the effects of technological change on employment and labor productivity. To meet the demands for better data on ICT use and digital competencies, Eurostat launched the CSIS on a voluntary basis in 2010 and as a mandatory data-transmission request starting in 2011. The CSIS survey gathers information on Internet penetration, computer- and Internet-use patterns, and digital skills at the individual level. The current study employs three CSIS survey waves with reference years 2017, 2019, and 2021. These data contain a comprehensive measure of digital skills at the individual level and information on digital access at the household level. Because the study investigates the link between digital capacity and labor market outcomes, the empirical analysis focuses on individuals of prime working age (i.e., 25–54 years old) and their households.

This study provides micro-evidence regarding the relationship between employment status and broadband Internet access and digital skills before and after the breakout of the COVID-19 pandemic. The potential endogeneity of the measure of digital skills is considered in the joint framework that estimates individuals' digital skills conditional on their household characteristics and regional aggregate variables as external controls based on Eurostat statistics. In addition, the data structure, which nests individuals into households, enables an investigation into intra-family spillover effects, such as positive externalities for employment stemming from the highest education level possessed at the household level. To the authors' knowledge, this is the first study to estimate the individual-level effects linking digital skills and employment status pre- and post-COVID-19 in a large number of European countries. The findings capture how COVID-19 accelerated the digital transformation. COVID-19 has roughly tripled the labor market advantages from having household members with tertiary education, with tentative evidence that governments' COVID-19 response measures magnified the role of family members' educational attainment on labor-market outcomes. The pandemic has increased employment benefits from formal education conditional on the level of digital skills and Internet access. It has improved the employment outcomes of people with basic digital skills relative to the digitally illiterate. In contrast, the benefits of more advanced digital skills shrank relative to those with only basic digital skills.

The next section reviews the literature on digital skills and employment and surveys recent research on how COVID-19 and the digital transformation affect the labor markets. Section 3 introduces the data and outlines the empirical strategy. Section 4 reports and Section 5 discusses the results. Finally, Section 6 summarizes and concludes the study.

2. Literature review

2.1. Digital skills and employment

From a labor-supply perspective, it is crucial to understand the complementarities and substitutability of skills stemming from digitalization. Brynjolfsson and McAfee (2012) claim that a shortage of skills and stagnant work organization may hamper the technological acceleration. Van Deursen and Van Dijk (2011) note that to use the Internet effectively, strategic Internet skills and information-seeking skills are required that go beyond formal and operational skills and point out that research on strategic digital skills is limited.

Bejaković and Mrnjavac (2020) find a positive correlation between digital skills and employment in European countries. Akerman et al. (2015) report that broadband Internet technology is skill biased. Their study found that broadband adoption in Norway complemented the productivity of skilled workers and improved their labor market outcomes but it substituted for the labor of unskilled workers. Krutova et al. (2022) study skill-biased technological change and show that while productivity gains from "traditional" technologies complement labor and improve employment outlooks, the introduction of innovative/digital technologies displaces labor and increases the risk of permanent job loss. The introduction of ChatGPT, an artificial intelligence (AI) chatbot, marks a new era of human-centered technologies that raise discussions on the ethical aspects of technology-augmented decisions and the need for human upskilling (De Cremer et al., 2022; OECD, 2017).

On a positive note, digitalization diminishes the necessity of task-specific working places, thus increasing the spread of "telecommuting" and decreasing the need for proximity between the home and work locations (Goldfarb and Tucker, 2019). Besides allowing for more flexible work organization, the communication features of digital technologies also facilitate the direct meeting of labor supply and demand via employer–employee matching platforms or indirectly via social media and other information-sharing or search environments (Kuhn and Mansour, 2014; Goldfarb and Tucker, 2019). The outcome may be higher labor market participation as well as qualitatively better job matches (Evangelista et al., 2014).

While the literature on economic returns to education is vast (Psacharopoulos and Patrinos, 2018), the evidence regarding labor market returns to ICT skills is still limited. Falck et al. (2021) estimate returns on ICT skills on Programme for the International Assessment of Adult Competencies (PIAAC) data across countries and find an almost 24 percent increase in wages in response to one standard deviation increase in ICT skills.[1] To counter causality issues pointed out by DiNardo and Pischke (1997), the study by Falk et al. (2021) employs instrumental variable estimation that exploits technology-induced variation in Internet availability across countries. Among earlier studies, DiMaggio and Bonikowski (2008) and Hanushek et al. (2015) have documented positive correlations between digital skills and labor earnings, whereas Oosterbeek and Ponce (2011) found no evidence of an ICT-skill wage premium.

The eminent literature on individuals' occupational choices and self-selection in the labor market recognizes the importance of heterogeneous skills (Roy, 1951; Heckman and Sedlacek 1985, 1990; Sullivan, 2010). The job-search models by Mortensen and Pissarides (1994) and its extensions (see Cairó and Cajner, 2018) explain the mechanisms behind labor market outcomes and postulate that individuals' outlook in the labor market improve if job-arrival rates increase and weaken if job-separation rates grow. Job-separation rates have an endogenous relationship with on-the-job training, in that accumulation of valuable job or occupation specific skills reduces the likelihood for job separation. Cairó and Cajner (2018) have shown that higher education increases accumulation of job-specific human capital and leads to lower job-separation rates but does not significantly affect job-finding rates. According to Frijters and Van der Klaauw (2006), loss of skills and drop in reservation wage over the out-of-employment spell is the main determinant of unemployment and not job offer arrival rates that remained largely unchanged. Occupations vary strongly in remuneration, job-offer and job-security rates that all determine individual utility from occupational choice. Sullivan (2010) shows that occupational choice has by far the largest effect on individual utility as compared to the effect of on-the-job human capital accumulation within chosen occupation. Work on the links between digital skills, the acquisition of job-specific human capital, and job-finding and job-separation rates is still in its infancy (see Eggenberger and Backes-Gellner, 2021; Non et al., 2021).

Non et al. (2021) investigate the link between digital skills and labor-market outcomes over the pre-COVID-19 years 2012–2019 in the Netherlands. They find that the individuals with lower digital skills are older, less educated, and more frequently female. Individuals with at least basic skills have higher labor-force participation and are about 10 percent more likely to be employed compared to digitally unskilled individuals. The unemployment spell, however, is not different for individuals with below-basic skills and those with basic or above-basic skills. This suggests that, like formal education (Cairó and Cajner, 2018), digital skills have no significant impact on job-finding rates. At the same time, there is evidence that digital skills increase productivity, and Non et al. (2021) report a 4–6 percent wage premium for a one-standard-deviation increase in digital skills. This productivity effect is likely to have implications for job-separation rates, in that individuals who are more digitally skilled accumulate more job-specific capital, which improves their outlooks for longer job tenure.

2.2. COVID-19 and digital transformation of the labor market

The COVID-19 lockdown and broadly implemented remote-work regimes have substantially increased work from home, a shift with a lasting effect (Aksoy et al., 2022). Flexible modes of work may alleviate labor market disadvantages for individuals facing higher commuting costs or having caretaking roles at home (Chung et al., 2021). Sostero et al. (2020) estimate a 36% share of teleworkable employment in Europe but also note that a considerable share of it, equivalent to 20% (over 40 million workers), were not regularly engaged in teleworking before the COVID-19 pandemic. They note that while the strongest expansion of telework post COVID-19 was observed among high-pay, high-skill occupations, the most radical changes in work organization concerned middle-skill workers, who did not have teleworking opportunities or experience before. In a similar vein, Von Gaudecker et al. (2020) show that in the Netherlands, working hours declined more for those with lower educational degrees and the self-employed in the early months after the COVID-19 breakout in March 2020.

Soh et al (2022) investigated whether Covid-19 recession changed demand for digital occupations in the United States. They find that digital employment remained more resilient during COVID-19 recession, but there was no temporary nor permanent increase in absolute demand for digital occupations. More importantly, Soh et al (2022) separate cognitive, routine, and manual digital occupations and find that the resilience of digital employment during COVID-19 arises predominantly from the group of cognitive digital workers.[2]

Another line of research seeks to explain the dynamics of unemployment in a context of cyclical fluctuations and disruptive crises. Fujita and Ramey (2009) show that while job-separation rates are countercyclical and have a contemporaneous effect, pro-cyclical job-finding rates follow productivity increases with a lag. Using data from the US Current Population Survey, Barnichon (2012) finds that hiring and separation respectively contribute approximately 60% and 40% to unemployment dynamics, except for business cycle turning points, when job separations become dominant triggers of unemployment. His results are in line with those of Fujita and Ramey (2009), who report a 40–50% share of job separations in unemployment dynamics and an even stronger effect when

[1] In the sample of German municipalities, Falck et al. (2021) find an ICT wage reward of 31%.

[2] Soh et al (2022) define digital employment that corresponds to occupations with a digital score in the top 50th percentile. The digital score (Muro et al, 2017) measures digital skills and their relevance and importance for occupation.

considering dynamic interaction with the job-finding rate. In the European context, Hairault et al. (2015) reveal an even (50/50) contribution of hiring and separation to unemployment in France over the 1994–2002 period and a 60/40 to 65/35 rate over the 2004–2010 period. Hobijn and Şahin (2009) estimate monthly job-finding and job-separation rates for 20 OECD countries, identifying considerable variation in both rates, with the US standing out with the highest job-finding rate in contrast to Western European countries, which have considerably lower hiring rates. Gallant et al. (2020) provide evidence from the US labor market of a different dynamics in unemployment mechanisms during the COVID-19 recession compared to past recessions. During the COVID-19 recession, like in previous crises, job separations began to increase rapidly after the outbreak; however, no significant drop in hiring rates followed along the usual lines of labor-market distress dynamics. The temporary nature of the COVID-19 recession implied high re-hiring and has meant that job creation has remained mostly resilient.

The COVID-19 crisis is also unprecedented in terms of the measures taken by governments for the protection of public health and to cushion employees and employers against economic distress. The comparative data on COVID-19 infection rates and governments' responses reveal high regional and country variation.[3] This variation in governments' public health and economic support responses is not explained by the COVID-19 incidence rates only as different nations have taken very different stances on how to combat the virus. In response to the severe economic disturbances provoked by the COVID-19 outbreak, the European Commission implemented a temporary support instrument, a so-called "social bond," to mitigate unemployment risks in an emergency (SURE).[4] By the end of May 2021, nineteen European member states were granted a loan amounting to over 94 billion euros in total.[5] The conditions for receiving SURE funding were related to how significantly COVID-19 increased the public expenditures of the member state, and no specific design was imposed on the particular labor-market measures to protect employment. The member states eventually implemented considerably varying schemes, which have been labeled as "short-time work schemes," "employment protection schemes," or "job retention schemes" in the academic literature (Müller et al., 2022). Drahokoupil and Müller (2021) proposed a typology of the varying job-retention schemes, and Müller et al. (2022) identified a set of criteria that enable the efficient and socially adequate use of SURE resources.

Despite growing research on the implications of the COVID-19 pandemic, our understanding of how COVID-19-related economic and social disruptions have mediated skills–employment relationships in Europe remains limited.[6] The pandemic has created new demands in terms of households' access to the Internet and individuals' digital skills. A shift of production from a designated work place to the home has also affected spillover effects between household members. This paper sets out to provide empirical estimates of these effects and establish whether and to what extent the mediating role of the COVID-19 crisis stems from the actual cumulative rate of COVID-19 cases or the public containment measures aimed at keeping the spread of the virus under control.

3. Data and methodology

3.1. Data sources, sample, and variables

The study focuses on the pre- and post-COVID-19 waves of the CSIS survey conducted in 2017, 2019, and 2021. The dataset includes 26 EU member countries and Norway.[7] The CSIS surveys individuals aged 16 to 74 years and nests them into households that report information on household size, location, income, and access to the Internet. The households' location is available at the NUTS1 (Nomenclature of territorial units for statistics) level for 56 regions and at the NUTS0 or national level for 14 countries.[8] At the level of the individuals, the survey contains information on the respondents' age, gender, educational attainment (based on International Standard Classification of Education [ISCED 2011] categories), employment status, and occupational category. The broad occupational categories are manual workers (The International Standard Classification of Occupations [ISCO] levels 6–9), non-manual workers (ISCO levels 1–5), and ICT professionals (sub-categories at ISCO levels 1–3 that capture ICT assistants, operators, engineers, and managers).

The current analysis complements the CSIS survey microdata with Eurostat NUTS1-level aggregate regional statistics on the unemployment rate, tertiary educational attainment level, and the regions' broadband Internet coverage rate.

The information on cumulative COVID-19 incidence rates per 10 000 inhabitants was retrieved from the COVID-19 European Regional Tracker, an open data source at the sub-national level covering 26 European countries and created by Asjad Naqvi (see Naqvi, 2021). The merge with the CSIS dataset takes place at the NUTS1 regional level, except for the smaller countries that do not have NUTS1-level regional classification and Germany, for which there is no NUTS1 regional information in the CSIS. For these countries,

[3] Hale et al. (2021) compiled a worldwide comparative database regarding country governments' responses to the COVID-19 pandemic, the Oxford COVID-19 Government Response Tracker. The dataset comprises indexes of containment stringency, which include social-distancing restrictions and lockdowns but also information on economic support. Naqvi's (2021) work is a source for the COVID-19 European Regional Tracker, an open data source at the sub-national level for 26 European countries.

[4] Council Regulation 2020/672 was published on 19 May 2020.

[5] https://www.europarl.europa.eu/RegData/etudes/BRIE/2021/659638/IPOL_BRI(2021)659638_EN.pdf.

[6] See Brodeur et al. (2021), Padhan and Prabheesh (2021) for literature reviews of the economics of COVID-19.

[7] Austria (AT), Belgium (BE), Bulgaria (BG), Cyprus (CY), Czech Republic (CZ), Germany (DE), Denmark (DK), Estonia (EE), Greece (EL), Spain (ES), Finland (FI), France (FR), Croatia (HR), Hungary (HU), Ireland (IE), Italy (IT), Lithuania (LT), Luxembourg (LU), Latvia (LV), Malta (MT), Netherlands (NL), Norway (NO), Poland (PL), Portugal (PT), Sweden (SE), Slovenia (SI), Slovakia (SK).

[8] CY, CZ, DE, DK, EE, HR, IE, LT, LV, LU, MT, NO, SK, SI. Note that Germany does not report NUTS1 regions in the CSIS.

information on the cumulative confirmed COVID-19 cases at the national level was retrieved from the Our World in Data COVID-19 dataset.[9]

The comparative country level statistics on governments' responses to COVID-19 is based on the Oxford COVID-19 Government Response Tracker (OxCGRT), a database that aims to track and consistently compare government responses to the pandemic worldwide (Hale et al., 2021).[10] The estimations account for the effect of national COVID-19 containment and closure measures on the labor market using OxCGRT's stringency index and controlling for the Economic Support Index (ESI) for 2021.

For the investigation of the relationship between digital empowerment and employment, the study sample focuses on respondents in their prime working age (i.e., 25 to 54 years old) who are either employed, self-employed, unemployed or inactive.[11] The study sample excludes students who are not in the labor force. The total sample for analysis includes 262,277 individual observations across the three survey waves (2017, 2019, and 2021). Of all observations, 79.7% correspond to individuals in employment with 21.12% holding manual occupations, 2.74% being employed in ICT occupations, and 55.84% working in other non-manual occupations. The underlying ISCO occupational classification codes for these three broad employee groups are detailed in the Appendix. 9.45% of the sample are unemployed, and 10.85% are inactive. The total number of observations is divided evenly between 2017 (34.73%), 2019 (32.36%), and 2021 (32.91%).

Table 1 in the Appendix summarizes the descriptive statistics for the estimation sample.

The digital divide is measured based on two main aspects: the availability and speed of Internet access from home and the level of digital skills. Both variables were retrieved from the statistics of the 2017, 2019, and 2021 waves of the CSIS. Fig. 1 shows that the share of respondents without Internet access from home is the highest among the individuals not employed. The group of individuals engaged in non-manual work has considerably higher average Internet access rate compared to manual workers.

The 2017, 2019, and 2021 waves of the CSIS contain a comprehensive measure of digital skills encompassing four dimensions: (1) information-retrieving skills, (2) communication skills, (3) problem-solving skills, and (4) software skills. This division is in line with the core 21st-century digital skills defined and investigated by van Laar et al. (2017, 2020), who distinguish information-management, communication, problem-solving, technical, and other skills (e.g., collaboration, creativity, and critical thinking). The survey maps the level of digital skills only for individuals who have used the Internet at least once within the last 3 months. These individuals are categorized as "Internet users" in the current study. "Internet non-users" are individuals with no Internet use over the last 3 months, those who could not respond to the question "When did you last use the Internet?," and those who reported having no Internet skills. The latter group forms the lowest (reference) category for the ordinal digital skills variable. The upper digital-skill categories are "low skills," "basic skills," and "above-basic skills." The digital-skill level takes the value of "above basic" for individuals who report at least two activities within each of the four skill dimensions, including information, communication, problem-solving, and software skills. The "basic" skill level is assigned to individuals reporting at least one activity in all four dimensions, and the "low" skill level concerns individuals who report activity in at least one digital-skill dimension but not all. Appendix B contains detailed information on digital-skill dimensions and levels. Fig. 2 portrays descriptively the frequency of Internet use and the level of digital skills across four respondent groups.

Panel A of Fig. 2 demonstrates that almost all non-manual workers aged 25–54 years in Europe are Internet users (i.e., used the Internet at least once in the past 3 months). The share of individuals who never used Internet is the highest among those not employed, followed by manual workers. Non-manual workers have the highest share of above basic digital skills, while the share of digitally illiterate is highest in the group of individuals not employed. However, the share of respondents with above average digital skills is higher among the not employed than in the group of manual workers.

3.2. Estimation framework

The main associations of interest are captured by the estimates for formal education, internet access, digital skills, and within-household spillovers stemming from members with tertiary education. The theoretical foundations for the analysis rely on Roy (1951) framework of individuals' self-selection in occupational choices and the empirical estimation employs random utility approach.

Individuals gain pecuniary and non-pecuniary utility[12] from utilizing their skills in the labor market, whereas improvement in occupation–skill match leads to higher utility. This implies that high skill level increases the probability of labor market participation and more skill-intensive employment.[13] This paper makes a few considerable simplifications that allow for a more straightforward empirical approach. First, it assumes a single ordinal scale for the utility gain from the labor supply at the extensive (participation/non-participation) and intensive (occupation–skill ladder) margins. Second, it does not separate the utility effects from voluntary and involuntary labor-market non-participation. This issue is moderately alleviated by narrowing down on individuals in their prime working age (25–54 years) who are not students and do not work for this reason. The utility of working and willingness to work are the

[9] https://ourworldindata.org/explorers/coronavirus-data-explorer; https://github.com/owid/covid-19-data/tree/master/public/data.

[10] https://data.humdata.org/dataset/oxford-covid-19-government-response-tracker.

[11] Although the statutory pension age in most European countries is 65 years or above, early retirement schemes mostly apply from age 55.

[12] Non-pecuniary utility includes individual heterogeneities in innate preferences for schooling, for working in specific occupation and disutilities of labor market participation (Sullivan, 2010).

[13] Underutilization of skills increases alternative costs for the individual.

Table 1
Summary statistics by employment status, pre COVID-19 (CSIS 2017/2019) and post COVID-19 (CSIS 2021).

	Pre Covid-19: CSIS2017/2019					Post Covid-19: CSIS2021				
	Unemployed/inactive	Manual worker	Non-manual worker	ICT professional	Total	Unemployed/inactive	Manual worker	Non-manual worker	ICT professional	Total
No of observations	36 218	38 403	97 041	4 309	175 971	17 027	17 002	49 407	2 870	86 306
Percentage from total	21%	22%	55%	2%	100%	20%	20%	57%	3%	100%
Proportions										
Broadband access in household	0,8665	0,9130	0,9682	0,9928	0,9373	0,9265	0,9500	0,9750	0,9886	0,9606
Internet use: within 3 months	0,8194	0,8868	0,9770	0,9956	0,9275	0,8977	0,9330	0,9831	0,9907	0,9560
Internet use: between 3 and 12 months	0,0196	0,0174	0,0054	0,0012	0,0107	0,0144	0,0129	0,0039	0,0011	0,0077
Internet use: more than 1 year ago	0,0299	0,0187	0,0063	0,0026	0,0134	0,0242	0,0171	0,0060	0,0065	0,0119
Internet use: Never	0,1311	0,0770	0,0113	0,0007	0,0484	0,0637	0,0369	0,0070	0,0017	0,0243
Digital skills: none	0,2003	0,1284	0,0271	0,0053	0,0820	0,1503	0,1011	0,0258	0,0106	0,0657
Digital skills: low	0,3646	0,4528	0,1785	0,0281	0,2708	0,3557	0,4530	0,2319	0,0738	0,2965
Digital skills: average	0,2521	0,2714	0,3149	0,1703	0,2892	0,2655	0,2972	0,3281	0,1919	0,3046
Digital skills: above average	0,1831	0,1474	0,4795	0,7963	0,3579	0,2285	0,1487	0,4142	0,7237	0,3332
Education: below secondary	0,3771	0,3150	0,0800	0,0294	0,1874	0,3223	0,2891	0,0723	0,0279	0,1653
Education: secondary	0,4490	0,6057	0,4368	0,3306	0,4738	0,4412	0,6137	0,3981	0,2718	0,4463
Education: tertiary	0,1739	0,0793	0,4833	0,6400	0,3388	0,2365	0,0972	0,5296	0,7003	0,3884
Female	0,6543	0,2692	0,5557	0,1669	0,4998	0,6234	0,2552	0,5646	0,1736	0,5006
Age: 25–34	0,2955	0,2497	0,2932	0,3518	0,2856	0,3432	0,2502	0,2823	0,3593	0,2907
Age: 35–44	0,3203	0,3477	0,3530	0,3731	0,3462	0,2955	0,3448	0,3560	0,3552	0,3415
Age: 45–54	0,3842	0,4026	0,3538	0,2751	0,3683	0,3613	0,4050	0,3617	0,2855	0,3679
Densely populated	0,3914	0,2950	0,4412	0,5712	0,4027	0,4262	0,2862	0,4500	0,5991	0,4170
Intermediate	0,3482	0,3349	0,3340	0,3059	0,3361	0,3568	0,3489	0,3324	0,2873	0,3392
Thinly populated	0,2605	0,3701	0,2247	0,1229	0,2611	0,2170	0,3649	0,2175	0,1136	0,2438
Less developed	0,3112	0,3138	0,1951	0,1378	0,2420	0,2738	0,3338	0,2135	0,1775	0,2489
Transition region	0,1421	0,1290	0,1118	0,0869	0,1207	0,1621	0,2134	0,2006	0,1355	0,1932
Highly developed	0,5407	0,5493	0,6772	0,7606	0,6251	0,5564	0,4467	0,5694	0,6666	0,5451
EEA region	0,0060	0,0079	0,0159	0,0146	0,0122	0,0078	0,0061	0,0165	0,0204	0,0128
Means (standard deviations)										
Children	0,4520	0,4685	0,4608	0,4453	0,4604	0,4136	0,4441	0,4640	0,4071	0,4479
	(0.4977)	(0.4990)	(0.4985)	(0.4971)	(0.4984)	(0.4925)	(0.4969)	(0.4987)	(0.4914)	(0.4973)
No household	3,2710	3,3143	3,0329	2,9336	3,1381	3,1610	3,2600	3,0372	2,8007	3,0995
	(1.5386)	(1.5085)	(1.3534)	(1.3504)	(1.4317)	(1.5109)	(1.4890)	(1.3384)	(1.3122)	(1.4091)
Unemployment, % by NUTS1	9,4868	7,5291	6,9485	6,5473	7,5487	8,1869	6,9572	6,5894	6,1760	6,9724
	(6.1264)	(4.9160)	(4.6531)	(4.3621)	(5.1085)	(5.0946)	(4.3687)	(3.9683)	(3.4942)	(4.3319)
Cumulative cases, per Mill						12,3157	13,0794	13,1162	13,6553	12,9654
						(4.3105)	(4.5253)	(4.5453)	(4.8526)	(4.5184)
Containment stringency						62,1228	60,5339	61,0766	59,7815	61,1340
						(8.6896)	(8.2377)	(8.1000)	(8.0581)	(8.2687)
Economic Support Index						66,1311	64,2981	61,8548	61,5708	63,2037
						(21.1043)	(21.3863)	(21.6921)	(21.3096)	(21.5712)

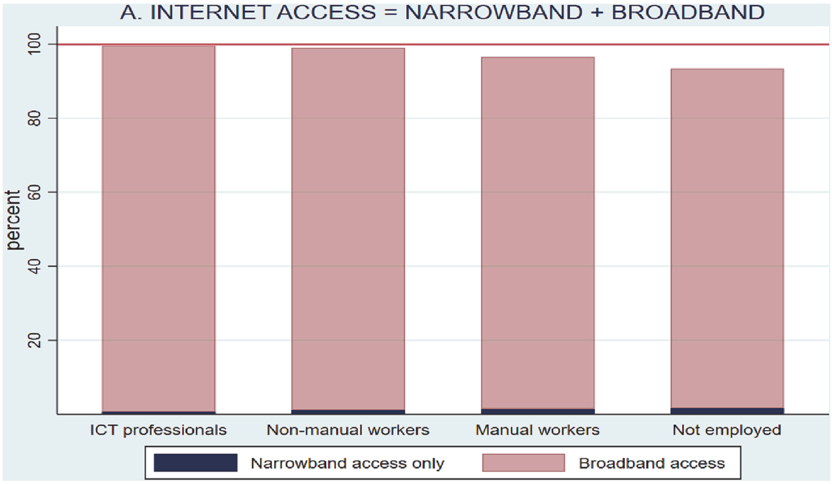

Fig. 1. Percentage of respondents' households having either narrowband or broadband Internet access from home. The sample includes households with one or more individuals aged 25–54 years, except for student households with no members in the labor force. Fixed broadband connections include DSL, ADSL, VDSL, cable, optical fiber, satellite, and public Wi-Fi connections. Mobile broadband connections via a mobile phone network must enable at least 3G, including UMTS, using a SIM card or USB key, mobile phone, or smartphone as a modem. Narrowband connections include dial-up access over a normal telephone line or ISDN, as well as mobile narrowband connections via a mobile phone network below 3G (e.g., 2G+/GPRS), using a SIM card or USB key, mobile phone, or smartphone as a modem. Source: Eurostat, CSIS 2022. Authors' calculations.

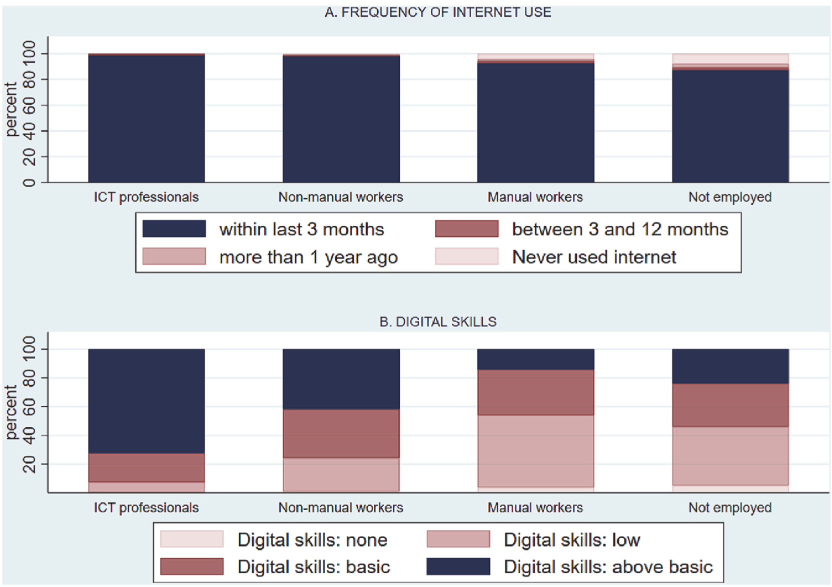

Fig. 2. Panel A: Percentage of individuals who reported last accessing the Internet within the past 3 months, between 3 and 12 months ago, more than 1 year ago, or having never accessed the Internet. Panel B: Percentage of individuals with missing, low, basic, or above-basic digital-skill levels. Note that digital-skill levels were measured only for individuals who reported most recently accessing the Internet within the past 3 months at least. The sample includes individuals aged 25–54 years who are employed, self-employed, unemployed, or inactive (including retired and in compulsory military service). Students who are not in the labor force are excluded. Source: Eurostat, CSIS 2022. Authors' calculations.

highest in prime working age. Thirdly, the estimation approach does not explicitly separate labor supply and demand, however the latter is implicitly controlled for by NUTS1 level unemployment rate (age 20–64) in the occupational outcome equation.[14]

The association between individuals' employment outcomes, Internet access, and digital skills is estimated in both a univariate and a bivariate framework. The univariate ordered probit model estimates a single employment equation and treats all regressors as exogenous to the employment status of the individual. The extended bivariate regression estimates separate equations for employment status and digital skills treating the latter as potentially mismeasured or otherwise endogenous. The joint estimation allows for different parameters in the employment and digital skills equations and instruments digital skills with exogenous regional aggregate digitalization indicators and individual's family composition variables.

Skills form the underlying dimension for the ISCO occupational classification and this enables to investigate a single distribution function of occupational outcomes as depending on skill levels (educational attainment), skill specialization (digital skill level) and tastes for work (individual and household characteristics) at four different segments (see Appendix A for the details on ISCO concept). Occupational outcome is observed as an ordinal variable with four categories. Individuals not participating in the labor market (voluntarily or involuntarily) are assigned to the lowest category. The upper categories are formed and grouped according to the ISCO occupational classification. The second category is comprised of individuals employed in manual occupations (ISCO levels 6–9), the middle or third category represents individuals in non-manual occupations (ISCO categories 0–5) but who are not employed as ICT professionals, and the highest or fourth category represents individuals employed as ICT professionals (according to ISCO subcategories; see Appendix A for the details).

Within-household spillovers stemming from members with tertiary education are measured with a dummy variable taking the value of 1 if the respondent has at least one household member (beyond herself) aged 25–54 years who has a tertiary education, and 0 otherwise. The interactions of the main covariates with the COVID-19 incidence rate and governmental containment stringency are expected to capture the COVID-19-moderated skill–employment link. Hence, the hypothesis to be tested concerns the interaction effect of skills with the regions' exposure to COVID-19 and countermeasures, both of which are considered exogenous to the individual.

The ordinal scale of the main variables of interest implies a non-linear estimation. Treating digital skills as exogenous allows for an ordered probit estimation of the employment status. The exogeneity of the digital skills assumption might, however, be violated for two reasons. First, the digital skills variable may be prone to measurement errors; second, employment status may be a reverse cause of digital skills. Relaxing these assumptions requires a joint estimation of two ordered variables and results in a bivariate ordered probit model. This generalized conditional likelihood framework handles separate equations for digital skills and employment simultaneously, allowing for covariation in their stochastic (error) components while imposing a triangular set-up for the dependency between digital skills and employment status. The joint recursive estimation relies on full information maximum likelihood (FIML), where for reasons of computational feasibility, the likelihood function is defined as a product of marginal and conditional density.[15]

The identification of parameters has to rely on exclusion restrictions and not only on non-linearity and functional form (Maddala and Lee, 1976; Sajaia, 2008). Falck et al. (2021) use regional variation in broadband Internet availability to trace the effect of ICT skills on wages. This study applies a similar strategy in that the Internet use and high-speed connection rollout variables at the regional level serve as instruments for individuals' digital skills. In addition, family size and other family members' age-gender composition variables serve as further instruments that capture variation in digital skills at the individual level. This identification strategy relies on the assumption that regional digitalization indicators and household demographics are adequate measures of individuals' supply of digital skills but do not explicitly determine the individual supply of labor at different skill levels. The underlying rationale, then, is that the digitalization network at the regional level has an effect on individuals' digital skills earlier than on employment likelihood at different occupational-skill levels. Hence, the digital skills equation has several covariates at the regional and household levels that are excluded from the employment equation, including NUTS1-level Internet access and the prevalence of use, percentage of the population with tertiary education, country-age groups mean digital skills and households' gender-age composition.

The triangular system with latent equations for joint estimation is defined as follows:

$$
\begin{aligned}
D_i^* &= \boldsymbol{x}_{1jt}'\gamma_1 + \boldsymbol{x}_{1h}'\gamma_2 + \delta_{1j} + \delta_{1t} + \varepsilon_{1i} \\
E_i^* &= Covid_j \times \boldsymbol{x}_{2i}'\alpha_1 + \boldsymbol{x}_{2i}'\alpha_2 + \boldsymbol{z}_i'\beta + \delta_{2j} + \delta_{2t} + \varepsilon_{2i}
\end{aligned} \tag{1}
$$

The subscript *i* stands for the individuals, *j* captures the variation across NUTS1 regions, and *t* the variation across survey waves. D_i^* denotes the digital-skill level of the individual, and E_i^* stands for employment status. The covariate vectors in the digital skills equation contain the regional and household level variables (with respect to members other than the respondent) as instruments, $\boldsymbol{x}_{1jt}' = \left(constant, tertiary_{jt}, broadband_{jt}, access_{jt}, neverused_{jt}\right)$, and $\boldsymbol{x}_{1h}' = (\max education_h, malemember_h, memberage35to44_h, memberage45to54_h)$. The regional rates of Internet access, Internet use, and tertiary-education attainment as well as household-composition variables are expected to correlate with the digital skills of the individuals. The covariate vector $\boldsymbol{x}_2'$ in the employment equation incorporate the

[14] Brinca et al. (2021) found that labor supply was accountable for two-thirds of the spring 2020 drop in aggregate growth rate of work hours in the United States.

[15] The results are estimated using the STATA eoprobit routine. Sajaia's (2008) *bioprobit* would be another equivalent command for retrieving the estimation results. Because survey weights at the levels of individuals and households across the countries may be incompatible, the estimates are calculated as unweighted. See also Solon et al. (2015) on the caveats of using survey weights.

constant and the main variables of interest including endogenous digital skills D, the household-level dummy for broadband Internet access, the formal education level according to the ISCED classification, and the dummy for another member of the household possessing tertiary education. The variable vector z' controls for individuals' age and the gender–family size interaction variable as well as the NUTS1 regional unemployment level. Both equations include year effects δ_t and NUTS1 regions' fixed effects δ_j. The COVID-19 mediator variable varies across j regions and, depending on the model specification, stands for the cumulative rate of confirmed cases or the index of governmental containment stringency. While one acts as the interaction variable in the employment equation, the other is included in the control variable vector z'. Parameter vector γ_1 includes the intercept term and the parameters of the NUTS1 regional-level instruments, and γ_2 includes the parameters of household-level instruments in the digital skills equation. Parameter vector α_1 in the employment status equation includes the COVID-19 main effect and exposure–skill interaction effect parameters, whereas it contains the interaction parameter for the recursive term. Vector α_2 contains the intercept term and the skill variables' main effects on employment outcomes, including the main parameter for the recursive term. Vector β stands for the parameters of the control variables in the employment equation.

The error terms of the two equations are assumed to satisfy $\mathrm{E}(x_{1i}\varepsilon_{1i}) = 0$ and $\mathrm{E}(x_{2i}\varepsilon_{2i}) = 0$ and follow the standard bivariate normal distribution.

$\varepsilon = (\varepsilon_1, \varepsilon_2)'\ \mathrm{N}(0, \Sigma)$ where $= \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$.

The ordered outcome variables for digital skills and employment status are both measured on four levels: $k = 1(\textit{noskills})$, $2(\textit{lowskills})$, $3(\textit{basicskills})$, and $4(\textit{above} - \textit{averageskills})$ and $l = 1(\textit{notemployed})$, $2(\textit{manualwork})$, $3(\textit{non} - \textit{manualwork})$, and $4(\textit{ICTwork})$, respectively. The log-likelihood function for the individual is:

$$\ln L_i = \sum_{k=1}^{4}\sum_{l=1}^{4} I(D_i = k, E_i = l)\ln Pr(D_i = k, E_i = l)$$

where the probability $Pr(D_i = k, E_i = l)$ given the cut-offs that satisfy $c_{11} < c_{12} < c_{13}$ and $c_{21} < c_{22} < c_{23}$ is:

$$\Pr(D_i = k, E_i = l) = \Pr(c_{1k-1} < D_i \le c_{1k}, c_{2l-1} < E_i \le c_{2l})$$

$$= \Pr(D_i \le c_{1k}, E_i \le c_{2l})$$

$$- \Pr(D_i \le c_{1k-1}, E_i \le c_{2l})$$

$$- \Pr(D_i \le c_{1k}, E_i \le c_{2l-1})$$

$$+ \Pr(D_i \le c_{1k-1}, E_i \le c_{2l-1})$$

Given the assumption of bivariate standard normal distribution of the error term and denoting the linear indexes in the digital skills and employment equation $L_D = x'_{1jt}\gamma_1 + x'_{1h}\gamma_2 + \delta_{1j} + \delta_{1t}$ and $L_E = Covid_j \times x'_{2i}\alpha_1 + x'_{2i}\alpha_2 + z'_i\beta + \delta_{2j} + \delta_{2t}$ correspondingly, the probability of the outcome that $D_i = k$ and $E_i = l$ can be written as:

$$\Pr(D_i = k, E_i = l) = \Phi_2(c_{1k} - L_D, (c_{2l} - L_E)\zeta, \widetilde{\rho})$$

$$- \Phi_2(c_{1k-1} - L_D, (c_{2l} - L_E)\zeta, \widetilde{\rho})$$

$$- \Phi_2(c_{1k} - L_D, (c_{2l-1} - L_E)\zeta, \widetilde{\rho})$$

$$+ \Phi_2(c_{1k-1} - L_D, (c_{2l-1} - L_E)\zeta, \widetilde{\rho})$$

Where Φ_2 stands for the bivariate standard normal cumulative distribution function,
$\zeta = \frac{1}{\sqrt{1+2\theta\rho+\theta^2}}$, and $\widetilde{\rho} = \zeta(\theta + \rho)$, where θ stands for the parameter of the recursive term in the employment equation.

This empirical set-up allows the COVID-19 pandemic to have a moderating role in shaping the link between skills, Internet access and employment status. The interaction terms in the employment equation let the skill parameters vary in the pre- and post-COVID-19 pandemic periods depending on the NUTS1 regions' cumulative confirmed infection rates or on countries containment measures accordingly. In contrast, the formation of individuals' digital skills as depending on the regions' aggregate digitalization and education indicators and family composition variables is not considered to be fundamentally reshaped by the COVID-19 outbreak. While the post-COVID-19 regime may have an effect on how individuals acquire digital skills in interaction with the changed environment in the longer term, the assumption in the present paper is that this fundamental change has not yet taken place or has been negligible by the year 2021.[16] The intra-household correlations between individuals are accounted for by household-level clustered standard errors.

[16] The model does not consider further interaction effects on employment status with respect to the control variables, such as individual demographics and regional aggregate and dummy variables. Year dummies capture the shift induced by COVID-19 in both the employment status and the digital skills equations.

Table 2
Marginal effects on the probability of non-employment, ordered probit, and bivariate ordered probit estimates pre and post COVID-19.

Probability of non-employment	Conditional on marginal effects Pre- and post-COVID-19 samples		Unconditional marginal effects Total sample including 2017, 2019, and 2021							
	Ordered probit		Ordered probit				Extended ordered probit			
		Stringency	Cumulative Cases		Stringency		Cumulative Cases		Stringency	
	Pre-Covid19	Post-Covid19	Pre-Covid19	Post-Covid19	Pre-Covid19	Post-Covid19	Pre-Covid19	Post-Covid19	Pre-Covid19	Post-Covid19
Broadband Internet access	−0.0413***	−0.0574***	−0.0435***	−0.0610***	−0.0450***	−0.0526***	−0.0439***	−0.0607***	−0.0453***	−0.0525***
	(0.0045)	(0.0087)	(0.0031)	(0.0061)	(0.0032)	(0.0058)	(0.0032)	(0.0061)	(0.0032)	(0.0058)
Digital skills, base "none"										
Skills, low	−0.0940***	−0.1133***	−0.1019***	−0.1139***	−0.1033***	−0.1087***	−0.1017***	−0.1148***	−0.1031***	−0.1093***
	(0.0051)	(0.0079)	(0.0035)	(0.0057)	(0.0036)	(0.0053)	(0.0212)	(0.0219)	(0.0216)	(0.0221)
Skills, basic	−0.1737***	−0.1803***	−0.1911***	−0.1831***	−0.1922***	−0.1784***	−0.1926***	−0.1855***	−0.1937***	−0.1802***
	(0.0054)	(0.0081)	(0.0037)	(0.0058)	(0.0038)	(0.0055)	(0.0337)	(0.0332)	(0.0343)	(0.0338)
Skills, above basic	−0.2441***	−0.2288***	−0.2619***	−0.2373***	−0.2651***	−0.2274***	−0.2616***	−0.2384***	−0.2647***	−0.2285***
	(0.0054)	(0.0082)	(0.0037)	(0.0059)	(0.0038)	(0.0056)	(0.0421)	(0.0417)	(0.0429)	(0.0426)
Education, base "below secondary"										
Secondary education	−0.1269***	−0.1335***	−0.1237**	−0.1413***	−0.1242***	−0.1384***	−0.1243***	−0.1395***	−0.1247***	−0.1369***
	(0.0039)	(0.0057)	(0.0025)	(0.0039)	(0.0025)	(0.0038)	(0.0026)	(0.0039)	(0.0026)	(0.0037)
Tertiary education	−0.2363***	−0.2541***	−0.2417***	−0.2650***	−0.2441***	−0.2585***	−0.2424***	−0.2639***	−0.2446***	−0.2579***
	(0.0040)	(0.0058)	(0.0026)	(0.0039)	(0.0026)	(0.0039)	(0.0027)	(0.0039)	(0.0028)	(0.0039)
Household other, tertiary education	−0.0128***	−0.0328***	−0.0113***	−0.0273***	−0.0102***	−0.0296***	−0.0106***	−0.0255***	−0.0096***	−0.0278***
	(0.0021)	(0.0045)	(0.0015)	(0.0032)	(0.0015)	(0.0030)	(0.0015)	(0.0032)	(0.0015)	(0.0030)
Cut: unemployed & manual work	0.4078	−12.0656	0.4888**		0.4986**		−0.0322		−0.0222	
	(0.5891)	(7.1543)	(0.2452)		(0.2451)		(0.0281)		(0.0280)	
Cut: manual & non-manual work	1.2061**	−11.3740	1.2247***		1.2346***		0.6920***		0.7026***	
	(0.5891)	(7.1544)	(0.2452)		(0.2451)		(0.0248)		(0.0247)	
Cut: non-manual & ICT work	3.7681***	−8.9702	3.7635***		3.7735***		3.1948***		3.2068***	
	(0.5892)	(7.1546)	(0.2452)		(0.2452)		(0.0243)		(0.0243)	
Cor(employment status, digital skills)							0.1903***		0.1866***	
							(0.0483)		(0.0494)	
Log-Likelihood	312 168 497.2	−162 382 447.4	−246 395.66		−246 386.88		−568 900.3		−568 894.7	
Observations	175 971	86 306	262 277		262 277		262 277		262 277	
Households	108 850	72 683	129 413		129 413		129 413		129 413	
Wald Chi-square	23 688.26	10 295.82	60 526.39		60 663.41					
Pseudo R-square	0.1350	0.1074	0.1269		0.1269					

Table 3
Marginal effects on the probability of non-manual employment, ordered probit, and bivariate ordered probit estimates pre and post COVID-19.

Probability of employment in non-manual occupations (ISCO 0–5)	Conditional on marginal effects Pre- and post-COVID-19 samples Ordered probit		Unconditional marginal effects Total sample including 2017, 2019, and 2021 Ordered probit				Extended ordered probit			
		Stringency	Cumulative Cases		Stringency		Cumulative Cases		Stringency	
	Pre-Covid19	Post-Covid19	Pre-Covid19	Post-Covid19	Pre-Covid19	Post-Covid19	Pre-Covid19	Post-Covid19	Pre-Covid19	Post-Covid19
Broadband Internet access	0.0488***	0.0633***	0.0493***	0.0710***	0.0506***	0.0616***	0.0497***	0.0707***	0.0510***	0.0615***
	(0.0053)	(0.0094)	(0.0035)	(0.0070)	(0.0036)	(0.0067)	(0.0036)	(0.0071)	(0.0037)	(0.0067)
Digital skills, base "none"										
Skills, low	0.1037***	0.1207***	0.1082***	0.1262***	0.1094***	0.1211***	0.1076***	0.1269***	0.1088***	0.1214***
	(0.0053)	(0.0079)	(0.0035)	(0.0060)	(0.0036)	(0.0056)	(0.0192)	(0.0208)	(0.0195)	(0.0212)
Skills, basic	0.2064***	0.1998***	0.2184***	0.2135***	0.2190***	0.2098***	0.2199***	0.2160***	0.2206***	0.2118***
	(0.0058)	(0.0083)	(0.0039)	(0.0062)	(0.0039)	(0.0059)	(0.0347)	(0.0353)	(0.0352)	(0.0363)
Skills, above basic	0.3079***	0.2590***	0.3151***	0.2857***	0.3183***	0.2758***	0.3144***	0.2868***	0.3174***	0.2770***
	(0.0061)	(0.0086)	(0.0040)	(0.0064)	(0.0041)	(0.0061)	(0.0477)	(0.0477)	(0.0484)	(0.0491)
Education, base "below secondary"										
Secondary education	0.1507***	0.1476***	0.1391**	0.1611***	0.1393***	0.1586***	0.1397***	0.1591***	0.1397***	0.1570***
	(0.0044)	(0.0060)	(0.0027)	(0.0041)	(0.0027)	(0.0040)	(0.0029)	(0.0041)	(0.0030)	(0.0040)
Tertiary education	0.3076***	0.3013***	0.2960***	0.3320***	0.2983***	0.3255***	0.2967***	0.3312***	0.2989***	0.3252***
	(0.0051)	(0.0066)	(0.0031)	(0.0044)	(0.0032)	(0.0045)	(0.0043)	(0.0047)	(0.0045)	(0.0047)
Household other, tertiary education	0.0154***	0.0367***	0.0129***	0.0324***	0.0116***	0.0354***	0.0121***	0.0303***	0.0109***	0.0332***
	(0.0025)	(0.0050)	(0.0017)	(0.0038)	(0.0017)	(0.0036)	(0.0017)	(0.0038)	(0.0018)	(0.0037)
Cor(employment status, digital skills)							0.1903***		0.1866***	
							(0.0483)		(0.0494)	
Log-Likelihood	−312 269 963.5	−162 519 185.8	−246 395.66		−246 386.88		−568 900.3		−568 894.7	
Observations	175 971	86 306	262 277		262 277		262 277		262 277	
Households	108 850	72 683	129 413		129 413		129 413		129 413	
Wald Chi-square	23 645.04	10 287.07	60 526.39		60 663.41					
Pseudo R-square	0.1347	0.1067	0.1269		0.1269					

Note: The marginal effects and standard errors are calculated as contrasts. The stars denote significance levels: * $p < .0.1$, ** $p < .05$, and *** $p < .01$. Clustered standard errors at household survey wave level. The dependent variable is the labor-market status category: 0 = unemployed/inactive; 1 = manual workers; 2 = non-manual employees; 3 = ICT professionals. Manual workers correspond to ISCO groups 6–9. Non-manual employees belong to ISCO groups 0–5 for non-manual occupations, including: 0 = armed forces; 1 = legislators, senior officials, and managers; 2 = professionals; 3 = technicians and associate professionals; 4 = clerks; 5 = service workers and shop and market sales workers. ICT employees are classified according to more specific ISCO sub-categories, presented in Appendix A. Estimations control for gender, education, the household's gender and skill composition, the region's unemployment rate, urbanization level, and region and year dummies. The digital skills equation controls for the mean digital skills in a given NUTS1 region. The sample includes respondents between 25 and 54 years of age who are in employment (employed or self-employed) or not employed (unemployed or inactive). It excludes students not in the labor force. The estimation sample with binary employment outcomes excludes ICT professionals and manual workers, respectively. See Appendix B for the definition of digital skills. The digital skills indicator takes the value of "above basic" for individuals having performed at least two activities within the four specific areas of information, communication, problem-solving, and software skills. The indicator takes the value of "basic" if the individual has performed at least one activity in all four areas, "low" if the individual has not performed any activities in up to three of the areas, and "no skills" if the individual has not performed any of the listed activities. The availability of broadband Internet is measured by the percentage of households that are connectable to an exchange that has been converted to support xDSL-technology, to a cable network upgraded for Internet traffic, or to other broadband technologies. It includes fixed and mobile connections. Low education is defined as ISCED 2011 levels 0–2, medium education as levels 3–4, and high education as levels 5–8.
NUTS1-level regional instruments tertiary education percentage from population [edat_lfse_04], broadband Internet access [isoc_r_broad_h], and unemployment rate [[lfst_r_lfu3rt].
Sources: Eurostat Community Statistics on Information Society microdata for 2017, 2019, and 2021; European NUTS1 regional-level data, Eurostat (2022); Oxford COVID-19 Government Response Tracker (Hale et al., 2021); COVID-19 European regional tracker (Naqvi, 2021).

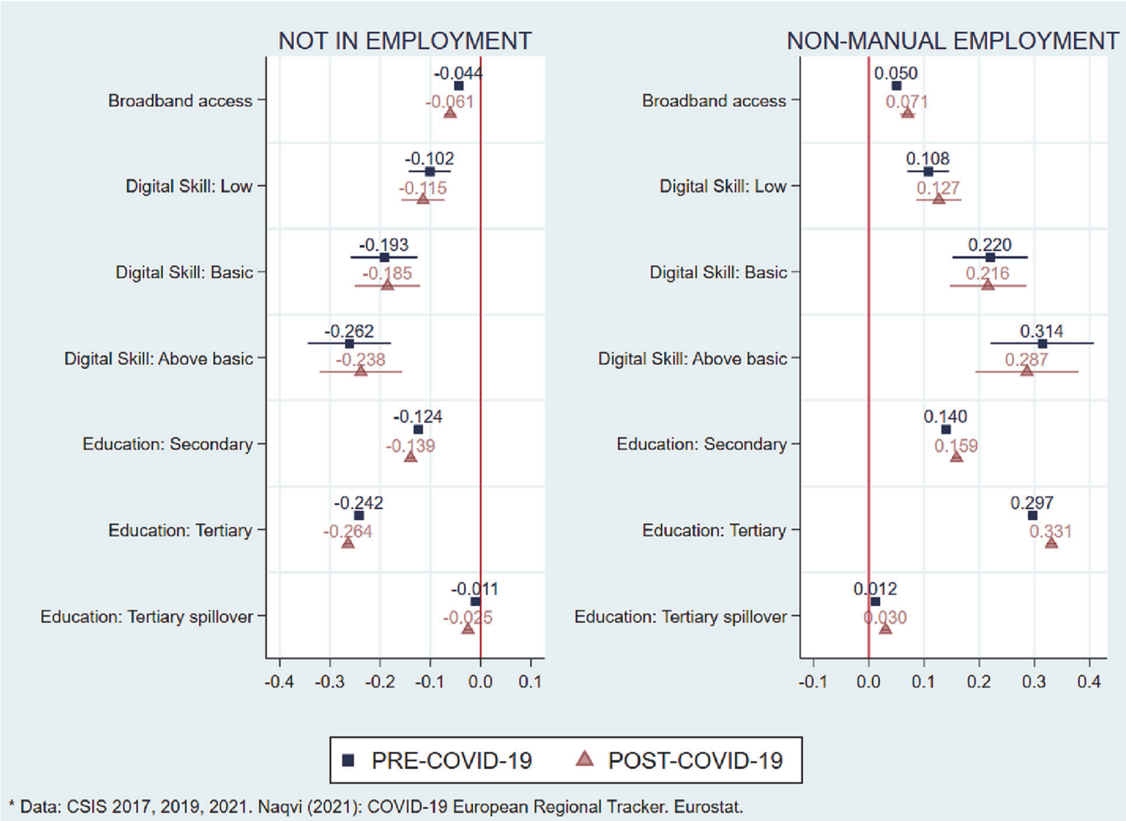

Fig. 3. Extended ordered probit estimates for not in employment and non-manual employment outcomes before and after COVID-19 measured in cumulative rate of infections in the region.

4. Results

This section reports the marginal effects of ordered probit and bivariate ordered probit estimates for the pre- and post-COVID-19 periods for educational-attainment, digital skills, and broadband-access variables, see Table 2, Table 3 and Fig. 3. Table 2 presents the results for being not employed in the labor market and Table 3 for doing non-manual work.[17,18] The differences between the conditional marginal effects estimated separately for the pre-COVID-19 and post-outbreak samples and the unconditional marginal effects estimated over the total period are small. The unconditional marginal effects are estimated on a total sample and enable a comparison of pre- and post-COVID-19 parameter estimates. The COVID-19 interaction terms let the education, digital access and skill parameters change in the employment outcome equation before and after COVID-19 outbreak. Since COVID-19 is measured with two alternative continuous variables, the aggregate cumulative confirmed COVID-19 cases in corresponding NUTS1 regions (COVID-19 Regional Tracker) and the stringency of governmental containment measures (OxCGRT), the parameter changes in the employment outcome equation are proportional to these two measures. Alternative model specifications show that COVID-19-related changes in the effect of broadband connection availability and individuals' skills on employment outcomes are greater if conditioned on cumulative cases rather than on the stringency of public containment measures. Clogg et al (1995) cross-model Wald test proves the strongest statistical differences between coefficient estimates for tertiary education and above average digital skills, followed by intra-family spillover effect and broadband access (see Appendix D). This suggests that the shift in the demand for digital capacity and human skills triggered by COVID-19 was suppressed by the governments' responses aiming to alleviate economic setbacks resulting from stringent containment measures.

Access to broadband Internet improved employment outcomes, especially the likelihood for maintaining ones' non-manual job,

[17] The results for manual-job outcomes and ICT-professional job outcomes are available upon request.

[18] The unconditional marginal effects on the total sample enable a potential outcome comparison with a strong assumption of conditional independence over the pre- and post-COVID-19 periods.

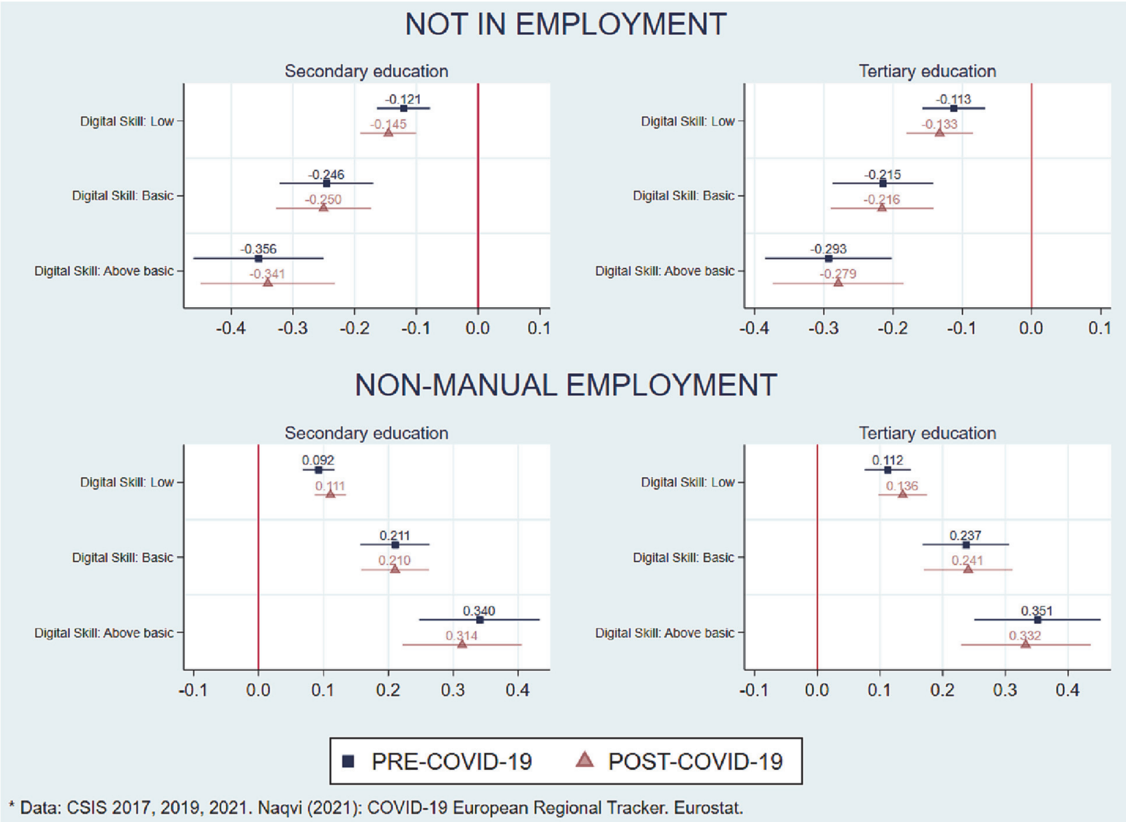

Fig. 4. Extended ordered probit estimates for not in employment and non-manual employment outcomes before and after COVID-19 measured in cumulative rate of infections in the region. Digital skill effect at secondary and tertiary levels of education.

more strongly in the post-COVID-19 period than in pre-COVID-19 years and increasingly so for the individuals located in the regions with higher exposure to COVID-19 infections. While controlling for the level of cumulative infections, tighter public containment measures lead to a somewhat smaller hike in marginal effects, which indicates that public policy has at least partially reduced the labor-market disadvantages for individuals belonging to households without a high-speed Internet connection.

Upper skill levels in both digital literacy and formal education have a stronger effect on non-manual employment than on the probability of being not employed. This indicates that the skill level matters more for the type of employment than for participation in the labor market. The marginal effects for upper-level digital skills and tertiary education are of similar magnitude and both types of skills have considerable importance for labor-market status. Across education and digital skill levels, however, the absolute values of marginal effects differ substantially. The marginal effects of tertiary education are approximately twice of the size of secondary education effects. Similarly, the marginal effects of above basic digital skills are two- to-threefold of the size of low digital skill effects. In absolute levels these effects did not qualitatively change between pre- and post-COVID-19 estimations. There were, however, some noteworthy, though subtle changes in marginal effects pre- and post-COVID-19. While educational-attainment became more important post COVID-19 and the gaps between educational levels widened, the shifts across digital-skill levels were non-uniform. In the COVID-19 period, the largest relative shift arose for individuals with entry level digital skills, as opposed to digital illiteracy. At the same time the advantage from the upper digital skill levels did not grow. Hence, conditional on education level COVID-19 disproportionally favored novice level digital skills at the lower end of the skill distribution.

Fig. 4 and Table 4 show the marginal effects of digital skills on non-employment and non-manual employment at the secondary and tertiary levels of education. Digital skill level has a monotonous utility improving relationship with employment outcomes in that the highest digital skills grant the highest probability of employment and likelihood of having a more skill-intense occupation. As for probability of employment, digital skills have a stronger effect for the individuals with secondary level of education. In contrast, for the probability of having a more skill-intense employment, the digital skill effects are stronger for the individuals with tertiary education. Across both educational levels and occupational outcomes COVID-19 has favored the employment outcomes of people with entry level digital skills relative to the digitally illiterate. In contrast, the benefits of more advanced digital skills shrank relative to those with only novice digital skills.

Table 4
Marginal effects of digital skills on the probability of non-employment and employment in non-manual occupations, bivariate ordered probit estimates pre and post COVID-19 at the level of secondary and tertiary education.

Probability of occupational choice	Unconditional marginal effects at the level of educational attainment COVID-19 interacted: 2017, 2019, and 2021							
	Secondary education				Tertiary education			
	Cumulative cases		Stringency		Cumulative cases		Stringency	
	Pre-Covid19	Post-Covid19	Pre-Covid19	Post-Covid19	Pre-Covid19	Post-Covid19	Pre-Covid19	Post-Covid19
Probability of non-employment								
Skills, low	−0.1211***	−0.1454***	−0.1227***	−0.1385***	−0.1125***	−0.1327***	−0.1143***	−0.1255***
	(0.0219)	(0.0229)	(0.0223)	(0.0235)	(0.0230)	(0.0245)	(0.0235)	(0.0247)
Skills, basic	−0.2460***	−0.2504**	−0.2473***	−0.2440***	−0.2148***	−0.2160***	−0.2166***	−0.2088***
	(0.0386)	(0.0394)	(0.0393)	(0.0405)	(0.0371)	(0.0379)	(0.0379)	(0.0385)
Skills, above basic	−0.3557***	−0.3408***	−0.3604***	−0.3266***	−0.2932***	−0.2792***	−0.2974***	−0.2665***
	(0.0536)	(0.0555)	(0.0546)	(0.0568)	(0.0466)	(0.0481)	(0.0476)	(0.0490)
Probability of employment in non-manual occupations (ISCO 0–5)								
Skills, low	0.0923***	0.1108***	0.0931***	0.1073***	0.1123***	0.1363***	0.1136***	0.1304***
	(0.0125)	(0.0122)	(0.0126)	(0.0131)	(0.0185)	(0.0197)	(0.0187)	(0.0204)
Skills, basic	0.2105***	0.2104***	0.2105***	0.2087***	0.2371***	0.2407***	0.2380***	0.2357***
	(0.0271)	(0.0265)	(0.0273)	(0.0281)	(0.0352)	(0.0360)	(0.0356)	(0.0373)
Skills, above basic	0.3404***	0.3138***	0.3441***	0.3039***	0.3513***	0.3324***	0.3556***	0.3198***
	(0.0475)	(0.0469)	(0.0483)	(0.0486)	(0.0514)	(0.0528)	(0.0523)	(0.0543)
Cor(employment status, digital skills)	0.1903***		0.1866***		0.1903***		0.1866***	
	(0.0483)		(0.0494)		(0.0483)		(0.0494)	
Log-Likelihood	−568 900.3		−568 894.7		−568 900.3		−568 894.7	
Sample observations	262 277		262 277		262 277		262 277	
Household clusters	129 413		129 413		129 413		129 413	

Note: Refer to notes to Table 2 and Table 3.

After the COVID-19 outbreak the within-household spillovers from the externalities of tertiary education on employment status and labor-force participation increased substantially, from below a single percentage point to 2–3 percentage points. This hike was stronger in response to COVID-19 preventive containment and closure measures, than in response to cumulative COVID-19 incidence rates.

5. Discussion

The COVID-19 pandemic disrupted and rapidly reshaped the world of work. Access to broadband Internet, digital skills and educational attainment combine to shape employment outcomes. There are also positive spillovers if household members have higher education. The current study revisits the skill-employment link and investigates how four main capacities that empower individuals in the labor market have become even more important after COVID-19 struck: (1) access to the high-speed Internet; (2) level of educational attainment; (3) spillovers from tertiary educated family members; and (4) digital skills.

Not surprisingly, during COVID-19 access to high-speed Internet from home became more important for employment outcomes. The estimations show that the association of broadband Internet with taking up or keeping non-manual employment is stronger than the link with exit from non-employment. This finding is in line with Akerman et al.'s (2015) claim regarding the complementarity between broadband Internet and labor skills. Access to the Internet benefits more the skilled and those in non-manual employment for whom high-speed Internet access offers ways to maintain or even strengthen their labor market status. Access to the Internet has a smaller but positive and significant effect on taking up a job for individuals not in employment.

The results show that the level of educational attainment became more important post COVID-19, with a widening employment gap between below-secondary and secondary education and between secondary and tertiary education. This is consistent with Soh et al. (2022) who found positive employment effect of digital occupations in the United States, but within digital occupations the effect was mainly driven by cognitive occupations dominated by individuals with tertiary education.

Post COVID-19, the within-household spillovers from tertiary education tripled in size. This sheds light on the importance of higher education's non-monetary benefits and externalities that arise from home production, whose role has particularly increased with COVID-19-related containment and closure measures.[19]

Digital skills maintained a positive and strong effect on employment, but with contrasting outcomes across digital skill levels before and after the pandemic. COVID-19 disproportionally rewarded individuals with novice level digital skills and this narrowed the gap to individuals with basic or above basic digital skills. This observation gives testimony of skill-segmented and digitally disparate labor markets that witnessed asymmetric labor supply disruptions. COVID-19 triggered an abrupt demand for entry-level digital skills in occupations and jobs hitherto characterized by low level of digitalization and workers with absent or low digital skills. This evidence agrees with Von Gaudecker et al (2020) who report labor supply disruptions from COVID-19 disproportionately affecting middle- and

[19] See McMahon (2018) for the non-monetary benefits and externalities of higher education.

low-skilled workers. These workers tend to have little or no opportunity to telework and they have low digital literacy. The sudden demand shift in favor of employees with at least some digital skills seemingly increased employability of individuals able to support the implementation of new digital tools in fields of work with low pre-pandemic levels of digitalization. Hence, the asymmetric labour supply disruptions affected more strongly the lower end of digital skills distribution.[20]

Comparing results using regional statistics on cumulative COVID-19 incidence rates with the indicator of governments' containment and economic support measures finds that public containment and economic support measures alleviated the economic setback for households and individuals and suppressed some of the COVID-19 triggered demand for digital capacities and education. Using the cross-model Wald test from Clogg et al (1995) shows the strongest statistical differences between coefficient estimates for tertiary education and above average digital skills, followed by broadband access and within household educational spillovers (see Appendix D). The intra-household spillovers from tertiary education rose substantially comparing to the pre-pandemic years with the COVID-19 period. The preventive isolation closed individuals in their homes and made them more dependent on their family resources. Hence, the containment measures may have aggravated the role of socio-economic disparities on labor market outcomes.

6. Summary and conclusions

This paper adds to the existing evidence that access to broadband Internet, digital skills and educational attainment combine to raise employment outcomes and documents how COVID-19 has changed these relationships in important ways. Educational attainment and digital skills are found to be strong complements that jointly improve the employment outlook for the individual. Labor market outcomes are also positively shaped by the education level of household members. COVID-19 has roughly tripled the labor market advantages from having household members with tertiary education, with tentative evidence that governments' COVID-19 response measures magnified the role of family members' educational attainment on labor-market outcomes. A possible explanation for this could be that individuals with higher education would be better at supporting family members to gain or remain in employment when this increasingly requires digital interactions. A parallel could be drawn to findings that children with higher-educated parents had better learning outcomes in periods of remote schooling during the pandemic (Fisher et al 2020).

Conditional on the level of digital skills and Internet access COVID-19 has disproportionally improved the employment outcomes of people with some ("low") digital skills relative to the digitally illiterate. In contrast, the benefits of more advanced digital skills shrank in comparison to those with only low digital skills. A plausible explanation may be that the abrupt labor-market disruptions caused by COVID-19-related containment measures required a rapid transition from on-site to online modes of work. This transition happened mostly at the extensive margin, raising demand for teleworkable hours, as opposed to the intensive margin, which would have raised demand for more sophisticated digital skills. The switch to online work occurred more naturally among high-skilled workers, a considerable share of whom is digitally proficient and already in teleworkable jobs. A rapid digitalization drive in some middle-and low-skill occupations when physical contact was substituted for digital solutions due to COVID-19 confronted with insufficient supply of digitally literate labor at the lower end of the pay-skill distribution and this could explain the disproportionally improved employment outcomes for digital "survivors" among the middle- and low-skilled workers.

In general, the findings point in the direction that COVID-19 likely widened the employment gap between advantaged groups, with high skills, from educated families and digitally proficient, and less advantaged groups. These results underscore the need for intensified efforts to secure equal access to education and digital empowerment. Future research may show whether the changes in labor-market rewards for digital skills triggered by the COVID-19 pandemic will permanently reshape the distribution of the supply of digital skills and transform work more universally towards higher digitalization.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

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[20] Heredia et al (2022) show empirically that digital skills in countries with lower human development index have a more significant indirect effect on firm performance than in high human development countries.

Appendix

Table A1
Employment status, CSIS 2017/2019 and CSIS 2021.

Code	CSIS Definitions 2017/2019	CSIS Definitions 2021
1	Employed or self-employed (including family workers)	Employed
2	Unemployed	Unemployed
3	Student (not in the labor force)	Retired
4	Other not in the labor force (retired, inactive, in compulsory military service, etc.)	Unable to work due to long-standing health problems
5	N/A	Student, pupil (not in the labor force)
6	N/A	Fulfilling domestic tasks
7	N/A	Compulsory military or civilian service
8	N/A	Other
9	Not applicable (age = blank or age < 16 years or age > 74 years)	Used the Internet within the last 3 months, skill level "low"

Appendix A. 1: Employment status categories

The "not in employment" category includes categories 2 and 4 in the 2017 and 2019 CSIS surveys and categories 2, 3, 4, and 6 in the 2021 CSIS survey (note that category 8 does not include any observations). Students and pupils are excluded from the study.
Table A1

Appendix A. 2: Occupational categories

The study employs ISCO (The International Standard Classification of Occupations) definitions and categorization of occupations. ISCO arranges occupations into groups according to two main dimensions: (1) skill level and (2) skill specialization. Skill level refers to complexity and range of duties and tasks that relate to a specific occupation and it is measured with four ISCO occupational skill levels, the level of formal educations according to ISCED and with on-the-job training and extent of required work experience. The concept of skill specialization involves four aspects: (1) the required field of knowledge, (2) the tools and machinery used, (3) the materials worked on with, and (4) the kinds of goods and services produced (International Labour Office, 2012).

The CSIS includes four categories of occupational status: (1) not in employment (unemployed/inactive), (2) manual workers: ISCO 6 to 9, (3) non-manual workers: ISCO 1 to 5 and (4) ICT professionals: ISCO sub-categories under 1–3 (CSIS Methodological manual, 2006). The ISCO groups 1–3 correspond to skills that are supported by tertiary level of education (ISCED5 and above), ISCO groups 4–8 require at least secondary level of education (ISCED2-4) and only the lowest ISCO group 9, elementary occupations, correspond to a skill level that is provided by only primary level of education (ISCED1). In terms of CSIS broad groupings of non-manual and manual occupations, the non-manual workers (ISCO 1–5) would require at least secondary education, and manual workers (ISCO 6–9) would require no higher than secondary education (International Labour Office, 2012).

Manual workers. This category corresponds to major groups 6 to 9 of ISCO:
- Major group 6: Skilled agricultural and fishery workers (ISCED2-4);
- Major group 7: Craft and related trade workers (ISCED2-4);
- Major group 8: Plant and machine operators and assemblers (ISCED2-4);
- Major group 9: Elementary occupations (ISCED1).

Non-manual workers. This category corresponds to major groups 1 to 5 of ISCO:
- Major group (1): Legislators, senior officials, and managers (ISCED5-6);
- Major group 2: Professionals (ISCED5-6);
- Major group 3: Technicians and associate professionals (ISCED5);
- Major group 4: Clerks (ISCED2-4);
- Major group 5: Service workers and shop and market sales workers (ISCED2-4);
- Major group 0: Armed forces (ISCED1-2–4).

ICT professionals. This category consists of individuals in one of the following eight ISCO unit groups (unit groups correspond to the 4-digit level), see also the Methodological manual for Information Society Statistics 145.
– 1236: Computing services managers;
– 2131: Computer systems designers, analysts, and programmers.
– 2139: Computing professionals not elsewhere classified;
– 2144: Electronics and telecommunications engineers;

– 3114: Electronics and telecommunications engineering technicians;
– 3121: Computer assistants;
– 3122: Computer equipment operators;
– 3132: Broadcasting and telecommunications equipment operators.
– 213: Computing professionals;
– 312: Computer associate professionals.

Appendix B:. CSIS definition of digital skills

The CSIS survey measures digital skills solely for individuals who have used the Internet at least once within the past 3 months. The aggregate digital-skill level is composed of five sub-categories of digital skills: (1) information and data-literacy skills, (2) communication and collaboration skills, (3) problem-solving skills, (4) digital content–creation skills, and (5) digital-safety skills. These sub-categories are defined below.

The activities used for calculating **information and data-literacy skills** are the following: copying or moving files or folders; saving files on Internet storage space; obtaining information from public authorities/services' websites; finding information about goods or services; seeking health-related information.

The activities used for calculating **communication and collaboration skills** are: sending/receiving emails; participating in social networks; telephoning/placing video calls over the Internet; uploading self-created content to any website for sharing.

For the area of **problem-solving skills**, the individual must have performed one task in each of two specific sub-categories to qualify as "above basic": sub-category 1 (problem solving) consists of transferring files between computers or other devices, installing software and applications (apps), and changing the settings of any software, including operational systems or security programs; sub-category 2 relates to familiarity with online services, including online purchases (in the last 12 months), selling online, using online learning resources, and Internet banking.

For the area of **digital-content creation**, the individual must have performed one task in each of two sub-categories to qualify as "above basic": sub-category 1 includes using word-processing software, using spreadsheet software, and using software to edit photos, video, or audio files; sub-category 2 comprises creating a presentation or document integrating text, pictures, tables, or charts, using advanced functions of spreadsheets to organize and analyze data (sorting, filtering, using formulas, creating charts), and having written a code in a programming language.

For the area of **digital safety**, the individual must have carried out actions for managing and securing digital access to their personal data (e.g., name, date of birth, identity number, contact details, credit card number, photos, or geographical location).

The aggregate digital skills are ranked on four levels ("none," "low," "basic," and "above basic") as follows:

- Skill level "none" corresponds to an individual who has no digital skills across all five sub-skill categories or has missing skills in four out of five sub-skill categories.
- Skill level "low" corresponds to an individual who lacks at least one out of five sub-skills entirely but has a few or multiple skills in other digital sub-skill categories.
- Skill level "basic" corresponds to an individual who has a few or multiple skills in all five digital sub-skill categories but not multiple skills in all five sub-categories. In other words, individuals with a "basic" skill level have some digital skills in all five categories but are limited to a few skills in one or more of them.
- Skill level "above basic" corresponds to an individual who has multiple skills in all five digital sub-skill categories.

Table B1 presents the definitions for aggregate digital-skill levels for the 2017 and 2019 CSIS waves and the 2021 wave. The common scale is adopted according to the category divisions with the mapping as set out in Table B1.

Table B1
Digital skills, CSIS 2017/2019 and CSIS 2021.

Code	Definitions CSIS 2017/2019	Code	Definitions CSIS 2021
0	Skill level "none" or skill level not available because no Internet use within the last 3 months	0	Skill level "none" or skill level not available because no Internet use within the last 3 months
1	Skill level "low"	1, 2, 3	Skill level "limited," "narrow," "low"
2	Skill level "basic"	4	Skill level "basic"
3	Skill level "above basic"	5	Skill level "above basic"

Appendix C:. Internet access, Internet use and digital skills by countries

Fig. C1 illustrates the Internet penetration for working-age individuals' households in European countries according to the 2021 wave of the CSIS. The Internet coverage for households ranged from 94.2% in Bulgaria to 99.9% in Luxembourg, with six more countries (Finland, Norway, The Netherlands, Austria, Spain, and Cyprus) boasting Internet penetration levels above 99%. Moreover, a dominant part of European households accessed the Internet with high-speed broadband connections, with the highest coverage found in Norway (99.6%).

Panel A of Fig. C2 demonstrates that the vast majority of individuals aged 25–54 years in Europe are Internet users (i.e., used the Internet at least once in the past 3 months). The countries' ranking in terms of the frequency of Internet use resembles that of households' Internet access. The share of Internet users is the highest in Norway, Denmark, Luxembourg, Finland, Sweden, and Ireland, where over 99% of prime working-age individuals are Internet users. The countries at the lower end of the distribution are Bulgaria (86.5%) and Greece and Italy (approximately 90%).

The aggregated digital-skill composition across countries (Fig. 2, Panel B) has a more varied structure. The countries reporting a 50% or higher share of 25–54-year-old individuals with above-basic digital skills are the Netherlands, Finland, Croatia, Ireland, and Norway. In contrast, only 9% of individuals in Bulgaria have above-average digital skills.

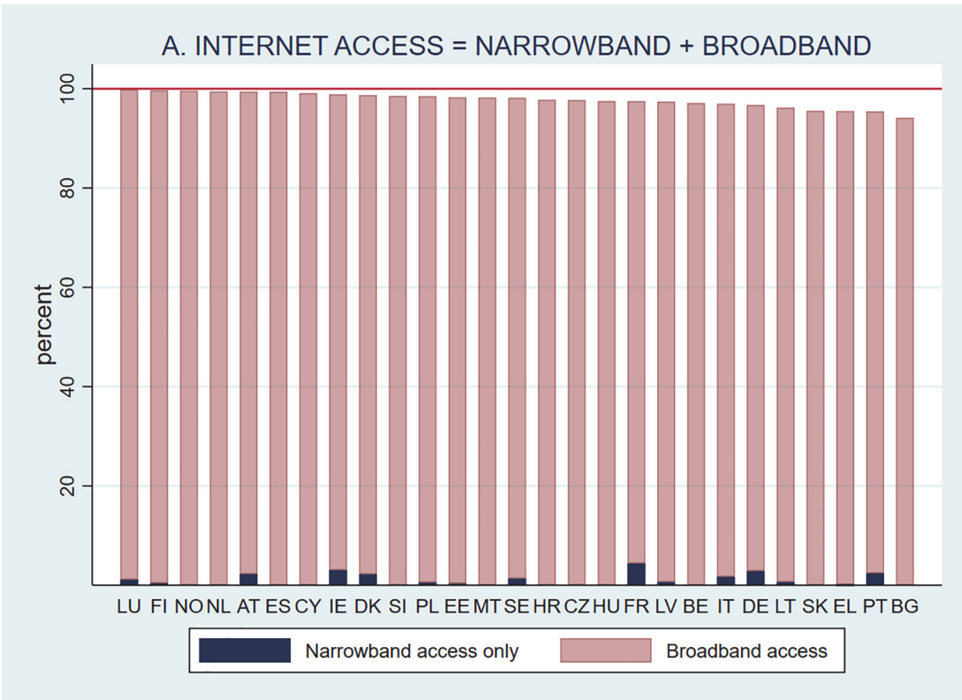

Fig. C1. Percentage of households having either narrowband or broadband Internet access from home. The sample includes households with one or more individuals aged 25–54 years, except for student households with no members in the labor force. Fixed broadband connections include DSL, ADSL, VDSL, cable, optical fiber, satellite, and public Wi-Fi connections. Mobile broadband connections via a mobile phone network must enable at least 3G, including UMTS, using a SIM card or USB key, mobile phone, or smartphone as a modem. Narrowband connections include dial-up access over a normal telephone line or ISDN, as well as mobile narrowband connections via a mobile phone network below 3G (e.g., 2G+/GPRS), using a SIM card or USB key, mobile phone, or smartphone as a modem. Source: Eurostat, CSIS 2022. Authors' calculations.

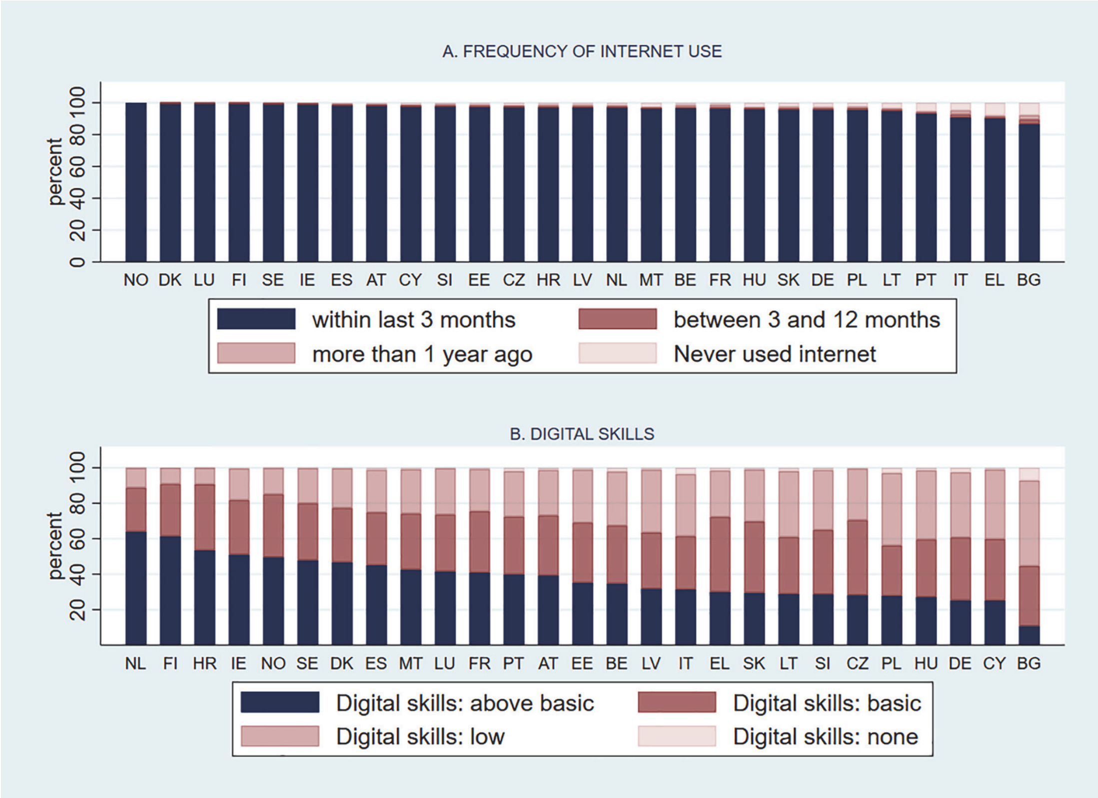

Fig. C2. Panel A: Percentage of individuals who reported last accessing the Internet within the past 3 months, between 3 and 12 months ago, more than 1 year ago, or having never accessed the Internet. Panel B: Percentage of individuals with missing, low, basic, or above-basic digital-skill levels. Note that digital-skill levels were measured only for individuals who reported most recently accessing the Internet within the past 3 months at least. The sample includes individuals aged 25–54 years who are employed, self-employed, unemployed, or inactive (including retired and in compulsory military service). Students who are not in the labor force are excluded. Source: Eurostat, CSIS 2022. Authors' calculations.

Appendix D:. Cross-model parameter tests Wald hypotheses test

Table D1

Table D1
2 Results for cross-model parameter equality comparing model specifications with COVID-19 cumulative cases and containment stringency index from ordered probit estimation.

Parameters	Wald chi-square	p-value
Broadband internet access (BIACC)	5.0522**	0.0246
Digital skills: base skills, none		
Skills, low	3.4284*	0.0641
Skills, basic	0.8507	0.3563
Skills, above basic	14.2419***	0.0002
Educational attainment: base primary education		
Secondary education	0.8908	0.3453
Tertiary education	25.6215***	0.0000
Household spillover, tertiary education	6.4265**	0.0112

Sample, N = 262277 individual observations.

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Appendix 4. The framework of twin transitions

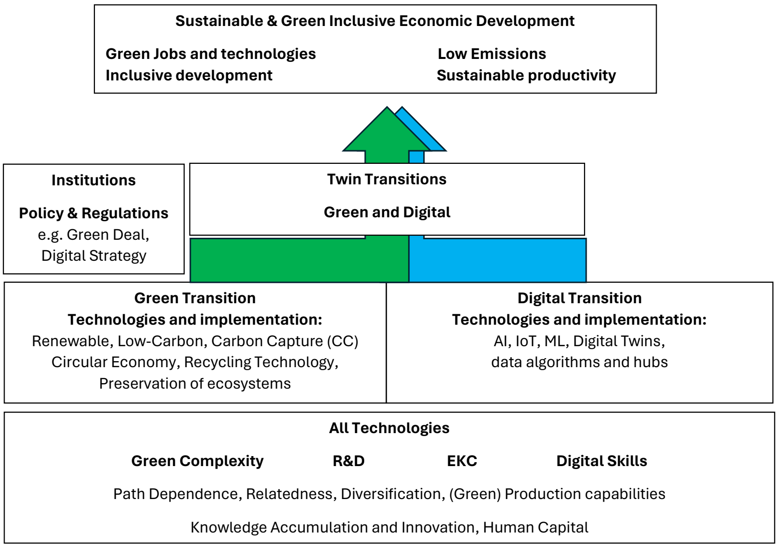

Figure 2. The framework of twin transitions.
Source: European Commission (2019, 2020a, 2020b, 2022b, 2022d, 2023a), Briglauer et al. (2023), Paiho et al. (2023), Rehman et al. (2023), compiled by the author.

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2020 – 2023	Individual Behaviour and Economic Performance: Methodological Challenges and Institutional Context (IBEP, H2020), VFP20046.
2019 – 2021	RITA 1 project: Climate change mitigation with CCS and CCU technologies (ClimMit, RITA), RITA1/02-20-04.
2017 – 2021	Institutions for Knowledge Intensive Development: Economic and Regulatory Aspects in South-East Asian Transition Economies (IKID, H2020), VFP16057.
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2023	Männasoo, K., Pareliussen, J. K., & **Saia, A.** Digital Capacity and Employment Outcomes: Microdata Evidence from Pre- and Post-COVID-19 Europe. *Telematics and Informatics*, 83. DOI: https://doi.org/10.1016/j.tele.2023.102024. (ETIS 1.1).

RECOGNITIONS AND AWARDS

2022	Tallinn University of Technology: the best research article in the field of Engineering and Technology: "Techno-economic assessment of CO_2 capture possibilities for oil shale power plants." **Saia, A.**, Nešumajev, D., Hazak, A., Sander, P., Järvik, O., Konist, A. Renewable and Sustainable Energy Reviews, 169.
2020	Tallinn University of Technology, School of Business and Governance, Institute of Economics and Finance: the best theses supervisor.
2005	3rd place in Portfolio Management Contest (LHV).

RELEVANT COURSES

2021	Bayesian statistics, Prof. Ü. Maiväli/T. Päll, PhD, University of Tartu
2021	Machine Learning (supervised/unsupervised ML in R), Prof. A. Strittmatter, CREST-ENSAE (Paris)/Bank of Estonia
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SCIENTIFIC PRESENTATIONS

2022	14. International Conference "Evolving Challenges in European Economies" (Tallinn, Estonia); presentation of the article: "Digitalization and CO_2 emissions"
2022	Department of Economics and Finance Research Seminar; presentation of the article: "Digitalization and CO_2 emissions"
2021	Doctoral seminar: presentation of the article: "Techno-economic assessment of CO_2 capture possibilities for oil shale power plants"
2019	Poster presentation related to the project (ClimMit, RITA): "Climate change mitigation with CCS and CCU technologies" at the XI Oil Shale conference, Jõhvi, Estonia

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2023	Männasoo, K., Pareliussen, J. K., & **Saia, A.** Digital Capacity and Employment Outcomes: Microdata Evidence from Pre- and Post-COVID-19 Europe. *Telematics and Informatics*, 83. DOI: https://doi.org/10.1016/j.tele.2023.102024. (ETIS 1.1).

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2020	Tallinna Tehnikaülikool, Majandusteaduskond, Majandusanalüüsi ja rahanduse instituut: aasta parim lõputööde juhendaja.
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