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

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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

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[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).

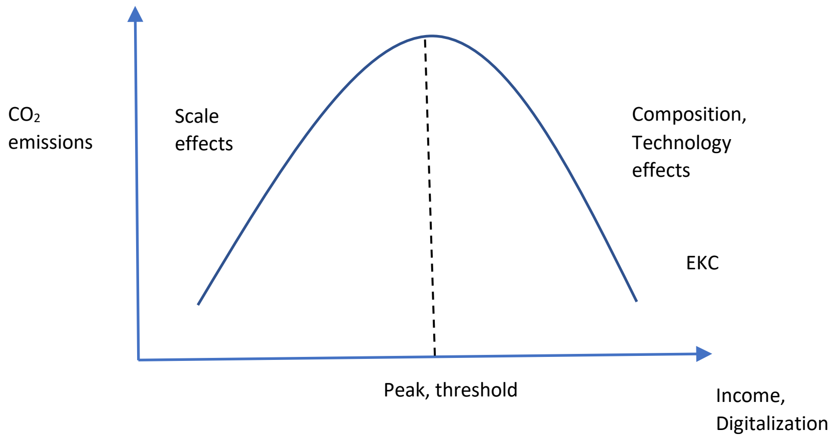

Figure 1. Environmental Kuznets curve (Grossman and Krueger, 1995; compiled by the author).

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.

List of Figures

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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 komplekset 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 püüdmistehnoloogiate rakendamist asjaomastes tehastes vaid juhul, kui CO_2 heitkogustest ja riigisiseste energiajulgeolekuga seotud probleemidest tulenevaid negatiivseid välismõjusid 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

This article "Digitalization and CO_2 emissions: Dynamics under R&D and technology innovation regimes" was published in *Technology in Society*, Vol 74, Artjom Saia, pp. 1–15, Copyright Elsevier, (2023). DOI: https://doi.org/10.1016/j.techsoc.2023.102323. (ETIS 1.1).

Appendix 2. Publication II

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

Publication II

This article "Techno-economic assessment of CO_2 capture possibilities for oil shale power plants" was published in *Renewable and Sustainable Energy Reviews*, Vol 169, Artjom Saia, Dmitri Neshumayev, Aaro Hazak, Priit Sander, Oliver Järvik, Alar Konist, pp. 1–11, Copyright Elsevier, (2022). DOI: https://doi.org/10.1016/j.rser.2022.112938. (ETIS 1.1).

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).

Appendix 4. The framework of twin transitions

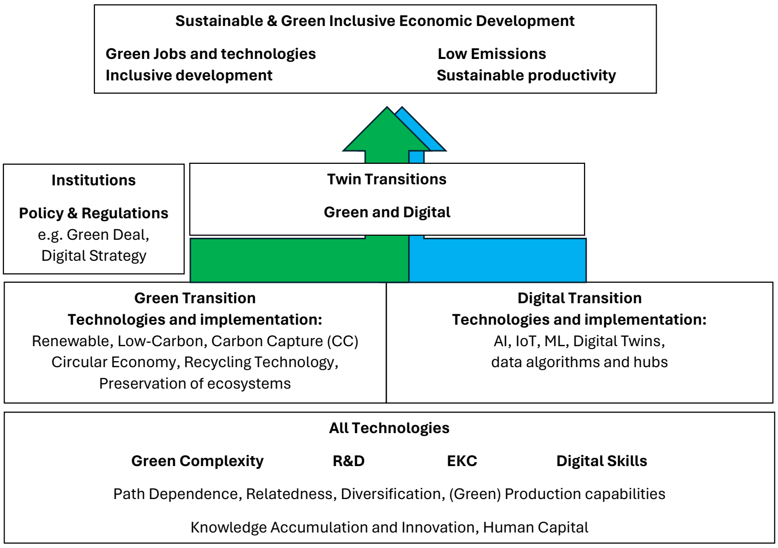

Figure 2. The framework of twin transitions.
Source: European Commission (2019, 2020a, 2020b, 2022b, 2022d, 2023a), Briglauer et al. (2023), Paiho et al. (2023), Rehman et al. (2023), compiled by the author.

Curriculum vitae

PERSONAL INFO

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EXPERIENCE

2018 –	**Tallinn University of Technology/TalTech,** *Institute of Economics and Finance,* Tallinn, Estonia *PhD candidate, Researcher*
2016 – 2019	**Compensa Life Vienna Insurance Group,** Tallinn, Estonia *Risk Manager – key function holder*
2011 – 2016	**Blue Mountain,** Tallinn, Estonia *Project Manager – Business Development*
2010 – 2010	**Evli Securities,** Tallinn, Estonia *Fund Manager*
2005 – 2009	**Danske Capital**/ **Mandatum/ Sampo Baltic Asset Management,** Tallinn, Estonia / Helsinki, Finland *Fund Manager*

EDUCATION

2018 –	**Tallinn University of Technology/TalTech,** *Institute of Economics and Finance,* Tallinn, Estonia *PhD in Economics, PhD candidate* *Supervisors*: Professors – Kadri Männasoo, PhD; Aaro Hazak, PhD.
2012 – 2015	**Tallinn University of Technology,** *School of Business and Governance,* Tallinn, Estonia Master of Arts M.A. in Social Sciences – Corporate Finance
2001 – 2003	Internship Program – **Council on International Educational Exchange (CIEE)**, New York, USA.
1996 – 2000	**University of Tartu**, *School of Business Administration,* Tartu, Estonia B.A. degree in Corporate Finance, Investments, International economy

RESEARCH AND DEVELOPMENT PROJECTS

2021 – 2023	Micro-level responses to socio-economic challenges in face of global uncertainties (Global2micro), ETAG21003.
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.

SCIENTIFIC PUBLICATIONS

2023	**Saia, A.** Digitalization and CO_2 emissions: Dynamics under R&D and technology innovation regimes. *Technology in Society*, 74. DOI: https://doi.org/10.1016/j.techsoc.2023.102323. (ETIS 1.1).
2022	**Saia, A.**, Neshumayev, D., Hazak, A., Sander, P., Järvik, O., & Konist, A. Techno-economic assessment of CO_2 capture possibilities for oil

	shale power plants. *Renewable and Sustainable Energy Reviews*, 169. DOI: https://doi.org/10.1016/j.rser.2022.112938. (ETIS 1.1).
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
2021	Innovation, Prof. E. Karo, Tallinn University of Technology
2021	Baltic Summer School of Digital Humanities, Estonia
2020	Forecasting with DSGE models (MatLab), Prof. M. Rubaszek, SGH Warsaw School of Economics
2020	GMM models, A. Võrk, University of Tartu
2019	Panel Data Econometrics in R, A. Võrk, University of Tartu
2018	Long Panel Data Models, Prof. T. Malinen, University of Helsinki

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

TEACHING AND SUPERVISING

	Courses: Fundamentals of Finance (in English and Estonian); Financial Modelling in R (in Estonian) *Supervision*: Master’s and Bachelor’s theses
	Member of the defense committee: “Corporate finance”, “Banking”.

Elulookirjeldus

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TÖÖKOGEMUS

2018 –	**Tallinna Tehnikaülikool/TalTech,** *Majandusanalüüsi ja rahanduse instituut*, Tallinn, Eesti *Doktorant-nooremteadur*
2016 – 2019	**Compensa Life Vienna Insurance Group,** Tallinn, Eesti *Riskijuht – võtmefunktsiooni kandja*
2011 – 2016	**Blue Mountain,** Tallinn, Eesti *Projektijuht – Äriarendus*
2010 – 2010	**Evli Securities,** Tallinn, Eesti *Fondijuht-Portfellihaldur*
2005 – 2009	**Danske Capital/ Mandatum/ Sampo Baltic Asset Management,** Tallinn, Eesti / Helsingi, Soome *Fondijuht-Portfellihaldur*

HARIDUS

2018 –	**Tallinna Tehnikaülikool/TalTech,** *Majandusanalüüsi ja rahanduse instituut,* Tallinn, Eesti *PhD Majandusteaduses, doktorikandidaat* *Juhendajad: Professorid – Kadri Männasoo, PhD; Aaro Hazak, PhD*.
2012 – 2015	**Tallinna Tehnikaülikool,** *Majandusteaduskond,* Tallinn, Eesti Sotsiaalteaduse Magistrikraad M.A. – Ärirahandus
2001 – 2003	Praktikaprogramm – **Council on International Educational Exchange (CIEE)**, New York, Ameerika Ühendriigid.
1996 – 2000	**Tartu Ülikool,** *Ettevõttemajanduse instituut,* Tartu, Eesti Bakalauruse kraad B.A. ettevõttemajanduse erialal, Ärirahandus ja Investeeringud ning Välismajandus

TEADUS- JA ARENDUSTEGEVUSE PROJEKTID

2021 – 2023	Sotsiaalmajanduslikud väljakutsed globaalsete ebakindluste tingimustes: mikrotasandi uuringud (Global2micro), ETAG21003.
2020 – 2023	Indiviidi käitumine ja majanduslik tulemuslikkus: Metodoloogilised aspektid ja institutsionaalne kontekst (IBEP, H2020), VFP20046.
2019 – 2021	RITA 1 projekt: Kliimamuutuste leevendamine läbi CCS ja CCU tehnoloogiate (ClimMit, RITA), RITA1/02-20-04.
2017 – 2021	Institutsioonid teadmistepõhise arengu saavutamiseks: Majanduslikud ja regulatiivsed aspektid Kagu-Aasia üleminekumajandustes (IKID, H2020), VFP16057.

TEADUSPUBLIKATSIOONID

2023	**Saia, A.** Digitalization and CO_2 emissions: Dynamics under R&D and technology innovation regimes. *Technology in Society*, 74. DOI: https://doi.org/10.1016/j.techsoc.2023.102323. (ETIS 1.1).
2022	**Saia, A.**, Neshumayev, D., Hazak, A., Sander, P., Järvik, O., & Konist, A. Techno-economic assessment of CO_2 capture possibilities for oil

	shale power plants. *Renewable and Sustainable Energy Reviews*, 169. DOI: https://doi.org/10.1016/j.rser.2022.112938. (ETIS 1.1).
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).

TUNNUSTUSED JA AUTASUD

2022	Tallinna Tehnikaülikooli parima teadusartikli preemia Tehnika ja Tehnoloogia valdkonnas: "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	Tallinna Tehnikaülikool, Majandusteaduskond, Majandusanalüüsi ja rahanduse instituut: aasta parim lõputööde juhendaja.
2005	3. koht aktsiaportfelli haldamise võistlusel (LHV).

TÄIENDUSÕPE

2021	Bayesian statistics, Prof. Ü. Maiväli/T. Päll, PhD, Tartu Ülikool
2021	Machine Learning, Prof. A. Strittmatter, CREST (Pariis)/Eesti Pank
2021	Innovation, Prof. E. Karo, Tallinna Tehnikaülikool
2021	Baltic Summer School of Digital Humanities, Eesti
2020	Forecasting with DSGE models (MatLab), Prof. M. Rubaszek, SGH Warsaw School of Economics
2020	GMM models, A. Võrk, Tartu Ülikool
2019	Panel Data Econometrics in R, A. Võrk, Tartu Ülikool
2018	Long Panel Data Models, Prof. T. Malinen, University of Helsinki

TEADUSETTEKANDED

2022	14. Rahvusvaheline Konverents "Evolving Challenges in European Economies": "Digitalization and CO_2 emissions" artikli ettekanne (Tallinn, Eesti)
2022	Majandusanalüüsi ja rahanduse instituudi teadusseminar: "Digitalization and CO_2 emissions" artikli ettekanne
2021	Doktoritöö seminar: "Techno-economic assessment of CO_2 capture possibilities for oil shale power plants" artikli ettekanne
2019	XI Põlevkivi konverents "Muutuste tuules": projekti "Kliimamuutuste leevendamine läbi CCS ja CCU tehnoloogiate" (ClimMit, RITA) raames posterettekanne (Jõhvi, Eesti)

ÕPPETÖÖ JA JUHENDAMISED

	Ainekursused: Rahanduse alused (eesti ja inglise keeles); Finantsmodelleerimine R-s (eesti keeles)
	Juhendamised: Magistri- ja Bakalaureusetööd
	Kaitsmiskomisjoni liige: "Ärirahanduse", "Rahanduse ja panganduse" erialal.