// NO.25-006 | 01/2025

DISCUSSION PAPER

// DIRK CZARNITZKI, ROBIN LEPERS,
AND MAIKEL PELLENS

Adoption of Circular Economy Innovations: The Role of Artificial Intelligence

Adoption of Circular Economy Innovations:

The Role of Artificial Intelligence

Dirk Czarnitzki [A,B,C], Robin Lepers [A,B] and Maikel Pellens [A,B,C 1]

A) *KU Leuven, Dept. of Management, Strategy and Innovation, Leuven, Belgium*
B) *Centre for R&D Monitoring (ECOOM) at KU Leuven, Belgium*
C) *Leibniz-Centre for European Economic Research (ZEW), Mannheim, Germany*

This version: December 2024

Abstract

The circular economy represents a systematic shift in production and consumption, aimed at extending the life cycle of products and materials while minimizing resource use and waste. Achieving the goals of the circular economy presents firms with the challenge of innovating new products, technologies, and business models, however. This paper explores the role of artificial intelligence as an enabler of circular economy innovations. Through an empirical analysis of the German Community Innovation Survey, we show that firms investing in artificial intelligence are more likely to introduce circular economy innovations than those that do not. Additionally, the results indicate that the use of artificial intelligence enhances firms' abilities to lower production externalities (for instance, reducing pollution) through these innovations. The findings of this paper underscore artificial intelligence's potential to accelerate the transition to the circular economy.

Keywords: Circular economy, Innovation, Artificial intelligence

JEL-Classification: Q55, O31

---

[1] E-Mail addresses: dirk.czarnitzki@kuleuven.be, robin.lepers@kuleuven.be and maikel.pellens@kuleuven.be
Acknowledgements: Dirk Czarnitzki acknowledges financial support from the Research Foundation Flanders (FWO, grant number: G0C6921N) and KU Leuven's basic research fund (BOF, grant number C14/24/023).

1 Introduction

In order to reach the environmental goals of the Paris Agreement and European Green Deal of zero net emissions by 2050, it is essential to transition towards more sustainable models of production and consumption. In this context, the Circular Economy (CE) model has emerged as a transformative approach, focusing on maximizing the utility of products and materials throughout their life cycle by reducing energy and material inputs, reusing resources, and designing for end-of-life (Geissdoerfer et al., 2017; Kirchherr et al., 2017). CE is critical for achieving a green, sustainable economy that also safeguards human welfare and economic growth (Millar et al., 2019). However, implementing CE principles challenges firms to innovate, i.e., to develop new products, production technologies, and even business models (Bocken et al., 2016; Chioatto et al., 2024). Understanding the factors driving circular economy innovations (CEI) is therefore high on the research and policy agenda,[2] addressing challenges ranging from the generation of new CE-focused technologies, challenges in their adoption and implementation, and challenges surrounding the orchestration of circular ecosystems. By addressing these challenges, businesses can contribute to enhancing circularity within the economic system, which has remained stagnant at around 11.5% in the EU over the past decade (Eurostat, 2023a).[3]

[2] For example, the Circular Economy Action Plan of the European Commission (2015, 2020) serves as a key component of the European Green Deal and highlights the need to identify determinants and barriers of CEI.

[3] Eurostat determines the circularity rate by analyzing the use of circular materials in countries and assessing the share of recycled materials in the total material consumption. This measure tends to be lower compared to other circularity indicators, such as recycling rates, which stood at approximately 46% in the EU in 2022 (Eurostat, 2023b).

This paper focuses on the first element, the development of CEI. We argue that artificial intelligence (AI) serves an enabler of CEI, due to its capacity to overcome the specific challenges that firms face when investing in CEI. Recent literature highlights the expanding role of AI in driving green innovations, particularly in sectors like transportation, energy, and industrial systems (Biggi et al., 2024; Ghoreishi & Happonen, 2020). Through an empirical investigation of the relation between CEI and AI based on the German part of the Community Innovation Survey, we show that firms investing in AI are more likely to introduce CEI than firms who do not invest in AI. Additionally, our findings suggest that firms using AI have better abilities to lower production externalities and thus pollution through CEI. We contribute to the literature on CEI and AI by showing this link at the firm level, improving on the regional level of analysis of extant literature (Wang et al., 2023; Yin et al. 2023).[4] As a whole, our findings indicate that AI can be an effective tool for businesses and policymakers to overcome the complex challenges that firms often face when investing in CEI (de Jesus & Mendonça, 2018; Kümmerer et al., 2020).

In what follows, we will discuss the conceptual background of this study (Section 2), the data and methods (Section 3), the econometric results (Section 4) and the conclusions (Section 5).

2 Conceptual Background

Innovation is considered a key element in enabling the transition towards the CE (de Jesus & Mendonça, 2018; Ellen MacArthur Foundation, 2019). Firms, therefore, play a central role in

[4] Yin et al. (2023) find a positive relationship between AI development and green technology innovation in different Chinese regions, with threshold effects of the environmental regulation intensity in these regions. Wang et al. (2023) show that countries with a higher stock of industrial robots relative to the number of employed people, as a proxy for AI, is positively related to the development of environmental innovations.

driving this systemic shift by innovating new circular products, technologies, and business models (Bocken et al., 2016). CEI is argued to not only yield environmental benefits, but also create economic advantages that could add up to net benefits of estimated 1.8 trillion euros in the EU by 2030 (Ellen MacArthur Foundation & McKinsey & Company, 2015). For instance, firms could benefit economically from CEI by entering or expanding green markets (Cainelli et al., 2020; Reif & Rexhäuser, 2018), or by gaining reputational benefits (Mazzucchelli et al., 2022; Veleva & Bodkin, 2018). Additionally, CEI can lead to cost savings through increased resource efficiency, which in turn allows firms to reduce product prices, ultimately leading to further increased demand (Horbach & Rammer, 2020).

However, developing CEI is also challenging, since it often requires integrating various systems, including supply chains, waste reduction technologies, and closed-loop production processes. Because of these integrations, developing CEI is often seen as more complex than general innovation (de Jesus & Mendonça, 2018; Geissdoerfer et al., 2017). Additionally, CEI often relies on relatively new technologies that require more fundamental research, which are typically complex and less likely to be aligned with the firm's core competencies (De Marchi, 2012; del Rio et al., 2011; Horbach et al., 2013; Kümmerer et al., 2020).

In this context, it has been suggested that AI is a potentially powerful tool to accelerate the transition towards CE (Ellen MacArthur Foundation & Google, 2019; Ghoreishi & Happonen, 2020). AI refers to a collection of technologies, including machine learning, natural language processing, and robotics, that allow machines to perform tasks typically requiring human intelligence (Trajtenberg, 2019). The rapid advancement of AI technologies in the last decade have transformed it as a General Purpose Technology (GPT), with applications spanning across a broad range of industrial sectors (Agrawal et al., 2019).

A crucial question is why AI would affect CEI. First, it has been acknowledged that AI has the potential to radically change innovation processes in a general sense (Agrawal et al., 2019). Deep learning and other forms of automated machine learning have shown to have (potential) applications in most industrial activities through the automation of human decision-making, with far-ranging consequences for production systems and supply chains. For instance, AI applications can improve both the pace and quality of R&D processes, such as through enhanced materials discovery in scientific research (Rammer et al., 2022; Toner-Rodgers, 2024). In organizational contexts, AI adoption facilitates improved decision-making and efficiency in the innovation process through automating (operational) tasks and overcoming information processing constraints (Gama & Magistretti, 2023; Haefner et al., 2021). Such applications of AI have been shown to positively impact firm productivity (Czarnitzki et al., 2023; Toner-Rodgers, 2024) as well as innovation outcomes (Babina et al., 2024; Rammer et al., 2022; Toner-Rodgers, 2024). Thus, expectations are high on the potential of AI for disruptive innovation in general (Baruffaldi et al., 2020; Brynjolfsson et al. 2019; OECD, 2020).

More interesting for the purposes of this study are reasons to believe that AI also benefits CEI in ways that align with the specific demands and challenges posed by the CE. Similar arguments have been made about the potential of the broader idea of industry 4.0, and the associated rise of ‘smart’ manufacturing, for unlocking (environmental and social) sustainability goals. One of the core arguments is that industry 4.0 technologies enable shorter production cycles, higher flexibility, and higher productivity through tight interconnection and advanced data analytics, for example (Bai et al., 2020). Such tighter integrations would, in theory, enable the system interconnections required for CE transformation (de Jesus & Mendonça, 2018; Geissdoerfer et al., 2017).

A first specific way in which AI can support the development of circular products and materials is by overcoming computational challenges that would otherwise be insurmountable (Ellen MacArthur Foundation & Google, 2019; Ghoreishi & Happonen, 2020, Roberts et al. 2024). This argument is especially relevant for the development of new materials: while traditional R&D methods in material science often rely on trial and error, which can be slow and resource-intensive, AI can accelerate this process through predictive modeling and computational design (Butler et al., 2018). This is particularly relevant for technologies related to CEI, as in many domains CE solutions will require rethinking products at the fundamental level (Kümmerer et al., 2020).[5] While Kümmerer et al. (2020) focus on the need for simplification in CE solutions, abundant examples exist of CEI contributions that are achieved by overcoming complexities with the aid of AI.[6]

Similarly, AI can simulate various design scenarios and their impacts on a product's lifecycle, helping firms make decisions that optimize resource use, durability, and recyclability simultaneously (Ellen MacArthur Foundation & Google, 2019; Ghoreishi & Happonen, 2020; Tsirigotis, 2024). By enabling such systemic optimization, AI helps firms achieve the goals of

[5] Kümmerer et al. (2020) describe the challenges as "*Modern circularity includes the design of products with adapted lifetime, reusability, ease of repair and recycling ability – all made with renewable resources. […] These efforts will help address the Earth's resource and waste challenges and contribute to sustainable development. However, greater success will have to come from changes at the product-design level, led by scientists who strive to decipher, at the atomic and molecular levels, how chemical products and their underpinning synthetic chemistry fit into a CE"* (p.369).

[6] For instance, the Chilean company NotCo uses AI to develop plant-based food substitutes by analyzing molecular patterns for ingredient selection and recipe formulation. Likewise, the 'Accelerated Metallurgy' project, funded by the European Space Agency, uses AI to design and test new alloy metal combinations aligning with CE principles through additive manufacturing (Ellen MacArthur Foundation and Google, 2019). More generally, AI is argued to play a critical role in catalyst design, where the large design space in terms of parameter selection makes design highly complex. In recent years, several experimentally validated catalyst technologies have been developed based on computational design (Kalikadien et al. 2024).

CE faster and more effectively than traditional methods, which may only address one part of the product lifecycle at a time.[7]

Furthermore, AI enables the detection of opportunities for CEI by allowing to track and analyze large volumes of complex data in real time (Acerbi et al., 2021; Ertz et al., 2022; Ghoreishi & Happonen, 2020; Roberts et al., 2024). Unlike traditional linear production models, where efficiency might be measured primarily in terms of costs or output, CEI is more complex since it also focuses on other (system-level) metrics such as material circularity (i.e., using recyclable materials), design parameters (i.e., building for upgradeability or disassembly), energy consumption, and environmental impact (Ellen MacArthur Foundation & Google, 2019). Rather than simply reducing costs, the primary goal of CEI is thus to maintain value within the system (Bocken et al., 2016; Ellen MacArthur Foundation, 2013; Geissdoerfer et al., 2017). AI's analytical capabilities are particularly well-suited for achieving this objective, for example through optimizing recycling protocols of complex materials (Acerbi et al., 2021), optimizing reverse logistics (Wilson et al, 2022), or for optimizing production processes with regard to CE parameters, for instance by optimizing materials and energy usage, or to predict equipment failures (Acerbi et al. 2021, Ellen MacArthur Foundation & Google, 2019, Li et al, 2023).[8]

---

[7] Examples of such optimization include Google, which leverages AI to optimize routes for eco-friendliness (Google, 2023). AI can also enable new circular business models, such as those relying on AI-based dynamic pricing or AI -supported resource infrastructure management (Ellen MacArthur Foundation & Google, 2019; Roberts et al., 2024). Stuffstr, for example, is a company from Seattle that utilizes AI algorithms for pricing used household items and apparel, as well as for managing resale inventory, facilitating the resale of used apparel (Ellen MacArthur Foundation & Google, 2019).

[8] For example, Google, whose data centers produced an equivalent of 14.3 million metric tons of carbon dioxide in 2023 and accounts for 0.1% of global electricity demand, employ AI algorithms to optimize the cooling systems in its data centers. By applying machine learning models trained on data from thousands of sensors, Google was able to reduce energy use by 40 percent (Google, 2024).

In summary, the literature on AI, innovation, and CE indicates that AI has the potential to help firms overcome specific challenges firms face with CEI by providing advanced data analytics and systemic optimization capabilities that allow firms to optimize resource use, extending product lifecycles, and minimize waste and pollution. This paper empirically tests this hypothesis using German firm-level data:

> **Hypothesis:** *Firms that adopt AI technology are more likely to introduce CEI than firms that do not adopt AI technology.*

3 Data and methods

3.1 Data source

The analysis is based on the Mannheim Innovation Panel (MIP), the German part of the Community Innovation Survey (CIS).[9] In particular, we use the 2021 wave of the MIP, which includes questions on CEI and questions on the use of AI for the reference period 2018-2020. In the robustness checks, we also build a short panel by combining the 2021 wave with the 2023 wave, which covers the reference period 2020-2022 and contains the same questions on AI and CEI, but lacks some interesting control variables that we can utilize only from the 2021 wave of the MIP.

[9] The CIS is a biennial representative large-scale survey, coordinated by Eurostat, that collects official innovation statistics for the EU. The survey is based on the guidelines laid down in the Oslo Manual (OECD and Eurostat 2018). For more details on the German CIS, which is conducted as a panel survey ('Mannheim Innovation Panel'), see Peters and Rammer (2013).

3.2 CEI variables

The main dependent variable indicates whether or not the firm introduced a CEI in the reference period (*CEI*). The variable is based on a question on environmental innovations, where firms could indicate, for 13 potential environmental impacts, whether or not the firm introduced innovations that had an environmental impact in 2018-2020.[10] Table 1 lists the potential environmental impacts. Firms could differentiate between a 'significant' and a 'rather small' environmental impact.

To determine which environmental benefits relate to the circular economy, we follow the 4R-framework, which is a commonly used principle within the CE framework by scholars (Ghisellini et al., 2016; Kirchherr et al., 2017; Kirchherr et al., 2023) and policymakers (e.g., European Commission, 2008, 2017). The 4R framework focuses on reducing resources and energy consumption (reduce), encouraging the use of products and materials for as long as possible (reuse), processing used materials into new products and designing products with recyclability in mind (recycle), and recovering energy or materials from waste when recycling is not feasible (recover), for example by converting non-recyclable waste into usable forms of energy (Kirchherr et al., 2017). Following this framework, we consider all the environmental impacts listed in Table 1 to be CE-related.[11] Consequently, *CEI* takes value one if the firm

[10] Environmental innovations are defined as follows: "Environmental innovations are new or improved products/services or processes/procedures that have led to a noticeable reduction in environmental impact compared to the products/services and processes/procedures previously offered by your company. The positive environmental effects can have been either an explicit goal or a side effect of the innovation. The positive environmental effects can have occurred either in your company (including in sales) or when the products/services are used by your customers or end users."

[11] Other versions of the CIS survey (e.g., Flanders) sometimes also include the other environmental impacts that can result from environmental innovations, such as the protection of biodiversity. This is an example of an environmental impact that CE literature does not commonly consider as an element of CE (Geissdoerfer et al., 2017; Kirchherr et al., 2017).

indicates to have introduced an innovation with at least one rather small or significant environmental impact, and zero otherwise.

Table 1: Types of environmental impact

Positive environmental effects in your firm
1. Reduction of energy consumption per unit/process
2. Reduction of material consumption/ water consumption per unit/process
3. Reduction of CO_2 emissions per unit/process
4. Reduction of other air emissions (e.g. SO_x, NO_x)
5. Reduction of water or soil pollution
6. Reduction of noise pollution
7. Replacement of fossil energy sources with renewable energy
8. Replacement of hazardous materials/ substances
9. Recycling of waste, waste water, or materials for own use or sale
Positive environmental effects when using your products/services
10. Reduction in energy consumption/ overall CO_2 balance
11. Reduction in emissions in the areas of air, water, soil noise
12. Improvement in the recyclability after use of products
13. Increase in the lifespan of products/ longer-lasting products

Furthermore, to get a better understanding of the specific pathways through which AI can enable CEI, we construct three further dependent variables that consider CEI that act through different channels. First, the variable *CEI_INPUT* captures CEI that reduce the input needs, taking value 1 if the firm responds affirmative to either item 1 or 2 in Table 1. These innovations align closely with productivity-enhancing mechanisms, as they lower production costs and improve operational efficiency (Horbach & Rammer, 2020). Second, *CEI_PROD* captures CEI that reduce production externalities, i.e., items 3 to 9 in Table 1. These innovations are also primarily supply-side measures focused on enhancing operational efficiency and minimizing environmental impacts. Third, *CEI_USE* captures CEI that deliver their environmental effects when product or service are used by customers, i.e., items 10 to

13 in Table 1. This channel predominantly operates through demand mechanisms by addressing consumer preferences environmentally beneficial products. Next to environmental policies and the overall environmental affinity of the firm, these innovations are likely to be mostly driven by green market demand (Cainelli et al., 2020; Reif & Rexhäuser) and/or reputational considerations (Mazzucchelli et al., 2022; Veleva & Bodkin, 2018).

3.3 AI variable and controls

The main explanatory variable is a dummy that takes value one if the company used AI methods in 2018-2020 (*AI*). The variable is based on the survey question: "Artificial intelligence is an information processing technology that allows computers to solve problems independently. Does your company use artificial intelligence methods?" Companies could then indicate AI methods and applications from a matrix designed to capture the diversity of uses of AI in businesses.[12] AI takes value one if the company indicates any of these.

We employ firm-level controls that may influence the probability of introducing CEI besides the use of AI technologies. First, we consider the firms' affinity towards environmental protection through four channels. The firms were asked, "How important were the following factors related to climate change for your business?"

1. Government policies or measures related to climate change;
2. Increasing customer demand for products that help mitigate or adapt to climate change (e.g. low-carbon products);

[12] Listed AI methods included language understanding and text generation, image/ pattern recognition, machine learning, and knowledge-based systems and decision support. Areas of application included products and services, automation of processes, communication with customers, data analytics, and other areas.

3. Increasing costs or input prices resulting from climate change (e.g. higher insurance fees, higher resource prices, adaptation of processes or facilities);
4. Impacts of extreme weather conditions (e.g. disturbances in transport/logistics, damages from storms, flooding, drought).

Firms could rate the importance of these items "not relevant" [0], "low" [1], "medium" [2], high [3]. We use these four questions as regressors (*CLIMATE1-CLIMATE4*) using the original ordinal scale.

Other control variables are firm size measured as the logarithm of employment (ln*EMP*), a dummy whether the firm received public investment support, not specific to CEI (*PUBSUPPORT*), a dummy indicating whether the firm is performing R&D activities on a permanent basis (*RDCON*), and another dummy if R&D is done occasionally (*RDOCC*). We supplement these survey variables by the firms' EPO[13] patent stock (*PATSTOCK*). We also use a dummy indicating whether the firm is a member of a corporate group (*GROUP*), and whether the firm is located in Eastern Germany (*EAST*). Finally, we use 12 industry dummies to control for unobserved heterogeneity across sectors.

3.4 Descriptive statistics

Table 2 displays descriptive statistics. 10.8% of the sample uses *AI* . Among firms that use *AI*, 77% introduced *CEI*, 19% more than *CEI* among firms without *AI* (58%) ($p<0.01$). *CEI* are roughly equally divided across *CEI_INPUT*, *CEI_PROD*, and *CEI_USE*

---

[13] EPO refers to patents filed at the European Patent Office. We collected patents from the Patstat database and calculated the stock with the perpetual inventory method using a 15% rate of obsolescence.

Table 2: Descriptive statistics of model variables

	Non-AI-using firms				AI-using firms				Diff.
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	
CEI	0.578	0.494	0	1	0.771	0.421	0	1	***
CEI_INPUT	0.404	0.491	0	1	0.572	0.495	0	1	***
CEI_PROD	0.476	0.499	0	1	0.626	0.484	0	1	***
CEI_USE	0.434	0.496	0	1	0.608	0.489	0	1	***
EMP	91.155	298.672	0.12	5754	323.15	946.274	1	9874	***
GROUP	0.297	0.457	0	1	0.452	0.498	0	1	***
RDCON	0.196	0.397	0	1	0.509	0.500	0	1	***
RDOCC	0.114	0.318	0	1	0.139	0.346	0	1	*
EAST	0.419	0.493	0	1	0.334	0.472	0	1	***
PUBSUPPORT	0.222	0.416	0	1	0.417	0.493	0	1	***
CLIMATE1	1.207	1.01	0	3	1.293	1.017	0	3	**
CLIMATE2	1.013	0.97	0	3	1.192	1.042	0	3	***
CLIMATE3	1.486	1.023	0	3	1.412	0.976	0	3	*
CLIMATE4	0.933	0.919	0	3	0.839	0.842	0	3	***
PATSTOCK	0.141	0.989	0	21.964	0.326	1.621	0	23.248	***
N		5930				719			

Notes: Diff. indicates p-value of t-test of equal means between firms with and without *AI*.
* p<0.10, ** p<0.05, *** p<0.01

Table 2 also shows that firms with *AI* are significantly larger, more likely to be part of a corporate group, and less likely to be situated in former East Germany. Firms with *AI* are also more innovation-active: they are more often engaged in continuous R&D activities, and hold a higher patent stock. They also are more likely to receive public support. Finally, firms with and without *AI* differ significantly in their attitude towards climate change, but the differences are small and not fully consistent across the items.

4 Econometric results

4.1 Main results

Table 3 shows the results of regressions of *CEI* on *AI* and controls. Column 1 shows an OLS model taking *CEI* as dependent variable. Column 2 shows seemingly unrelated regressions (SUREG) of *CEI_INPUT, CEI_PROD,* and *CEI_USE*. We estimate these jointly to account for any residual correlation across the forms of CEI yielding an efficient estimator (cf. the significant Breusch-Pagan test for independence and the high correlations among the residuals as presented in the table).

All models demonstrate a positive and significant relationship between the use of AI and CEI. Model 1 shows that *AI* relates to an increase of 10.2 percentage points in the likelihood of *CEI*. Compared to the base probability of *CEI* among firms without *AI* of 58%, this represents a relative increase in probability of 18%. Similarly, models 2-4 show positive impacts of 9.1, 7.9, and 7.4 percentage points on the probability of *CEI_INPUT*, *CEI_PROD*, *and CEI*_USE, respectively, reflecting relative increases of 23%, 17%, and 17%.

Among the control variables, employment, the presence of R&D activities (occasionally or permanent), public investment support, and all four variables indicating firms' affinity to environmental protection show a significant and positive association with CEI.

Table 3: Cross-sectional regressions

	(1)	(2)		
	OLS	SUREG		
	CEI	*CEI_INPUT*	*CEI_PROD*	*CEI_USE*
AI	0.102***	0.091***	0.079***	0.074***
	(0.016)	(0.019)	(0.018)	(0.018)
lnEMP	0.037***	0.047***	0.043***	0.023***
	(0.004)	(0.004)	(0.004)	(0.004)
GROUP	-0.009	0.008	-0.007	0.003
	(0.013)	(0.013)	(0.013)	(0.013)
RDCON	0.120***	0.098***	0.093***	0.169***
	(0.016)	(0.017)	(0.016)	(0.017)
RDOCC	0.129***	0.116***	0.107***	0.123***
	(0.017)	(0.019)	(0.018)	(0.019)
EAST	-0.037***	-0.017	-0.031***	-0.027**
	(0.012)	(0.012)	(0.012)	(0.012)
PUBSUPPORT	0.075***	0.068***	0.069***	0.040***
	(0.013)	(0.014)	(0.014)	(0.014)
CLIMATE1	0.054***	0.041***	0.053***	0.050***
	(0.008)	(0.008)	(0.008)	(0.008)
CLIMATE2	0.058***	0.050***	0.052***	0.091***
	(0.007)	(0.008)	(0.008)	(0.008)
CLIMATE3	0.059***	0.055***	0.062***	0.045***
	(0.007)	(0.007)	(0.007)	(0.007)
CLIMATE4	0.018**	0.019**	0.029***	0.013*
	(0.007)	(0.007)	(0.007)	(0.007)
PATSTOCK	0.001	-0.004	-0.008	0.006
	(0.004)	(0.006)	(0.005)	(0.004)
Constant	0.246***	0.139***	0.120***	0.100***
	(0.030)	(0.031)	(0.031)	(0.031)
N	6649		6649	
R^2	0.201	0.183	0.198	0.199
Joint significance of industry dummies	F(11,6625) =2.7***	$\chi^2(11)$ =73.7***	$\chi^2(11)$ =59.6***	$\chi^2(11)$ =33.1***
Breusch-Pagan test of independence	-		$\chi^2(3)$ =5333.5***	
Correlation matrix of residuals		*CEI_INPUT*	*CEI_PROD*	*CEI_USE*
	CEI_INPUT	1.000	-	-
	CEI_PROD	0.556	1.000	-
	CEI_USE	0.450	0.539	1.000

Robust standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

4.2 Robustness checks

We assess the robustness of our results in several ways. A primary concern is omitted variable bias, were unobserved factors drive engagement in *AI* as well as *CEI*. While fully excluding this possibility would require the use of fully exogenous variation in *AI*, we present several additional analyses in this section to assuage concerns. We first show that the results are robust when employing a matching estimator instead of linear regression. Second, we address potential endogeneity in AI adoption by using instrumental variable (IV) regressions with the firm's median software investment per employee between 2011 and 2017 and internal resistance to innovation as instruments for the use of AI in 2018-2020. We then show that the results are robust to a fixed-effects panel specification, making use of the 2023 wave of the MIP alongside the 2021 wave. Lastly, we use the panel to construct a matched treated and control group and estimate a conditional difference-in-differences model.

4.2.1 Nearest-neighbor matching

As a first robustness check, we use a nearest-neighbor matching estimator to balance the sample in terms of the control variables. We use Mahalanobis distances, robust Abadie-Imbens (2008) standard errors, and correct for large-sample bias in the continuous covariates, as suggested by Abadie and Imbens (2006, 2011). Table A.1 in the Appendix presents raw and matched standardized differences between firms with and without AI. The results are presented in Table 4. The result remains robust across all dependent variables, with all four models showing a significant positive relationship between the use of AI and the introduction of CEI. The coefficients of AI are also similar in size compared to the coefficients of the OLS models in Table 3.

Table 4: Matching

	(1)	(2)	(3)	(4)
	CEI	*CEI_INPUT*	*CEI_PROD*	*CEI_USE*
AI	0.112***	0.085***	0.091***	0.075***
	(0.023)	(0.026)	(0.026)	(0.025)
N	6649	6649	6649	6649

Robust standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

4.2.2 IV estimation

To further address potential endogeneity concerns in our study of AI's impact on CEI, we employ an IV approach (2SLS) as an additional robustness check. The decision to adopt AI could be endogenous, as firms implementing AI might have unobserved characteristics that drive both the adoption of AI and CEI. Omitted variables, such as higher innovation capacities, greater resource availabilities or broader digitalization strategies may correlate with AI adoption, leading to biased estimates. To account for this, we consider two instruments that are correlated with AI usage but not with unobserved shocks to CEI.

First, we compute a measure that indicates the firm’s median software investment per employee between 2011 and 2017 (*MEDSOFT*), which captures past investments in digital infrastructure and is expected to be associated with AI usage, but not directly with CEI. Similar measures are used in other studies to account for a firm’s digitalization progress (i.e., Brynjolfsson & Hitt, 2003; Czarnitzki et al., 2023). Second, we use a dichotomous variable capturing organizational rigidities and resistance to new technologies among the workforce, (*RESIST*), which reflects organizational barriers that may affect AI adoption but should not independently influence CEI. The variable is also used as lagged value and refers to the time period 2016 to 2018. This instrument has also been applied in related contexts (i.e., Czarnitzki et al., 2023), and is similar to instruments used by Brynjolfsson et al. (2011), who used internal barriers to IT adoption to assess the impact of data-driven decisions on firm productivity.

One drawback of using these instrumental variables is that we do not have this information for all firms in the sample. To avoid losing observations in the regressions due to missing values between the survey waves, we impute zeros and also include dummy variables in the regression for both instruments that take the value one when information is missing. These dummies capture the potential bias from the imputation.

The results of the IV regression are presented in Table 5. We observe that the significant and positive relationship between AI and CEI remains robust for all types of CEI, although coefficients in the IV estimation are notably larger than those obtained in the OLS regressions. This may reflect the correction of a downward bias in the OLS estimates caused by unobserved confounders. Alternatively, the inflation of the coefficients could signal that the instruments are potentially inappropriate. Diagnostic tests suggest otherwise, however, since both instruments show a significant and positive relationship to AI, with the F-statistic of the first-stage regression models always above the conventional threshold of 10 (Staiger and Stock 1997). The Hansen J-test also indicates that the instruments are valid and uncorrelated with the error term for all types of CEI at the 5% level of significance.

Table 5: IV regressions (2SLS)

	(1)	(2)	(3)	(4)	(5)
	CEI	*CEI_INPUT*	*CEI_PROD*	*CEI_USE*	*AI*
AI	0.736***	0.660***	0.431*	0.609**	-
	(0.251)	(0.254)	(0.244)	(0.253)	-
lnEMP	0.023***	0.035***	0.035***	0.011	0.022***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.003)
GROUP	-0.021	-0.003	-0.013	-0.007	0.015
	(0.015)	(0.015)	(0.014)	(0.015)	(0.009)
RDCON	0.032	0.019	0.044	0.095**	0.134***
	(0.039)	(0.040)	(0.038)	(0.039)	(0.013)
RDOCC	0.094***	0.085***	0.087***	0.093***	0.050***
	(0.023)	(0.025)	(0.023)	(0.024)	(0.013)
EAST	-0.027**	-0.009	-0.026**	-0.019	-0.015**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.007)
PUBSUPPORT	0.045**	0.042**	0.053***	0.015	0.046***
	(0.019)	(0.019)	(0.018)	(0.019)	(0.010)
CLIMATE1	0.059***	0.045***	0.056***	0.054***	-0.007
	(0.008)	(0.009)	(0.008)	(0.009)	(0.005)
CLIMATE2	0.052***	0.044***	0.049***	0.086***	0.009*
	(0.008)	(0.009)	(0.008)	(0.008)	(0.005)
CLIMATE3	0.058***	0.054***	0.062***	0.044***	0.001
	(0.008)	(0.008)	(0.007)	(0.008)	(0.004)
CLIMATE4	0.025***	0.025***	0.033***	0.019**	-0.012***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.004)
PATSTOCK	-0.000	-0.005	-0.008	0.005	0.002
	(0.005)	(0.007)	(0.006)	(0.005)	(0.005)
MEDSOFT	-	-	-	-	0.156***
	-	-	-	-	(0.054)
MEDSOFT(MISSING)	-	-	-	-	0.042***
	-	-	-	-	(0.008)
RESIST	-	-	-	-	0.054***
	-	-	-	-	(0.018)
RESIST(MISSING)	-	-	-	-	0.018*
	-	-	-	-	(0.009)
Constant	0.287***	0.175***	0.142***	0.135***	-0.097***
	(0.035)	(0.036)	(0.035)	(0.036)	(0.017)
N	6649	6649	6649	6649	6649
R^2	0.055	0.068	0.154	0.098	0.101
F-statistic on joint significance in first-stage regression	-	-	-	-	10.543
p-value of Hansen's J test	0.186	0.158	0.133	0.055	-
Industry dummies	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses. In the IV regressions, we use the following instruments: the firm's median software investment per employee between 2011 and 2017 (*MEDSOFT*) and internal resistance to innovation (*RESIST*). For both instruments, we also include a dummy variable in the first-stage regressions (column 5) that takes value 1 when the information is missing. * p<0.10, ** p<0.05, *** p<0.01

4.2.3 Fixed-effects panel

As a third robustness check, we estimate a fixed-effects (FE) model by enriching the dataset with observations from the 2023 version of the MIP. This approach allows controlling for unobserved heterogeneity across firms. In order to be usable for the FE model, firms in the sample needed to also answer the 2023 wave. This is the case for 2,942 of the firms, resulting in 5,884 firm-year observations. We control for time-variant characteristics, the time-invariant ones being absorbed by the firm FE. We also add a time dummy, taking value 1 for observations from the 2023 MIP wave, to account for general trends in the introduction of CEI.

The results are presented in Table 6. The coefficient of *CEI* is positive, significant, and comparable in magnitude to the OLS model. Among the channels of *CEI*, however, only *CEI_PROD* remains positive and significant. The coefficients of *CEI_INPUT* and *CEI_USE* remain positive, but turn small and insignificant. This suggests that AI may be a particularly effective tool in assisting the development of supply-side technologies that reduce emissions and pollution.

Table 6: Fixed effects estimation

	(1) *CEI*	(2) *CEI_INPUT*	(3) *CEI_PROD*	(4) *CEI_USE*
AI	0.090***	0.044	0.130***	0.037
	(0.031)	(0.036)	(0.032)	(0.032)
lnEMP	0.014	0.009	0.018	0.017
	(0.026)	(0.023)	(0.024)	(0.028)
GROUP	0.031	-0.004	-0.001	0.048**
	(0.024)	(0.026)	(0.024)	(0.025)
RDCON	0.077*	0.088**	0.093**	0.078*
	(0.040)	(0.043)	(0.039)	(0.042)
RDOCC	0.056*	0.075**	0.020	0.013
	(0.033)	(0.036)	(0.033)	(0.034)
PUBSUPPORT	0.072***	0.030	0.050**	0.039
	(0.023)	(0.025)	(0.024)	(0.025)
PATSTOCK	0.010	-0.006	-0.028	0.007
	(0.017)	(0.029)	(0.022)	(0.013)
Constant	0.483***	0.341***	0.388***	0.332***
	(0.084)	(0.076)	(0.078)	(0.091)
Time fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
N×T	5884	5884	5884	5884
R^2	0.096	0.079	0.079	0.080

Robust standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

4.2.4 Conditional difference-in-differences

To refine the panel approach of the previous robustness check, we construct a conditional difference-in-differences (CDID) framework (Heckman et al., 1998) to further mitigate selection bias based on observable factors. To that end, we use propensity score matching to find a nearest neighbor for all firms with *AI*, that does not use *AI* but is otherwise similar in all covariates used. We base the NN matching on the first period of the panel. This results in a sample of 397 firms with *AI,* and 397 matched control firms. These 794 firms are then each observed for two years, resulting in 1,588 firm-year observations. We then re-estimate the FE model.

The results of this exercise are presented in Table 7. The results of the FE model in Table 6 remain robust in this specification, with a comparable sign, magnitude, and significance across the outcome variables. The positive relationship between AI usage and the introduction of CEI persists, while only the coefficient of *CEI_PROD* remains significantly positive among the three channels of CEI. Once again, this result suggests that the use of AI enhances firms' abilities to lower production externalities (i.e., pollution and emissions) through these kinds of innovations.

Table 7: Conditional difference-in-differences

	(1)	(2)	(3)	(4)
	CEI	*CEI_INPUT*	*CEI_PROD*	*CEI_USE*
AI	0.103***	0.057	0.131***	0.047
	(0.032)	(0.037)	(0.033)	(0.032)
lnEMP	0.019	0.047	0.008	0.049
	(0.027)	(0.033)	(0.024)	(0.034)
GROUP	0.038	-0.020	0.004	0.095**
	(0.044)	(0.054)	(0.044)	(0.048)
RDCON	0.068	0.058	0.067	0.103
	(0.068)	(0.079)	(0.068)	(0.066)
RDOCC	0.053	0.042	-0.010	-0.013
	(0.056)	(0.066)	(0.054)	(0.057)
PUBSUPPORT	0.099***	0.020	0.055	0.062
	(0.037)	(0.044)	(0.040)	(0.042)
PATSTOCK	-0.002	0.017	-0.052	0.023
	(0.021)	(0.027)	(0.042)	(0.016)
Constant	0.474***	0.254*	0.440***	0.199
	(0.107)	(0.132)	(0.099)	(0.134)
Time fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
N×T	1588	1588	1588	1588
R^2	0.129	0.116	0.056	0.098

Robust standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

5 Conclusion

Transitioning towards the CE requires firms to innovate in products, technologies, and business models (Bocken et al., 2016; Chioatto et al., 2024). However, firms often face significant challenges when developing these innovations (de Jesus & Mendonça, 2018), since they typically require addressing complex and interconnected challenges that more general innovations may not face. In addition to improving cost efficiency or product performance, CE principles demand an integrated approach that optimizes resource use, minimizes waste, and reduces environmental impact across the entire product lifecycle (Ellen MacArthur Foundation & Google, 2019). In this context, AI's advanced capabilities in data analytics and system optimization have the potential to help firms overcome these challenges (Acerbi et al., 2021; Ellen MacArthur Foundation & Google, 2019; Ghoreishi & Happonen, 2020; Roberts et al., 2024).

Our study empirically tests this hypothesis by examining the relationship between the use of AI technologies and CEI using German firm-level data. The results indicate that firms investing in AI are significantly more likely to introduce CEI compared to firms that do not use AI methods. Moreover, we show that AI enhances firms' abilities to lower production externalities and thus pollution through CEI. This finding highlights the strength of AI to optimize complex production processes, analyze large datasets, and identify inefficiencies in real time (Acerbi et al., 2021; Ellen MacArthur Foundation & Google, 2019; Ghoreishi & Happonen, 2020; Roberts et al., 2024). These capabilities are particularly relevant for addressing externalities in production systems, where these inefficiencies often show up as pollution, waste, or emissions. Additionally, CEI focused on reducing production externalities can often benefit from AI's ability to integrate and process data across various interconnected systems, enabling firms to adopt systemic approaches to pollution reduction (Ellen MacArthur Foundation & Google, 2019; Ghoreishi & Happonen, 2020; Tsirigotis, 2024). For example, predictive maintenance and equipment failure detection, both common AI applications, are effective tools for reducing machine downtime and minimizing energy and resource waste (Ellen MacArthur Foundation & Google, 2019; Li et al., 2023).

The results further support and build on existing research on AI, innovation, and CE. Previous empirical studies highlight positive productivity effects of AI technologies (Czarnitzki et al., 2023; Toner-Rodgers, 2024) and their impact on general innovation outcomes (Babina et al., 2024; Rammer et al., 2022; Toner-Rodgers, 2024). Our findings expand our understanding of this broader potential of AI, highlighting its role in enabling and accelerating the transition toward the CE. This potential of AI to accelerate firms' transition to the CE may so far have been overlooked, as the public debate around AI is often centered on its potential impact on labor markets, or its potential applications for (new or existing) digital business models (e.g. Agrawal et al. 2019).

There are some limitations to our analysis. First, the reliance on survey data in our study does not allow for a direct identification of the specific AI methods or applications that contribute to the development of particular types of CEI. Future research could aim to address this gap, for example by analyzing AI-related patents in conjunction with CEI outcomes. Another limitation of our data is that we cannot quantify the extent to which the adoption of CEI have contributed to reductions in resource consumption, energy use, or emissions. This lack of measurable impact hinders our ability to assess the true effectiveness of AI in driving environmental improvements within the CE framework.[14] Furthermore, our results refer to German firms within a time period between 2018 and 2020, with an extension to 2022 in our fixed-effects and CDID estimations. As AI technologies and its adoption continue to evolve rapidly, it is likely that the emergence of new AI models and the broader diffusion among firms in the last few years have further enhanced AI's potential for

[14] A recent report by Boston Consulting Group and Google (2023) estimates that AI has the potential to help reduce greenhouse gas emissions by 5 to 10 percent globally by 2030.

the development of CEI and innovation in general (Calvino & Fontanelli, 2023; Rammer et al., 2022).

References

Abadie, A., & Imbens, G.W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica, 74*, 235-267. https://doi.org/10.1111/j.1468-0262.2006.00655.x

Abadie, A., & Imbens, G.W. (2008). On the failure of the bootstrap for matching estimators. *Econometrica,* 76: 1537–1557. https://doi.org/10.3982/ECTA6474

Abadie, A., & Imbens, G.W. (2011). Bias-corrected matching estimators for average treatment effects. *Journal of Business and Economic Statistics, 29* 1-11. https://doi.org/10.1198/jbes.2009.07333

Acerbi, F., Forterre, D. A., & Taisch, M. (2021). Role of artificial intelligence in circular manufacturing: A systematic literature review. *IFAC-PapersOnLine, 54*(1), 367–372. https://doi.org/10.1016/j.ifacol.2021.08.040

Agrawal, A., Gans, J., & Goldfarb, A. (Eds.). (2019). *The economics of artificial intelligence: An agenda*. University of Chicago Press.

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, *151*, 103745. https://doi.org/10.1016/j.jfineco.2023.103745

Bai, C., Dallasega, P., Orzes, G., & Sarkis, J. (2020). Industry 4.0 technologies assessment: A sustainability perspective. *International Journal of Production Economics*, *229*, 107776. https://doi.org/10.1016/j.ijpe.2020.107776

Baruffaldi, S., van Beuzekom, B., Dernis, H., Harhoff, D., Rao, N., Rosenfeld, D., & Squicciarini, M. (2020). Identifying and measuring developments in artificial intelligence: Making the impossible possible. *OECD Science, Technology and Industry Working Papers*. https://doi.org/10.1787/18151965

Biggi, G., Iori, M., Mazzei, J., & Mina, A. (2024). Green intelligence: The AI content of green technologies. *LEM Working Paper Series*. https://www.lem.sssup.it/WPLem/2024-23.html

Bocken, N.M.P., de Pauw, I., Bakker, C., & van der Grinten, B. (2016). Product design and business model strategies for a circular economy. *Journal of Industrial Product Engineering, 33*(5), 308–320. https://doi.org/10.1080/21681015.2016.1172124

Boston Consulting Group, & Google. (2023). *Accelerating climate action with AI*. https://www.bcg.com/publications/2023/how-ai-can-speedup-climate-action

Brynjolfsson, E., & Hitt, L. M. (2003). Computing productivity: Firm-level evidence. *The Review of Economics and Statistics*, *85*(4), 793–808. https://doi.org/10.1162/003465303772815736

Brynjolfsson, E., Hitt, L.M., Kim, H.H. (2011). Strength in numbers: How does data-driven decision making affect firm performance? http://dx.doi.org/10.2139/ssrn.1819486

Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligenge and the modern productivity paradox: a clash of expectations and statistics. In Agrawal, A., Gans, J., & Goldfarb, A. (Eds.). *The economics of artificial intelligence: an agenda*. University of Chicago Press, pp. 23-57. https://doi.org/10.7208/9780226613475-003.

Butler, K. T., Davies, D. W., Cartwright, H., Isayev, O., & Walsh, A. (2018). Machine learning for molecular and materials science. *Nature*, *559*(7715), 547–555. https://doi.org/10.1038/s41586-018-0337-2

Cainelli, G., D'Amato, A., & Mazzanti, M. (2020). Resource efficient eco-innovations for a circular economy: Evidence from EU firms*. Research Policy, 49*(1). https://doi.org/10.1016/j.respol.2019.103827

Calvino, F., & Fontanelli, L. (2023). A portrait of AI adopters across countries: Firm characteristics, assets' complementarities and productivity. *OECD Science, Technology and Industry Working Papers, 2023/02*. https://doi.org/10.1787/0fb79bb9-en

Chioatto, E., Zecca, E., & D'Amato, A. (2024). Which innovations for circular business models? A product life-cycle categorisation. *Industry and Innovation*, *31*(7), 809–831. https://doi.org/10.1080/13662716.2024.2340614

Czarnitzki, D., Fernández, G.P., & Rammer, C. (2023). Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization, 211*, 188-205. https://doi.org/10.1016/j.jebo.2023.05.008

de Jesus, A., & Mendonça, S. (2018). Lost in Transition? Drivers and Barriers in the Eco-innovation Road to the Circular Economy. *Ecological Economics, 145*, 75–89. https://doi.org/10.1016/J.ECOLECON.2017.08.001

De Marchi, V. (2012). Environmental innovation and R&D cooperation: Empirical evidence from Spanish manufacturing firms. *Research Policy*, *41*(3), 614–623. https://doi.org/10.1016/j.respol.2011.10.002

del Rio, P., Tarancon Moran, M. A., & Callejas Albinana, F. (2011). Analysing the determinants of environmental technology investments. A panel-data study of Spanish industrial sectors. *Journal of Cleaner Production*, *19*(11), 1170–1179. https://doi.org/10.1016/j.jclepro.2010.05.001

Ellen MacArthur Foundation (2019). *Completing the picture: How the circular economy tackles climate change*. https://www.ellenmacarthurfoundation.org/completing-the-picture

Ellen MacArthur Foundation, & Google. (2019) *Artificial Intelligence and the circular economy: AI as a tool to accelerate the transition*. https://www.ellenmacarthurfoundation.org/artificial-intelligence-and-the-circular-economy

Ellen MacArthur Foundation, & McKinsey & Company. (2015). *Growth within: A circular economy vision for a competitive Europe*. https://www.ellenmacarthurfoundation.org/growth-within-a-circular-economy-vision-for-a-competitive-europe

Ellen MacArthur Foundation. (2013). *Towards the circular economy: Economic and business rationale for an accelerated transition*. https://www.ellenmacarthurfoundation.org/towards-the-circular-economy-vol-1-an-economic-and-business-rationale-for-an

Ertz, M., Sun, S., Boily, E., Kubiat, P., & Quenum, G. G. Y. (2022). How transitioning to Industry 4.0 promotes circular product lifetimes. *Industrial Marketing Management, 101*, 125–140. https://doi.org/10.1016/j.indmarman.2021.11.014

European Commission. (2008). *Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2008 on waste and repealing certain directives*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A32008L0098

European Commission. (2015). *Closing the loop - An EU action plan for the circular economy*. https://eur-lex.europa.eu/resource.html?uri=cellar:8a8ef5e8-99a0-11e5-b3b7-01aa75ed71a1.0012.02/DOC_1&format=PDF

European Commission. (2017). *Public procurement for a circular economy: Good practice and guidance*. https://circulareconomy.europa.eu/platform/sites/default/files/knowledge_-_public_procurement_circular_economy_brochure.pdf

European Commission. (2020). *A new Circular Economy Action Plan for a cleaner and more competitive Europe*. https://eur-lex.europa.eu/resource.html?uri=cellar:9903b325-6388-11ea-b735-01aa75ed71a1.0017.02/DOC_1&format=PDF

Eurostat. (2023a). *Circular material use rate*. https://doi.org/10.2908/ENV_AC_CUR

Eurostat. (2023b). *Circular economy - Material flows*. [Accessed 8 October 2024]. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Circular_economy_-_material_flows

Gama, F., & Magistretti, S. (2023). Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications. *Journal of Product Innovation Management*. https://doi.org/10.1111/jpim.12698

Geissdoerfer, M., Savaget, P., Bocken, N. M. P., & Hultink, E. J. (2017). The Circular Economy – A new sustainability paradigm? *Journal of Cleaner Production, 143*, 757–768. https://doi.org/10.1016/j.jclepro.2016.12.048

Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production, 114*, 11–32. https://doi.org/10.1016/j.jclepro.2015.09.007

Ghoreishi, M., & Happonen, A. (2020). Key enablers for deploying artificial intelligence for circular economy embracing sustainable product design: Three case studies. *AIP Conference Proceedings, 2233*, 050008. https://doi.org/10.1063/5.0001339

Google (2023). *Environmental report*. https://sustainability.google/reports/google-2023-environmental-report/.

Google (2024). *Environmental report*. https://sustainability.google/reports/google-2024-environmental-report/

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological*

Forecasting & Social Change, *162*, 120392. https://doi.org/10.1016/j.techfore.2020.120392

Heckman, J., Ichimura, H., Smith, J., & Todd, P. (1998). Characterizing selection bias using experimental data. *Econometrica*, *66*(5), 1017–1098. https://doi.org/10.2307/2999630

Horbach, J., & Rammer, C. (2020). Circular economy innovations, growth and employment at the firm level: Empirical evidence from Germany. *Journal of Industrial Ecology, 24*(3), 615–625. https://doi.org/10.1111/jiec.12977

Horbach, J., Oltra, V., & Belin, J. (2013). Determinants and specificities of eco-innovations compared to other innovations: An econometric analysis for the French and German industry based on the Community Innovation Survey. *Industry and Innovation*, *20*(6), 523–543. https://doi.org/10.1080/13662716.2013.833375

Kalikadien, A. V., Mirza, A., Hossaini, A. N., Sreenithya, A., & Pidko, E. A. (2024). Paving the road towards automated homogeneous catalyst design. *ChemPlusChem*, *89*(7), e202300702. https://doi.org/10.1002/cplu.202300702

Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation and Recycling, 127*, 221–232. https://doi.org/10.1016/j.resconrec.2017.09.005

Kirchherr, J., Yang, N.-H. N., Schulze-Spüntrup, F., Heerink, M. J., & Hartley, K. (2023). Conceptualizing the circular economy (revisited): An analysis of 221 definitions. *Resources, Conservation and Recycling*, *194*, 107001. https://doi.org/10.1016/j.resconrec.2023.107001

Kümmerer, K., Clark, J. H., & Zuin, V. G. (2020). Rethinking chemistry for a circular economy. *Science*, *367*(6476), 369-370. https://doi.org/10.1126/science.aba4979

Li, J., Ma, S., Qu, Y., & Wang, J. (2023). The impact of artificial intelligence on firms' energy and resource efficiency: Empirical evidence from China. *Resources Policy, 82*, 103507. https://doi.org/10.1016/j.resourpol.2023.103507

Mazzucchelli, A., Chierici, R., Del Giudice, M., & Bua, I. (2022). Do circular economy practices affect corporate performance? Evidence from Italian large-sized manufacturing firms. *Corporate Social Responsibility and Environmental Management*, *29*(6), 2016–2029. https://doi.org/10.1002/csr.2298

Millar, N., McLaughlin, E., & Börger, T. (2019). The circular economy: Swings and roundabouts? *Ecological Economics, 158*, 11–19. https://doi.org/10.1016/j.ecolecon.2018.12.012

OECD (2020). Digital technology and advanced production. *The Digitalisation of Science, Technology and Innovation: Key Developments and Policies; OECD Publishing: Paris, France*, 119-142. https://doi.org/10.1787/b9e4a2c0-en.

Peters, B., & Rammer, C. (2013). Innovation panel surveys in Germany. In Gault, F. (ed.). *Handbook of innovation indicators and measurement*. Edward Elgar, 135–177.

Porter, M. E., & van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *The Journal of Economic Perspectives, 9*(4), 97–118. https://doi.org/10.1257/jep.9.4.97

Rammer, C., Fernández, G.P. & Czarnitzki, D. (2022) Artificial intelligence and industrial innovation: Evidence from German firm-level data. *Research Policy, 51*(7), 104555. https://doi.org/10.1016/j.respol.2022.104555.

Reif, C., & Rexhäuser, S. (2018). Good Enough! Are Socially Responsible Companies the More Successful Environmental Innovators? In J. Horbach & C. Reif (Eds.), *New developments in eco-innovation research, sustainability and innovation* (pp. 163–192). Springer. http://ftp.zew.de/pub/zew-docs/dp/dp15018.pdf

Roberts, H., Zhang, J., Bariach, B., Cowls, J., Gilburt, B., Juneja, P., Tsamados, A., Ziosi, M., Taddeo, M., & Floridi, L. (2024). Artificial intelligence in support of the circular economy: Ethical considerations and a path forward. *AI & Society, 39*(3), 1451–1464. https://doi.org/10.1007/s00146-022-01596-8

Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, *65*(3), 557–586. https://doi.org/10.2307/2171753

Toner-Rodgers, A. (2024). *Artificial intelligence, scientific discovery, and product innovation*. Unpublished manuscript, Cambridge. https://aidantr.github.io/files/AI_innovation.pdf

Trajtenberg, M. (2019). AI as the next GPT: A political-economy perspective. In Agrawal, A., Gans, J., & Goldfarb, A. (Eds.). *The economics of artificial intelligence: an agenda.* University of Chicago Press, pp. 175-186. https://doi.org/10.7208/9780226613475-003

Tsirigotis, F. (2024). Artificial intelligence and product lifecycle management systems. In J. Stark, *Product lifecycle management (volume 6)* (pp. 13–26). Springer. https://doi.org/10.1007/978-3-031-53521-5_2

Veleva, V., & Bodkin, G. (2018). Corporate-entrepreneur collaborations to advance a circular economy. *Journal of Cleaner Production, 188*, 20–37. https://doi.org/10.1016/j.jclepro.2018.03.196

Wang, Q., Sun, T., & Li, R. (2023). Does artificial intelligence promote green innovation? An assessment based on direct, indirect, spillover, and heterogeneity effects. *Energy & Environment*, 1-33. https://doi.org/10.1177/0958305X231220520

Wilson, M., Paschen, J., & Pitt, L. (2022). The circular economy meets artificial intelligence (AI): Understanding the opportunities of AI for reverse logistics. *Management of Environmental Quality, 33*(1), 9–25. https://doi.org/10.1108/MEQ-10-2020-0222

Yin, K., Cai, F., & Huang, C. (2023). How does artificial intelligence development affect green technology innovation in China? Evidence from dynamic panel data analysis. *Environmental Science and Pollution Research International, 30*(10), 28066–28090. https://doi.org/10.1007/s11356-022-24088-0

6 Appendix

Table A.1: Raw and matched standardized differences between firms with and without AI

	Standardized differences	
	Raw	Matched
lnEMP	0.472	-0.027
GROUP	0.323	0.028
RDCON	0.693	-0.008
RDOCC	0.075	0.041
EAST	-0.177	0.000
PATSTOCK	0.138	0.077
Industry: Food and beverages	-0.072	-0.011
Industry: Textiles	-0.125	-0.039
Industry: Paper, wood, and furniture	-0.157	0.053
Industry: Petroleum, plastics, and mineral products	-0.013	-0.018
Industry: Chemical and pharmaceutical industry	-0.145	-0.006
Industry: Metal, repair and installation of machinery	0.181	-0.005
Industry: ICT and electronics	0.093	0.026
Industry: Machinery and vehicles	-0.067	-0.093
Industry: Wholesale trade	0.011	0.017
Industry: Transportation, financial services, publishing, advertising and market research	0.342	0.029
Industry: Information services, film, audio, radio and TV	-0.134	0.003
KLIMA1	0.085	-0.016
KLIMA2	0.178	0.022
KLIMA3	-0.074	0.003
KLIMA4	-0.107	0.065
PUBSUPPORT	0.427	-0.003

Download ZEW Discussion Papers:

https://www.zew.de/en/publications/zew-discussion-papers

or see:

https://www.ssrn.com/link/ZEW-Ctr-Euro-Econ-Research.html
https://ideas.repec.org/s/zbw/zewdip.html

//
IMPRINT

ZEW – Leibniz-Zentrum für Europäische Wirtschaftsforschung GmbH Mannheim

ZEW – Leibniz Centre for European Economic Research

L 7,1 · 68161 Mannheim · Germany
Phone +49 621 1235-01
info@zew.de · zew.de