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Does circular economy mitigate the extraction of natural resources? Empirical evidence based on analysis of 28 European economies over the past decade

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ABSTRACT

Moving towards a circular economy (CE) has become one of the main strategic initiatives on a global scale in the search for sustainable economic systems. However, the conceptual relationship between sustainable development and the circular economy is a matter of ongoing debate. In particular, the extent to which CE initiatives are contributing to the mitigation of resource extraction seems to be a still unclear topic. This paper investigates the relationship between the extraction of natural resources and the CE, and also analyses the effects of critical socioeconomic drivers such as economic and population growth and economic structures. The analysis is based on a panel data covering 28 European countries during the period 2010–2019. Results confirm that promoting a shift towards more circular economic systems can reduce the extraction of primary resources. However, the mitigating effect of CE initiatives remains rather marginal when compared to the impact of economic growth. Namely, estimates show that the primary resources extracted annually linked to economic growth are roughly four times the resources saved by CE initiatives. The findings provide evidence that the circularity of economic systems should be approached from a systemic perspective that includes both production and consumption as well as waste management. In particular, complementary measures addressing behavioural consumption are needed if we want to achieve a sustainable development.

1. Introduction

The transition to a circular economy (CE) is increasingly seen as necessary to decouple economic growth from natural resource use and the ecological impacts generally associated with economic activities (Domenech and Bahn-Walkowiak, 2019; Geissdoerfer et al., 2017; Murray et al., 2017). Proponents of the CE emphasise that closing material cycles would make it possible to change our current linear systems of production and consumption, currently unsustainable due to limited stocks of non-renewable resources on the one hand, and the growing and increasingly affluent global population on the other hand (EEA, 2019; European Commission, 2020). While the CE concept encompasses a broad range of aspects and expectations (Hartley et al., 2020; Lazarevic and Valve, 2017; Tapia et al., 2021), the critical component of the CE is that it often aims to identify an optimal level of material loop closure to minimize the extraction of non-renewable virgin raw materials. Strategies to close material cycles and keep them at their highest value are often categorised according to the so-called 9R Framework (Potting et al., 2017). This includes, among others, reducing materials consumption and waste production, extending product lifetimes, facilitating reuse, recycling waste into secondary materials, as well as utilising renewable resources (Bassi et al., 2020; Cordella et al., 2020; Kjaer et al., 2019).

Thanks to the basic idea of CE, which is intuitive and compelling, CE practices have spread widely across academics, practitioners and policy makers (Ghisellini et al., 2016; Kalmykova et al., 2018; Merli et al., 2018). However, the conceptual relationship between sustainable development and circular economy is an issue of ongoing debate (Bauwens, 2021; Kirchherr, 2021; Schröder et al., 2019). Very recently, the CE has been criticized on several fronts (Corvellec et al., 2021), including the lack of a critical analysis of the social implications in CE practices (Mies and Gold, 2021; Schröder et al., 2020), the technical limits of circularity in relation to the quality and availability of secondary material (Korhonen et al., 2018; Skene, 2018; Velenturf et al., 2019), and the actual benefits of circular systems on the natural environment, an aspect that remains largely unexplored (Blum et al., 2020;

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Millar et al., 2019; Zink and Geyer, 2017).

This paper addresses the last research gap by asking how far CE initiatives and the current use of secondary material[1] are mitigating the extraction of virgin resources in Europe. Extracting and processing virgin raw materials is energy and material intensive and cause of environmental damage (Danish et al., 2019). Hence, defining the relationship between the use of secondary materials and resource extraction is key to understand the extent to which a CE can contribute to sustainable development, especially considering the challenge of satisfying an ever-increasing consumer demand (Korhonen et al., 2018; Zink and Geyer, 2017). With this goal in mind, this paper investigates the relationship between raw material extraction and CE by using a set of CE indicators included in the current EU CE monitoring framework (European Commission, 2018). These include, inter alia, the circular use of material, employment in CE related sectors and recycling rates of municipal waste. A panel data analysis covering the 28 EU countries for the period 2010–2019 is used to explore and quantify the interaction between CE and resource extraction. The contribution of this research is twofold: (1) it addresses the link between raw material extraction and CE, and (2) it provides an empirical analysis covering most of CE indicators currently available at EU country level.

With respect to (1), differently from previous works, which generally focus on "domestic material *consumption*" (DMC), we propose the use of "domestic material *extraction*" (DE) as dependant variable. This allows first to directly link the CE with the depletion of virgin raw materials and, second, to correctly model the relationship between primary and secondary materials, something that would not be possible using consumption-based indicators since they aggregate both primary and secondary materials. Regarding (2), we considered and empirically tested all CE-indicators provided by the EU CE monitoring framework.

The article is organised as follows: Section 2 presents the theoretical background, introducing main concepts and modelling approaches; Section 3 explains the data and the models employed in this study; Section 4 and Section 5 present and discuss the results, respectively; Section 6 draws the conclusions of the study.

2. Models and influential socioeconomic factors

In general, studies addressing the monitoring and assessment of CE at the macro-level rely on the method of material flow analysis (Haas et al., 2015; Harris et al., 2021; Mayer et al., 2019). In this context, the Economy-Wide Material Flow Accounting (EW-MFA) is one of the key methods of environmental accounting providing internationally harmonized, comparable and meaningful indicators of material resource flows (EUROSTAT, 2018; Wu et al., 2019). EW-MFA covers the flows that an economy extracts from its natural environment, i.e., domestic extraction (DE), the flows exchanged with other economies (imports and export) and the flows released as wastes or emissions to the natural environment. The flows are accounted for with the mass they have upon crossing the system boundary. This has two important implication for the correct interpretations of results: first, differently from the material footprint indicator (Wiedmann et al., 2015), the trade flows do not include upstream resource requirements (i.e., those resources required to produce the imported good or service); second, aggregate EW-MFA indicators such as DE or DMC will be much more representative of larger and heavier material flows, especially non-metallic minerals, which account for 53% of overall material consumption.[2]

While the use of EW-MFA applied to CE practices is relatively recent, EW-MFA indicators have long been used to model the relationship between the environment and socioeconomic systems. Two main modelling frameworks are generally applied: the Environmental Kuznets Curve (EKC) hypothesis (Stern, 2004) and the IPAT approach (Dietz and Rosa, 1994, 1997). The EKC attempts to explain the long-term trend of environmental degradation, which in EW-MFA studies is generally proxied by the domestic material consumption (DMC), as a function of economic growth (Auci and Vignani, 2014; Pothen and Welsch, 2019). According to EKC hypothesis, as an economy develops, market forces such as scale, composition and technological effects first increase and then decrease material consumption. In general, to test this inverted U-shaped relationship between growth and environmental degradation of the EKC, a sufficiently large period should be considered to allow observing the structural change and technological progress of an economy (Ulucak et al., 2020). While there is no certain rule as to what this period should be, EKC studies are usually conducted considering on average two or three decades (see e.g., the EKC review conducted by Arshad Ansari et al. (2020)).

On the other hand, the IPAT approach explains the environmental impacts (I), as a function of population (P), affluence (A) and technology (T). The IPAT approach has been extensively used in econometric studies in the form of the STIRPAT approach – Stochastic Impacts by Regression on Population, Affluence, and Technology (York et al., 2003). Unlike the EKC, the STIRPAT analysis does not aim to test long-term trajectories. Its use has a rather exploratory purpose, thus adapting to both cross-sectional analyses and longer time series. Therefore, given the limited availability of CE indicators over time, the present study builds upon the STIRPAT approach.

Thanks to its logarithm specification, the STIRPAT approach allows interpreting results in the form of elasticities. Over time, extended models have been proposed by scholars (West and Schandl, 2018). These include a broader range of explanatory variables, including geo-physical characteristics (Steinberger et al., 2010), economic structures (Fernández-Herrero and Duro, 2019; Gan et al., 2013), expenditure on R&D (Robaina et al., 2020) and economic specialisation indexes (Bianchi et al., 2021).

Notwithstanding the specificities of different works, often dictated by underlying data availability, scholars converge in recognising that the main driving forces of material consumption at aggregated level are: (1) economic status (often referred as affluence and proxied by GDP), (2) demography (i.e., population level or population density) and (3) economic structures (i.e., the weight of a specific sector in an economy). The most recent studies (Ulucak et al., 2020; West and Schandl, 2018) observed a positive relationship between material consumption and GDP, confirming Modigliani's life-cycle hypothesis that consumption is largely a function of income (Ando and Modigliani, 1963). Similar conclusions can be drawn for the relationship between population and material consumption. However, it has also been pointed out that while a larger population clearly requires greater material inputs, a higher population density could partly compensate it by reducing, in relative terms, the consumption of resources thanks to agglomeration scales (Bianchi et al., 2020). Finally, concerning the economic structures, an expansion of material intensive sectors like agriculture or construction generally lead to higher levels of material consumption. By contrary, a higher relevance of the tertiary sector is generally associated with lower levels of *apparent* material consumption[3] (Fernández-Herrero and Duro, 2019; Gan et al., 2013). Furthermore, some authors also warn about potential endogeneity problems when dealing with resource use patterns (Flachenecker, 2018; Robaina et al., 2020; Wu et al., 2019), as it is highly likely that current levels of resource use are highly dependent on past consumption levels. In this case, the lagged value of resource usage

[1] By secondary materials we mean recycled materials that can be used in manufacturing processes instead of or alongside virgin raw materials.

[2] According to EUROSTAT statistics, the total DMC of the EU economy was estimated at around 13.5 t per capita in 2020, of which 53% is non-metallic minerals, 24% biomass, 18% fossil energy material and 5% metal ores.

[3] It should be borne in mind that due to the limits of EW-MFA indicators, material consumption is denoted as "apparent" because it only accounts for the weight of the final product consumed, but not the raw materials consumed during its manufacturing process.

is generally included as an additional explanatory variable.

In order to address our research gap, we adapt the STIRPAT model by introducing two novelties: the use of domestic extraction (DE) instead of domestic material consumption (DMC) as dependant variable, and the use of a set of new explanatory variables addressing the CE. The reasoning behind the use of DE is the following: as a circular economy strives to reduce the use of virgin raw material and increase the use of secondary material, DMC is no longer a meaningful indicator as it aggregates both virgin material (i.e., resource extraction) and secondary material (i.e., imports and exports of waste). As for the second novelty, we reviewed all CE-indicators provided in the EU monitoring framework for the circular economy (European Commission, 2018). These are thoughtfully described in the following section.

3. Material and methods

3.1. Data collection

This study uses a panel data covering 28 EU countries from 2010 to 2019. The analysis was performed using R Language and Environment for Statistical Computing (R Core Team, 2020). The data were collected using the R package "Eurostat" v.3.3.5 (Lahti et al., 2019), while the R package "plm" (Croissant and Millo, 2008) was used for panel-data analyses. The dependent variable employed in this analysis is raw material Domestic Extraction (DE). DE reflects the amount of primary raw materials extracted domestically and is provided on national basis according to the EW-MFA methodology (EUROSTAT, 2018). Concerning the explanatory variables, we differentiate between macro socioeconomic drivers and CE-related driving forces. The first refers to orthodox socioeconomic variables generally included in similar STIRPAT approaches, i.e., affluence, which is proxied by GDP levels in purchasing power standards (PPS), population (POP), and structural variables reflecting the type of the domestic economy. The latter are the DE/DMC ratio and the share of value added generated by the construction sector, expressed as a percentage of national GDP (CONST/GDP). On the one hand, DE/DMC informs on the type of domestic economy and the reliance on domestic natural resource or, conversely, on imported goods. A ratio below 100% would suggest a territory scarce in natural resources and, eventually, more reliant on imports from foreign countries. Conversely, a DE/DMC above 100% would reflect a territory rich in natural resources, whose material consumption is mainly due to the extraction and refining of raw materials to meet foreign demand.[4] On the other hand, CONST/GDP controls for the domestic demand of construction materials, which, on overage, represents more than 50% of total DE. Due to their lower economic value when compared to other type of resources, construction materials are generally not traded over long distances. Therefore, the construction sector is a strong predictor of domestic mining, at least for non-metallic minerals.

Next to the socioeconomic drivers, the study considered a set of CE indicators partly addressing the four critical areas proposed by the European Commission to measure the progress towards a CE. These are:

1. Generation of municipal waste per capita (MWAS) for the production and consumption area.
2. Recycling rate of municipal waste (RECW) for the waste management area.
3. Circular material use rate (CMU) for the secondary raw materials area.
4. CE sectoral[5] employment (EMP_CE), gross private investment in tangible goods relating to CE sectors (INV_CE), gross value added by CE sectors (VA_CE) and number of patents relating to recycling and secondary raw materials (PAT_CE) for the competitiveness and innovation area.

A full definition of the selected CE indicators is provided in Annex A. Other CE variables provided in the EU CE monitoring framework were excluded from the analysis as available only at EU aggregated level (e.g., EU self-sufficiency for raw materials, Eurostat code: cei_pc010) or available only every two years (e.g., total waste indicators).[6]

Table 1 provides summary statistics of the selected variables, including their definition, unit of measure, number of observations and descriptive statistics.

3.2. Panel data modelling approach

A panel data analysis was used to empirically test and model the relationship between DE and the CE indicators. The general form can be specified as:

$$\begin{aligned} Ln(DE_{it}) = {} & \beta_1 Ln(GDP_{it}) + \beta_2 Ln(POP_{it}) + \beta_2 Ln(DE/DMC_{it}) \\ & + \beta_2 Ln(CONST/GDP_{it}) + \gamma_x Ln(CE_{it}) + \mu_i + \varepsilon_{it} \end{aligned} \tag{1}$$

Where DE_{it} denotes the annual domestic extraction in country i ($i = 1, \ldots, 28$) and year t ($t = 1, \ldots, 9$). The variables GDP_{it} and POP_{it} reflect the socioeconomic variables affluence and population, while DE/DMC_{it} and CONST/GDP_{it} accounts for economic structures. CE_{it} is a vector for the selected CE variables. Equally to the dependant variable DE_{it}, all explanatory variables differ over time (t) and across countries (i). μ_i is unobserved individual effects and ε_{it} is white noise disturbance. All data have been used in log scale.[7] Regression coefficients β_x and the vector γ_x measure the elasticity between explanatory variables and dependant variable, i.e., they indicate the percentage change in DE corresponding to 1% increase of the dependant variable, all else remaining equal.

The general form of model (1) was analysed by means of pooled, fixed and random effects regression (Wooldridge, 2013), the orthodox estimation methods generally applied in similar studies to correctly model the two error components μ_i and ε_{it} (Bianchi et al., 2021; West and Schandl, 2018). Upon estimating all the models, the results were assessed for validity and suitability using a suite of serial correlation tests (Wooldridge, 2013). Heteroskedasticity, which refers to the presence of error variance, was generally detected, hence a robust covariance matrix estimation was applied across all panels (Wooldridge, 2013). For test specification results the reader can refer to Annex B, Table B1.

It should be borne in mind that the selected CE variables are subject to different availabilities (in terms of both years and countries) and including them all at once in model (1) would have greatly undermined the size of the panel. Therefore, a two-steps strategy was applied. First, starting from the basic STIRPAT model, which includes affluence, population, and economic structures, we tested one CE variable at a time.

[4] Ideally, the effect of imports/exports on DE should be considered using specific explanatory variables in the regression model. However, after testing several indicators for trade, including EW-MFA based imports/exports, we could not find any reasonable solution. One of the reasons for the poor relationship between trade and resource extraction is that imports/exports are accounted for in economic terms or based on the weight of the products traded. Both measures have little correlation with the physical quantity of resource extracted.

[5] CE sectors include the recycling sector, repair and reuse sector and rental and leasing sector. The detailed list of NACE Rev. 2 codes used for CE indicators calculation (Private investments, jobs and gross value added related to circular economy sectors) can be found at https://ec.europa.eu/eurostat/documents/8105938/8465062/cei_cie010_esmsip_NACE-codes.pdf

[6] At the time when this work has been carried out, the European Commission was reviewing its CE monitoring framework (2021–2022) to also include material footprint indicators. These indicators are not included in the present analysis.

[7] Note that we actually used the logarithm transformation of (1+ patents) to avoid generating missing values when patents = 0.

Table 1
Variables summary statistics.

Variables	Definition	EUROSTAT CODE	Unit of measure	Obs	Descriptive Statistics				CAGR
					Mean	CV	Min	Max	
Dependent variable									
DE	Domestic extraction	env_ac_mfa	1,000 t	280	207,962	1.13	1,520	1,046,260	−0.11
Socioeconomic and structural variables									
GDP	Gross Domestic Product	nama_10_gdp	Million PPS	280	500,713	1.41	9,100	3,209,112	2.84
POP	Population	demo_gind	Million inhabitants	280	17.71	1.29	0.41	83.09	0.22
DE/DMC	Economy reliance on domestic extraction	env_ac_mfa	% of DMC	280	0.90	0.39	0.14	2.56	0.01
CONST/GDP	Gross value added by construction sector	nama_10_a10	% of total gross value added	280	4.87	0.31	1.00	8.20	0.00
CE-related variables									
MWAS	Municipal waste per capita	cei_pc031	kilograms per capita	273	484	0.26	247	862	−0.30
RECW	Recycling rate of municipal waste	cei_wm011	%	273	34.22	0.45	4.00	67.20	2.56
CMU	Circular Material Use rate	cei_srm030	%	280	8.75	0.72	1.20	30.00	1.23
CE_EMP	Employment in CE sectors	cei_cie010	% of total employment	205	1.79	0.23	1.10	2.89	0.25
CE_INV	gross private investment in tangible goods in CE sectors	cei_cie010	% of GDP	186	0.14	0.51	0.02	0.35	−1.14
CE_VA	Gross value added by CE sectors	cei_cie010	% of GDP	208	0.95	0.20	0.35	1.56	−0.14
CE_PAT	Number of patents related to recycling and secondary raw materials	cei_cie020	Nr.	161	0.80	1.64	0.00	12.10	−1.71

Note: Data refer to the period 2010–2019. Obs denotes the number of observations. CV denotes the coefficient of variation and it is calculated as the ratio of standard deviation and the mean. CAGR denotes the compound annual growth rate computed for the period 2010–2019 (or shorter periods depending on data availability).

This exercise allowed to 1) explore the type of relationship between DE and CE variables and 2) identify the CE variables that have a significant contribution to DE. Based on the result of step one, a full model is defined in step two by including all significant CE variables.

In addition, as anticipated previously, we address the issue of endogeneity, and thereby, further tested the robustness of our results by applying the dynamic panel approach based on the generalized method of moments (GMM) estimator devised by Blundell and Bond (1998). This estimator, which is designed for datasets with large panels and a relatively short time dimension as in our case, provides asymptotically valid inference with a minimal set of statistical assumptions (Arellano and Bond, 1991), and allows the use of the lagged value of DE to tackle endogeneity problems (Blundell and Bond, 1998). Therefore, under the assumption that past resource extraction levels influence current extraction, we include the lagged variable of DE as follows:

$$Ln(DE_{it}) = Lag(Ln(DE_{it})) + \beta_1 Ln(GDP_{it}) + \beta_2 Ln(POP_{it}) + \beta_2 Ln(DE/DMC_{it}) + \beta_2 Ln(CONST/GDP_{it}) + \gamma_x Ln(CE_{it}) + \mu_i + \varepsilon_{it} \tag{2}$$

Where $Lag(Ln(DE_{it}))$ denotes the Lag 1 of the natural logarithm of DE. The estimates of the GMM system model are tested by the Arellano–Bond test for first- (AR1) and second-order (A2) residual autocorrelation (Arellano and Bond, 1991). In addition, we use the Sargan test for instrument validity. Settings of instrumental variables are considered reasonable if the Sargan *P*-value cannot reject the null hypothesis. Test specification results for the GMM model (eq. (2)) are provided in Annex B, Table B1.

In addition to the results based on the full panel (i.e., $N = 28$, $t = 10$), we also present the results obtained from testing of panels with reduced time periods, namely "2010–2015" and "2013–2018" time frames. While these additional tests are generally carried out to confirm the robustness of the empirical model to eventual changes in the sample (Flachenecker, 2018; Pothen and Welsch, 2019), in this case the temporal division also allows to check if there have been changes with respect to the entry of the former CE action plan (European Communication, 2015), in particular as regards the relationship between DE and CE variables.

4. Results

4.1. Exploratory analysis results

Table 2 presents the results of exploratory analysis for model (1), in which selected CE variables are tested one at a time. According to the specification tests (Annex B, Table B1), individual fixed effects was the best specification form.[8] Further, since heteroskedasticity was generally detected, all estimated parameters are provided considering robust standard errors. As anticipated previously, the selected CE variables are available for different time periods and countries. In this sense, CMU is the most complete CE variable, as it presents the longest time series, i.e., from 2010 to 2019, and covers all 28 EU countries. This is followed by MWAS and RECW, which are also available from 2010 to 2019 but have minor data gaps in some countries. Shorter time series, i.e., from 2010 to 2018, are instead available for EMP_CE, VA_CE and INV_CE, while the PAT_CE variable is only available until 2016. To also note that EMP_CE, VA_CE and INV_CE only cover a reduced number of EU countries, i.e., 25. The structure of each data panel is provided at the bottom of Table 2, while the reader can refer to the supplementary material (SM1) for a comprehensive overview of data availability.

Despite the use of different panels, the estimated models seem to converge towards similar results for what concern the basic STIRPAT variables, therefore confirming the theoretical correctness of this modelling approach. Socioeconomic (GDP and POP) and structural explanatory variables (DE/DMC and CONST/GDP) are significant and with expected sign across all models. Interestingly, GDP and POP seem to have an opposite behaviour on DE. While increasing levels of GDP are associated with higher levels of DE – namely, a 1% increase in GDP appears to increase DE in a range of 0.33% to 0.50% – the relationship between POP and DE is inverse, i.e., higher levels of population translate into lower amounts of resource extracted (−1.56%, on average). Although it may seem counterintuitive, the inverse relationship between POP and DE indicates that less populated areas, which benefit from greater availability of land, extract (on average) more resources than areas densely populated. Further discussion of the DE-POP relationship is provided in Section 5. Concerning the variables controlling for economic structures, both DE/DMC and CONST/GDP contribute to DE increase. This reflects the link of DE with, on the one hand, the overall

[8] The only exception is the model tested for the period 2013–2018, for which the random effect seems the most suitable specification form.

Table 2
Fixed-effects exploratory models results.

Coefficient	FE (1:1) MWAS 2010–2019	FE (1:2) RECW 2010–2019	FE (1:3) CMU 2010–2019	FE (1:4) CE_EMP 2010–2018	FE (1:5) CE_INV 2010–2018	FE (1:6) CE_VA 2010–2018	FE (1:7) CE_PAT 2010–2016
GDP	**0.335** ** (0.140)	**0.500** *** (0.142)	**0.410** *** (0.102)	**0.476** *** (0.128)	**0.396** *** (0.146)	**0.417** *** (0.134)	**0.344** ** (0.164)
POP	**−0.963** * (0.495)	**−1.434** ** (0.623)	**−1.214** *** (0.445)	**−2.182** *** (0.560)	**−1.826** *** (0.627)	**−2.087** *** (0.640)	**−1.413** * (0.820)
DE/DMC	**0.343** ** (0.133)	**0.342** *** (0.126)	**0.330** ** (0.134)	**0.979** *** (0.224)	**0.915** *** (0.233)	**0.939** *** (0.222)	**0.316** ** (0.154)
CONST/GDP	**0.370** *** (0.100)	**0.357** *** (0.096)	**0.349** *** (0.101)	**0.447** *** (0.099)	**0.467** *** (0.116)	**0.498** *** (0.120)	**0.398** *** (0.144)
MWAS	0.101 (0.144)						
RECW		**−0.090** * (0.049)					
CMU			**−0.101** ** (0.045)				
CE_EMP				**−0.486** *** (0.163)			
CE_INV					0.069 (0.040)		
CE_VA						−0.084 (0.104)	
CE_PAT							**0.039** * (0.023)
R	0.4154	0.4427	0.4585	0.5181	0.4782	0.4739	0.3730
R2	0.3374	0.3684	0.3883	0.4373	0.3812	0.3872	0.2499
F-statistic	9.7224	7.7555	7.8180	9.6608	8.5327	8.8642	4.7927
Panel structure	n = 28, T = 10, *N* = 273	n = 28, T = 10, N = 273	n = 28, T = 10, *N* = 280	*n* = 24, *T* = 9, *N* = 196	*n* = 25, T = 9, *N* = 186	n = 24, T = 9, *N* = 199	n = 28, *T* = 7, N = 196

Note: FE (1: i): fixed effects eq. (1), CE variable i (i, 1...7) tested; n: number of countries; T: number of time periods; N: number of observations; values in brackets refers to heteroskedasticity robust standard errors; Significance (p-value) is denoted as * (10%), ** (5%) and *** (1%), significant results are additionally highlighted in bold.

dependence of an economy on domestic extraction and consumption of resources and, on the other hand, the strong component of construction materials in DE.

With respect to the CE variables, the coefficients are not always significant.[9] Starting with the most relevant, the coefficients show that for every 1% increase in CE_EMP and CMU, the average DE decreased by 0.49% and 0.10%, respectively, while a 1% increase in RECW resulted in a 0.09% reduction in DE. Contrarywise, CE_PAT coefficient was found significant and with positive sign, implying that a 1% increase in the number of patents related to recycling and secondary raw materials appears to increase DE by 0.04%. Finally, MWAS, CE_INV and CE_VA coefficients were found not significant.

In summary, the results for RECW, CMU and CE_EMP are consistent and aligned with theoretical expectations and will be further analysed and discussed in sections 4.2 and 5, respectively, while the lack of significance for MWAS, CE_INV and CE_VA led to the exclusion of these variables from further analysis. Otherwise, in order to ensure a panel as complete as possible, CE_PAT was also excluded from the complete model, as its consideration would have limited the panel to 2016, thus not capturing the years following the introduction of the CE action plan. However, the results for the full panel including CE_PAT may be made available upon request to the author.

4.2. Full model results

Table 3 presents full FE and GMM models for eqs. 1 and 2, respectively. In addition, next to the FE (1) results, we also present results for the FE (1a) sub-panel, which covers the period 2010–2015, and FE (1b), which covers the period 2013–2018. The comparison between FE (1a) and FE (1b) might help identify any significant change due to the CE action plan. It should be noted that the Hausman specification test for model (1b) suggests the use of the Random Effect (RE) model. However, to allow for a consistent comparison between (1a) and (1b), we present in Table 3 the results obtained with the fixed effects specification. The results for RE (1b) are provided in the Annex B, Table B2.

Compared to the partial models tested before, a significant increase in the explanatory power of the model can be noted (R-adjusted ~0.5). This supports both the correct strategy applied to identify and select the relevant variables for CE, and the overall goodness of the specified complete model. In general, the type of relationship between DE and selected explanatory factors did not change in FE (1) from the exploratory analysis conducted in the previous step. Regarding socioeconomic and structural variables, we can infer similar conclusions as above, i.e., GDP, POP, DE/DMC and CONST/GDP remain good predictors of DE, all being positively correlated, with the exception of POP which again appears to behave as a constraining factor – even if it seems that the significance of POP seems to lose power over the years (−4.13% in 2010–2015 vs −0.91% in 2013–2018). Some different trends can instead be observed for the CE variables. First, RECW is significant in FE (1) and FE (1a) with similar elasticities to FE (1: 2), i.e., ~ 0.09, while it is not significant if we consider the period 2013–2018 in FE (1b). An opposite pattern is instead observed for CMU, as it is not significant in FE (1) and FE (1a), while it is significant in FE (1b). While the different behaviour of CMU between FE (1a) and FE (1b) might be explained by the implementation of the CE action plan in 2015,[10] the lack of significance in FE (1) is somehow not consistent with FE (1:3) results. Further analyses showed that this inconsistency might be due to the different size of the panels. In fact, if excluding CE_EMP from FE (1) and taking advantage of the period 2010–2019, both CMU and RECW are significant and with negative value (−0.07* and − 0.08**). CE_EMP elasticity is −0.42, in line with the elasticity assessed above (−0.48).

[9] Significance in statistical terms refers to the claim that a result from data generated by testing or experimentation is likely to be attributable to a specific cause. If a statistic has high significance, then it is considered more reliable (with the confidence interval measuring the degree of (un)reliability).

[10] This conclusion is further supported by the Circular Material Use (CMU) trend over time. Indeed, at the EU level, the CMU experienced an upward trend immediately after 2015.

Table 3
Fixed-effects and GMM full models results.

Coefficient	FE (1) 2010–2018		FE (1a) 2010–2015		FE (1b) 2013–2018		GMM (2) 2010–2019	
GDP	**0.673**	***	**0.872**	***	**0.506**	***	**0.307**	***
	(0.127)		(0.219)		(0.071)		(0.142)	
POP	**−2.815**	***	**−4.126**	***	**−0.911**	*	**0.105**	**
	(0.544)		(0.902)		(0.507)		(0.041)	
DE/DMC	**1.006**	***	**0.761**	***	**0.804**	***	**1.117**	***
	(0.187)		(0.190)		(0.129)		(0.319)	
CONST/GDP	**0.431**	***	**0.433**	***	**0.218**	*	**0.183**	***
	(0.084)		(0.110)		(0.087)		(0.056)	
RECW	**−0.088**	***	**−0.156**	***	0.034		0.033	
	(0.030)		(0.053)		(0.031)		(0.045)	
CMU	−0.060		−0.055		**−0.141**	***	**−0.112**	**
	(0.039)		(0.046)		(0.043)		(0.050)	
CE_EMP	**−0.415**	***	−0.341		0.039		**−0.338**	***
	(0.138)		(0.260)		(0.152)		(0.099)	
Lag 1 DE							**0.545**	***
							(0.142)	
R	0.5853		0.5991		0.5027		AR (1) p-value	0.0109
R2	0.5095		0.4751		0.3550		AR (2) *p*-value	0.1140
F-statistic	10.1682		9.6070		56.3115		Sargan test p-value	1.0000
Panel structure	n = 24, T = 9, *N* = 195		n = 24, *T* = 6, *N* = 128		n = 24, T = 6 *N* = 132		n = 28, T = 10, *N* = 321	

Note: FE (1): fixed effects eq.1; GMM (2): generalized method of moment, eq. 2; n: number of countries; T: number of time periods; N: number of observations; values in brackets refers to heteroskedasticity robust standard errors; Significance (p-value) is denoted as * (10%), ** (5%) and *** (1%), significant results are additionally highlighted in bold.

Interestingly, the effect of CE employment is only captured on longer terms (i.e., FE (1)), since for the shorter panels FE(1a) and FE(1b) it was found to be insignificant.

As regards the GMM (2) model, some fundamental differences from the FE (1) model can be noted due to the inclusion of the delayed variable DE. First, as anticipated, we can confirm that past DE levels significantly affect current levels of DE. This seems reasonable as resources extraction is generally planned with medium to long-term contracts in which the amount of resources extracted each year is optimized based on market demand and residual reserves. In this sense, the first lag of DE has an influence on the current DE equals to 0.55. The inclusion of the first DE lag also significantly affected the behaviour of POP, which under the GMM (2) has a positive elasticity (0.11). The GMM (2) results for GDP, DE/DMC and CONST/GDP are similar to those obtained by the FE (1) model. Likewise, the GMM (2) also confirms the beneficial effects of CMU and CE_EMP (closely associated with the deployment of circular business models) on DE. Namely, for each 1% increase in CMU and CE_EMP, the average DE decreased by 0.11% and 0.34%, respectively.

5. Discussion

Our findings confirm that a CE can have a beneficial effect on the extraction of virgin resources. In particular, CMU and CE_EMP appear to be the most relevant drivers of DE reduction, as these variables were confirmed to be significant and inversely related to DE across the several models tested. This means that on average, countries that have higher employment in CE related sectors and that reintroduce larger amounts of secondary material into the economy extract fewer natural resources, all else remaining equal. However, it should be borne in mind that the estimated elasticities refer to different types of variables that have very different trend over time from each other. Saying that for example CE_EMP more than offsets the effect of GDP on DE because of their similar and opposite elasticities (−0.34 and 0.31) makes little sense as GDP increased at a compound annual growth rate (CAGR) of 2.84% in the period 2010–2019, while CE_EMP only increased at a 0.67% CAGR. Therefore, to make sense of the estimated results, it is important to contextualise the elasticities by considering the behavioural patterns of the selected variables and try to understand the likely DE variations linked to said patterns. To this end, we first evaluate the final percentage impact on DE of the selected variables by multiplying the CAGR of each variable by its respective elasticity; secondly, we calculate the corresponding tonnes of DE on the basis of the aggregate EU28 DE recorded in 2019, which is 5.76 Gt. The results are shown in Table 4.

Once the growth rate of the selected variables is taken into account, it can be seen that economic growth is responsible in absolute terms for approximately 50 million additional tonnes of DE each year. This is nearly 4 times the DE savings achieved by the combined CE drivers, CMU and CE_EMP, which is 12.82 Mt. This finding suggests that progresses towards closed loops are only marginally reducing the extraction of primary resources. To a great extent, this could be due to the continued expansion of in-use stocks. In fact, recent studies estimate that up to 40% of global raw materials mined each year accumulate as in-use stocks, e.g., buildings, infrastructures, means of transport (Aguilar-Hernandez et al., 2021). Similar findings were also highlighted in Europe. In 2019, the EU28 net material accumulation (Eurostat code: env_ac_sd) amounted to 3.13 Gt, which is around the 54% of DE for the same year. Therefore, it is evident that primary extraction will remain necessary as long as the raw materials demanded for in-use stocks with long lifetimes (e.g., buildings and infrastructure) exceed the amount of materials that can be supplied from recycled materials. Likewise, a significant amount of extracted resources, i.e., most of fossil energy carriers and part of the biomass, cannot support loops closure as they are used to provide energy (Mayer et al., 2019). In this regard, it is also important to remember that recycling, or in general the recovery processes of secondary materials, can also be very energy-intensive and thus lead to the consumption of other energy carriers' resources.

Interestingly, the final effect of CE_EMP and CMU on DE is different

Table 4
Impacts of socioeconomic and CE drivers on DE.

Explicative variables	CAGR	GMM (2) elasticities	Final % impact on DE	DE variation (Mt)
GDP	2.84%	0.307	0.87%	50.031
POP	0.22%	0.105	0.02%	1.314
DE/DMC	0.01%	1.117	0.01%	0.520
CONST/GDP	0.00%	0.183	0.00%	0.000
CE_EMP	0.25%	−0.338	−0.09%	−4.901
CMU	1.23%	−0.112	−0.14%	−7.922

Note: CAGR: compound annual growth rate computed for the period 2010–2019 (Due to data availability CAGR for CE_EMP refers to 2010–2018); RECW not included as not significant.

from the interpretation we could have had by only focusing on the calculated elasticities. Indeed, based on elasticities, the expansion of CE-related employment appears to be the major catalyst for reducing DE, possibly reflecting the broader scope of CE activities, which go beyond the recycling and recovering of materials. However, although the elasticity of CE_EMP is higher than the elasticity of the CMU (−0.34 vs −0.11), the CMU grew at a much faster rate than CE_EMP (1.23 vs 0.25), thus contributing more to DE mitigation during the analysed period. This is also confirmed from an historical perspective. The higher CMU rates typically reflect those countries whose waste policy has been heavily focused on recycling in past years. For example, countries like the Netherlands, Luxembourg or Belgium have circularity rates above 20% (the Netherlands and Luxembourg even reached 30%). As these countries are already at the forefront of recycling in Europe, their circularity targets, and the strategies deployed to achieve them, will differ from less circular countries such as those of Eastern Europe. For less circular countries, reducing landfills and increasing recycling are the most immediate, and ongoing, means to achieve substantial progress towards circularity. For countries with an already high CMU rate, the main challenge will be to apply high-grade quality recyclate in new products, and to focus on other circularity strategies, such as ecodesign, repair, reuse, sharing and refurbishing (Bianchi et al., 2022).

Regarding the structural variables DE/DMC and CONST/GDP, we note that although they are strong predictors of the overall *levels* of DE, they explain very little for the *variation* of DE, as the type of economic structure remained rather unchanged over time. Likewise, the impact of POP is also very marginal as population growth is almost stagnant – even declining in some countries – thus contributing less and less to the change in DE. It is also worth mentioning the different POP behaviour between FE and GMM models. On the one hand, within FE approach, POP behaves as a constraining factor, i.e., the more the population the less the availability of space for mining activities.[11] In this context, the “level effect” of POP (i.e., the greater the population, the higher the consumption of resources) seems to be totally captured by GDP. Conversely, in the GMM model the availability of resources is explained by the inclusion of Lag 1 DE, while POP only accounts for the impact on DE due to population variation.

A number of relevant policy messages emerge from these findings. First, CE initiatives should not be limited to optimizing the management of waste streams, as the reuse and recycling of materials can do little against an ever-increasing demand for goods. While it is important to further improve the share of secondary material reintroduced into the economy, the steady pace of welfare growth also implies that consumer behaviour remains the most critical driver of DE and there are no signs of a potential disconnection between the use of primary resources and final consumption. While questioning our economic paradigm is beyond the scope of this research, we highlight the need for more effective policy interventions to break the link between economic growth and material use. Certainly, institutional tools such as product-based certification and effective labelling systems would improve resource governance by promoting the supply of more resource efficient products and allowing consumers to make informed (and economically affordable) choices. However, more ambitious goals should also be pursued to encourage both the reduction of the use of non-renewable resources and the competitiveness of CE jobs. In this sense, new taxation systems that shift tax burdens from labour to the environment would improve the competitiveness of CE labour-intensive activities such as maintenance and repair of products. Likewise, financial incentives (e.g., VAT exemptions) with which to promote more sustainable economic activities and the purchase of more sustainable products could represent effective economic tools to incentivise the transition to a circular economy. Similar economic instruments already exist, for example, in the case of energy (carbon taxes). Therefore, it seems reasonable to explore the possibility of applying such instruments to other non-energy, non-renewable resources within a strategy for increasing resource efficiency.

6. Conclusion

The transition to circular and sustainable economic systems represents one of the main goals of the European Green Deal, the Europe’s new agenda for sustainable growth. Applying circular economy principles across the EU economy is expected to reduce pressure on natural resources and create sustainable growth and jobs. These are also prerequisite to achieve the EU’s 2050 climate neutrality target, to halt biodiversity loss and ensure that no person and no place are left behind. In this line, a major goal of associated political strategies, such as the European Circular Economy Action Plan, is to decouple the use of resource from economic growth by using materials more efficiently, maintaining their value through closed material loops and supporting the market for secondary raw material. Therefore, this research questions how far advances towards circular systems and, in particular, the increasing use of secondary material are mitigating the extraction of virgin resources in Europe, which is a major driver of environmental degradation. More specifically, this paper analyses the relationship between CE factors and resource extraction over the past decade in Europe and provides an empirical evidence of the mitigating effect of a CE on the extraction of primary resource.

According to the results, the combined effect of the circular use of material and the employment in CE-related sectors would save roughly 13 Mt. annually. In particular, every 1% increase in CE_EMP and CMU, the average DE decreased by 0.34% and 0.11%, respectively. The higher elasticity of CE_EMP suggests that expanding the share of CE jobs represents the most promising driver for DE reduction as it encompasses –and stimulates – CE activities well beyond waste recycling. However, in the last decade most of the efforts seem to have prioritised the waste industry (Merli et al., 2018), perhaps due to the fact that most of the national and international CE initiatives have so far set objectives aimed at maximizing waste reuse as a source of material and energy. Consequently, the resources saved linked to the increase in CMU levels are higher than those linked to the increase in CE employment shares (7.9 vs 4.9 Mt, respectively).

The results, while confirming that the pursuit of circular schemes can lead to a lower consumption of natural resources, also indicate that a CE still has a marginal effect with respect to the demand for resources linked to economic growth. In other words, it is far from certain that higher recycling or circularity rates necessarily reduce the extraction of primary resources, as global trends such as increased consumption could more than offset the gains in circularity. Unless contemporary consumption patterns are reviewed, CE strategies might risk remaining a technical tool that does not change the course of the current unsustainable development.

From a methodological perspective, this work also provides some important advancements in relation to traditional STIRPAT approaches. On the one hand, we use DE –instead of DMC– as a dependent variable. Since DMC does not distinguish between primary and secondary materials, it is no longer meaningful to model the relationship between CE and primary material consumption. On the contrary, by focusing only on the extraction of primary resources, DE turns out to be a better indicator in this context. On the other hand, this analysis tested for the first time a set of new explanatory variables related to the CE. Among these, CMU and CE_EMP seem the most representative for capturing the progress towards a CE. In addition, we confirmed the importance of considering past values of resource consumption to correctly model current resource consumption. In this sense, the use of the GMM approach seems a preferred modelling choice compared to FE models. Furthermore,

[11] In general, the per capita endowment of natural resources, being these mineral resources, biomass, or even livestock, is higher in scarcely populated area than in densely populated areas. For a broader discussion on the relation between population density and resource consumption see Weisz and Duchin, 2006 or Bianchi et al. (2020).

similar to previous studies, we used structural variables to account for the type of domestic economy. However, these variables are not able to clearly grasp the impact of imports/exports of materials on DE. Likewise, current import/export indicators are poorly correlated with DE because they are generally measured in economic terms or based on the weight of the products traded. Therefore, further research could address this problem by proposing import/export indicators based on material footprint. These could help verify whether countries are genuinely reducing resource extraction or, instead, a “burden-shifting” from one country to another is occurring.

Finally, it is worth pointing out that this paper attempts to provide new evidence on the impact of a CE on resource extractions whereas measuring circularity remain a challenging issue. First, even though we initially considered all data currently available from the EU CE monitoring framework, due to data availability, only a reduced set of CE variables were successfully employed in our models. Therefore, these variables may not be fully representative of what the transition to circular systems entails. In this context, as new and better data and longer time series become available, further research could deepen and update the modelling approach we have proposed. As an example, material flow accounts in raw material equivalents were published very recently in EUROSTAT and the material footprint indicator is considered for the CE monitoring framework. The use of the material footprint would help to better understand if the consumption or extraction of material is actually decreasing, or a *burden-shifting* effect to countries outside of Europe is taking place.

Second, being a mass-based indicator, the total CMU is much more representative of recovered/recycled waste of heavy material flows, namely mineral waste from construction and demolition. These also constitute the largest material flows in DE (58%) and DMC (50%). In this context, further studies could investigate whether our results also apply to specific material streams or whether different patterns exist instead.

Third, it should be borne in mind that resource extraction is only one of the potential indicators linking the circular economy to environmental degradation and sustainable development. As an example, follow-up analyses could explore the relationship of the circular economy with other dependent variables such as territorial and consumption-based GHG emissions, air pollution or biodiversity loss.

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CRediT authorship contribution statement

Marco Bianchi: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Mauro Cordella:** Supervision, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

Data are available in the supplementary material "dataset"

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Annex A

Full description of selected CE indicators based on EUROSTAT metadata:

- Generation of municipal waste per capita (MWAS):

The indicator measures the waste collected by or on behalf of municipal authorities and disposed of through the waste management system. It consists to a large extent of waste generated by households, though similar wastes from sources such as commerce, offices and public institutions may be included. Reducing municipal waste generation is an indication of the effectiveness of waste prevention measures and changing patterns of consumption on the part of the citizens. Concentrating on municipal waste rather than on industrial waste has the advantage that it reflects the consumption side and is not affected by the presence or lack of strong manufacturing sectors in a country. This indicator focuses on municipal waste. Even though municipal waste only represents about 10% of the total waste generated or about 30% of the generated amount of waste excluding major mineral waste, following up on its evolution can give a good indication of changing consumption patterns and of Member States’ waste prevention performance and where citizens’ actions and involvement is most relevant. For the amount of municipal waste generated, the data refer to the handover over the waste to the waste collector or to a disposal site.

- Recycling rate of municipal waste (RECW):

The indicator measures the share of recycled municipal waste in the total municipal waste generation. Recycling includes material recycling, composting and anaerobic digestion. The ratio is expressed in percent (%) as both terms are measured in the same unit, namely tonnes. Recycling rate of municipal waste gives an indication of how waste from final consumers is used as a resource in the circular economy.

- Circular material use rate (CMU) for the secondary raw materials area.

The circular material use rate (CMU) is an indicator to measure the circularity rate of economies. This indicator is part of the monitoring framework released by the European Commission to monitor progress towards the circular economy (European Commission, 2018). The CMU rate measures the share of material recovered and fed back into the economy – thus saving extraction of primary raw materials – in overall material use. A higher circularity rate means that more secondary materials replace primary raw materials, thus reducing the negative environmental impacts associated with resource extraction.

The formula for CMU rate is:

$$CMU = \frac{RCV_R - IMP_w + EXP_W}{DMC + (RCV_R - IMP_w + EXP_W)}$$

Where RCV_R is the amount of waste recycled in domestic recovery plants and it comprises the recovery operations R2 to R11 – as defined in the Waste Framework Directive 75/442/EEC; IMP_W amount of imported waste bound for recovery; EXP_W amount of exported waste bound for recovery and *DMC* is the domestic material consumption. This latter should be considered as a proxy for raw material consumption. In fact, data show that the development over time of DMC and RMC is rather similar for the EU economy, thus DMC is a good proxy. The data source is economy-wide material flow accounts (EW-MFA). Data are collected on annual basis, from every Member State.

- CE sectoral employment (EMP_CE):

The indicator measures employment in recycling, repair and reuse sectors as a percentage of total employment. The detailed list of NACE Rev. 2 codes used for jobs calculation can be found at https://ec.europa.eu/eurostat/documents/8105938/8465062/cei_cie010_esmsip_NACE-codes.pdf

- Gross private investment in tangible goods relating to CE sectors (INV_CE):

The indicator measures gross investment in tangible goods in the recycling sector and repair and reuse sector. It is expressed as a percentage of gross domestic product (GDP) and it is defined as investment during the reference year in all tangible goods. Investments in intangible and financial assets are excluded.

- Gross value added by CE sectors (VA_CE):

The indicator measures value added at factor costs in the recycling sector and repair and reuse sector. Value added at factor costs is the gross income from operating activities after adjusting for operating subsidies and indirect taxes. Gross value added is expressed as a percentage of gross domestic product (GDP).

- Number of patents relating to recycling and secondary raw materials (PAT_CE) for the competitiveness and innovation area:

The indicator measures the number of patents related to recycling and secondary raw materials. The attribution to recycling and secondary raw materials was done using the relevant codes in the Cooperative Patent Classification (CPC). The indicator is used to monitor progress towards a circular economy on the thematic area of 'competitiveness and innovation'. Patent statistics are one of the indicator families widely used to assess technological progress in a specific industrial sector. They are widely accepted as output-oriented indicators on innovation.

Annex B

Table B1
Specification tests.

Type of test	H0	Eq. 1 MWAS	Eq. 1 RECW	Eq. 1 CMU	Eq. 1 CE_EMP	Eq. 1 CE_INV	Eq. 1 CE_VA	Eq. 1 CE_PAT	Eq. 1 Full	Eq. 1 Full (a)	Eq. 1 Full (b)	Eq. 2 GMM
F Test for Individual and/or time effects based on the comparison of fixed and pooled effects models	No significant time and/ or individual effects	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Lagrange FF multiplier tests for individual and/or time effects based on the results of the pooling model (type Breusch-Pagan);	No significant time and/ or individual effects	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Hausman model specification test: based on the comparison of random and fixed effects models	No correlation between the unique errors and the regressors	0.00	0.00	0.05	0.00	0.00	0.02	0.00	0.00	0.00	**0.67**	
Breusch-Pagan Heteroskedasticity test	Presence of homoskedasticity	**0.07**	**0.05**	0.00	**0.05**	0.00	0.00	0.01	0.00	0.00	0.00	
Arellano-Bond test for second order autocorrelation (AR1)	No first-order autocorrelation											0.01
Arellano-Bond test for first order autocorrelation (AR2)	No second-order autocorrelation											0.11
Sargan test	Instruments as a group are exogenous											1.00
Wald test for coefficients	The coefficient of interest in the model are equal to zero											0.00

Table B2
Result random-effect full model eq. (1), period 2013–2018.

Coefficient	RE (1b) 2013–2018	
GDP	**0.545**	***
	(0.076)	
POP	**0.333**	***
	(0.086)	
DE/DMC	**1.049**	***
	(0.104)	
Constr/GDP	**0.160**	**
	(0.075)	
RECW	**0.051**	*
	(0.029)	
CMU	**−0.169**	***
	(0.043)	
CE_EMP	0.007	
	(0.155)	
intercept	−0.332	
	(0.839)	
R	0.8927	
R2	0.8866	
Panel structure	n = 24, T = 6 N = 132	

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2022.107607.

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