“Heterogeneous associations between organizational circularity and enterprise economic performance in Ukraine and the EU”

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HETEROGENEOUS ASSOCIATIONS BETWEEN ORGANIZATIONAL CIRCULARITY AND ENTERPRISE ECONOMIC PERFORMANCE IN UKRAINE AND THE EU

Abstract

The performance-related associations of circular practices may differ because waste recovery, recycled-input use, and circularity-related investment involve distinct costs, investments, and organizational mechanisms. This study examines heterogeneous associations between organizational circularity components and economic performance across 25 industrial enterprises in the Ukrainian operating and European comparison subsamples during 2013–2023. Fixed-effects regressions, decomposition, lagged and subgroup models, a non-imputed subsample, a balanced common-support window, pooled interactions, wild-cluster-bootstrap inference, and Holm adjustment were applied.

The aggregate circularity index shows no statistically significant short-term association with EBITDA margin ($\beta = +0.0222$; $p = 0.894$).

The decomposed components show different coefficient profiles, but formal heterogeneity is sample-sensitive: coefficient equality is not rejected in the full-panel decomposed model (M2) ($p = 0.101$) but is rejected in the non-imputed model (M3) ($p = 0.002$). Recycled-input use is predominantly negative and nominally significant in the one-period lag-only (M4) and Ukrainian operating subsample (M6) models, although neither coefficient survives Holm adjustment and the lagged estimate is not reproduced in the combined model. Circularity-related eco-capex is positive in M3 and the European comparison subsample model (M5), where it is supported by unadjusted wild-cluster-bootstrap ($p = 0.0198$) and Holm-adjusted CR1 inference ($p = 0.0273$). The country-context interaction block is jointly significant ($p = 0.042$), with RI × UA as the only individually significant interaction ($\beta = -1.566$; $p = 0.038$).

The findings indicate that aggregate measures may conceal component-specific patterns, but most associations remain sample- or specification-sensitive and should not be interpreted causally. Enterprise assessment should distinguish recovery, material-substitution, and investment-modernization channels.

Keywords organizational innovations, circularity, recycling, EBITDA, enterprise economics, investment

JEL Classification M11, Q56, M21, C33

INTRODUCTION

Strengthening environmental constraints, unstable resource supply, and growing requirements for production resilience are shaping new operating conditions for industrial enterprises. Under these conditions, the circular economy is considered a direction of production system transformation that improves resource efficiency, reduces material losses, and decreases dependence on primary raw materials. For industrial enterprises, this transition has both environmental and economic significance, as it affects cost structure, capital allocation, and the ability to maintain long-term competitiveness.

At the enterprise level, circularity is formed through the integration of relevant principles into management systems, production organization, material supply, and investment processes. Therefore, it should be considered not as a set of separate environmental actions, but as a characteristic of organizational transformation. In this sense, organizational circularity becomes an economic phenomenon whose association with enterprise performance cannot be defined in advance as unambiguously positive or negative.

Despite the growing diffusion of the circular economy, the economic performance profile of such transformations remains debatable. In some cases, these practices are associated with improved resource efficiency and lower costs; in others, they coincide with substantial expenditure on production modernization, technology adaptation, quality control of secondary inputs, and logistics restructuring. This points to the heterogeneity of performance-related associations and to their dependence on the content of specific managerial, production, and investment decisions.

The unresolved issue is that, at the enterprise level, circularity is often assessed through aggregate indicators without sufficient consideration of differences between its components. Recycled resources, circularity-related eco-capex, and waste recovery practices may differ in economic nature, coefficient profile, and time horizon. As a result, an aggregate assessment may conceal heterogeneous component-specific associations of organizational circularity with enterprise performance. This issue is particularly relevant for industrial enterprises in Ukraine and the EU, which operate under different institutional, investment, and resource conditions of the circular transition.

1. LITERATURE REVIEW

Circular economy research has gradually shifted from macro-level sustainability concepts toward firm-level and organizational interpretations of circularity. Early studies viewed the circular economy as a systemic alternative to the linear "take-make-dispose" model, emphasizing resource efficiency, waste minimization, and material recirculation. Ghisellini et al. (2016) associate circularity with resource regeneration and closed-loop production, while Geissdoerfer et al. (2017) conceptualize it as a sustainability paradigm requiring changes in production systems, value creation, and organizational structures. Nevertheless, the concept remains heterogeneous: Kirchherr et al. (2017) identify substantial variation among existing definitions, whereas Korhonen et al. (2018) highlight institutional, managerial, and systemic constraints that complicate practical implementation.

Enterprise-level research increasingly interprets circularity not as a collection of isolated environmental initiatives but as an organizational phenomenon embedded in managerial coordination, production, procurement, investment, inter-organizational cooperation, and strategic adaptation. Bocken et al. (2016) link circular transformation to product design and value-preservation mechanisms, while related business-model research emphasizes the redesign of value creation and organizational integration (Lewandowski, 2016; Urbinati et al., 2017; Pieroni et al., 2019; Geissdoerfer et al., 2020). Their implementation also depends on coordination, innovation, learning, and process adaptation (Fernandez de Arroyabe et al., 2021). Stewart and Niero (2018) show that firms increasingly incorporate circular economy principles into corporate sustainability strategies, although their integration into measurable organizational and performance-management systems remains uneven. Empirical studies similarly associate circular economy adoption with eco-innovation, leadership, organizational culture, skills, and resource-efficiency practices (Bag et al., 2022; Chowdhury et al., 2022; Dey et al., 2022). Organizational circularity is therefore understood here as a multidimensional enterprise-level phenomenon integrating circular principles into managerial, production, investment, and coordination systems.

Institutional conditions also shape circular transformation. Regulatory frameworks may support circular investment, whereas institutional voids and stakeholder constraints may limit firms' abil-

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ity to translate circular business models into improved performance outcomes (Ranta et al., 2018; Jabbour et al., 2020). In Europe, the EU Emissions Trading System and carbon pricing provide signals for emission reduction and environmentally oriented investment, while the GHG Protocol, Global Reporting Initiative (GRI), and CDP frameworks contribute to standardizing environmental measurement and disclosure (European Commission, n.d.; EEX, n.d.; GHG Protocol, n.d.; Global Reporting Initiative, n.d.; CDP, n.d.). These differences are relevant to comparisons between the Ukrainian operating and European comparison subsamples.

Measurement remains a central methodological problem because no generally accepted enterprise-level circularity framework has emerged. Existing indicators differ in scope, purpose, and analytical level (Elia et al., 2017; Saidani et al., 2019; D'Adamo et al., 2024), while manufacturing enterprises require multidimensional measures covering production, resource, investment, and recovery activities (Negri et al., 2021). Micro-level indicators often focus predominantly on physical material flows and may insufficiently reflect organizational and managerial dimensions (Kristensen & Mosgaard, 2020). Aggregate measures may therefore combine practices, outcomes, and capabilities characterized by different implementation horizons, managerial objectives, and levels of maturity (Moraga et al., 2019; Sacco et al., 2021; Vinante et al., 2021). Comparability is further constrained by uneven corporate circularity disclosure (Heras-Saizarbitoria et al., 2023; Vitolla et al., 2023). The CEI-360 framework developed by Suslikov et al. (2026) provides an integrated assessment of circular transformation, although it addresses broader economic, environmental, and social performance rather than direct associations with financial outcomes.

Recent evidence increasingly supports heterogeneous rather than universal circularity and performance relationships. Reported financial associations vary across industries, countries, circular practices, and performance indicators (Yin et al., 2023; Pan et al., 2024). Firm-level studies likewise identify context-dependent associations across innovation characteristics and firm conditions (Horbach & Rammer, 2020; Mazzucchelli et al., 2022; Akinwale, 2024), while organizational and supply-chain conditions are linked to differences in the implementation and performance profiles of circular practices (Zhu et al., 2011; Calzolari et al., 2021). Related sustainability research also identifies asymmetric financial associations across firms and contexts (Lin et al., 2021). From a mechanism-based perspective, circularity-related eco-capex may coincide with short-term financial pressure, while potential operational benefits may depend on investment type, implementation stage, and observation horizon. At the same time, circularity-related investment may be associated with process renewal, technological reliability, and production resilience when it forms part of a broader organizational modernization pathway (Bocken et al., 2016; Geissdoerfer et al., 2020; Fernandez de Arroyabe et al., 2021). Greater reliance on recycled inputs may involve additional costs related to quality control, logistics, supplier coordination, and process adaptation.

These measurement and performance differences support the decomposition of organizational circularity into distinct channels. In this study, waste recovery and recycling share (*WR*) represents an operational recovery channel, recycled input share (*RI*) represents a material-substitution channel, and circularity-related eco-capex share (*ECS*) serves as a proxy for an investment-modernization channel. Combining them into a single index may conceal component-specific associations with enterprise operating performance.

Overall, two research gaps remain. First, enterprise-level research lacks sufficiently transparent operationalization that combines observable material-flow and investment manifestations of organizational circularity while clearly distinguishing them from its broader managerial, coordination, and capability dimensions. Second, limited research formally tests whether individual circularity components differ in the direction, magnitude, and temporal profile of their associations with enterprise operating performance. Addressing these gaps, the present study analyzes organizational circularity through an aggregate circularity index and its *WR*, *RI*, and *ECS* components. These indicators are treated as observable proxies for recovery, material-substitution, and investment-modernization channels rather than as a complete

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measure of all organizational circularity dimensions. The analysis evaluates whether their conditional associations with operating performance differ across components, temporal specifications, and the Ukrainian operating and European comparison subsamples.

This study aims to identify and quantify heterogeneous associations between organizational circularity components and the economic performance of industrial enterprises in Ukraine and the European comparison subsample. In line with this aim, the following research hypotheses are formulated:

H1: *The aggregate index of organizational circularity has a statistically identifiable association with enterprise economic performance.*

H2: *The associations between organizational circularity components and the economic performance of an industrial enterprise are heterogeneous, since individual components differ in the direction and magnitude of their coefficients.*

H2a: *An increase in the share of secondary inputs in the enterprise's resource structure is associated with a decline in its short-term economic performance.*

H2b: *A higher share of circularity-related eco-capex is positively associated with enterprise economic performance, with a possible delayed profile.*

H3: *The associations between organizational circularity components and enterprise economic performance differ between enterprises in the Ukrainian operating and European comparison subsamples.*

2. METHOD

The study applies a panel design to examine conditional associations between organizational circularity and enterprise operating performance across firms and over time under different imputation-status, sectoral, and country-context settings. Estimated coefficients are interpreted as associations rather than causal effects. The empirical procedure comprised five stages:

- construction of the firm-level panel;
- collection and harmonization of financial, environmental, circularity-related, regulatory, and shock variables;
- operationalization of organizational circularity through an aggregate circularity index (*CI*) and three components: waste recovery and recycling share (*WR*), recycled input share (*RI*), and circularity-related eco-capex share (*ECS*);
- estimation of fixed-effects, lagged, subgroup, and interaction models; and
- robustness analyses using the non-imputed subsample *M3* and the balanced common-support sample.

The empirical analysis is based on a balanced panel of 25 large industrial enterprises observed from 2013 to 2023, yielding 275 firm-year observations. The panel was constructed purposively because continuous financial reporting and sufficiently detailed non-financial disclosures were required to construct or reconstruct the study variables. The initial screening frame comprised 126 enterprises. Successive screening for reporting availability, circularity-data availability, reporting-boundary consistency, and balanced-panel eligibility reduced this number to 74, 39, 31, and finally 25 enterprises. The sample-selection stages and the number of enterprises retained at each stage are reported in Table A1. Candidate firms represented sectors in which circular transformation has material economic significance, including metallurgy, mining, energy, chemicals, cement and building materials, recycling and waste management, pulp and paper, pharmaceuticals, agro-industry, oil and gas, utilities, and automotive manufacturing.

The final panel contains 10 Ukrainian operating and 15 European comparison enterprises. The Ukrainian operating subsample comprises Metinvest Group, Ferrexpo Plc, Kernel Holding S.A., DTEK Energy, MHP SE, Astarta Holding PLC, Ukrnafta PJSC, Farmak JSC, IMC Agro SA, and Energoatom SE. The European comparison subsample comprises ArcelorMittal S.A., Holcim AG, HeidelbergMaterials AG, Veolia Environnement, Umicore NV/SA, Renewi Plc, Stora Enso Oyj, BASF SE, Enel SpA, UPM-Kymmene Oyj, Covestro AG, Befesa S.A., Plastic Omnium SE, LANXESS AG, and ENGIE SA. Classification is based on dominant operating geography rather than legal incorporation. Accordingly, the European comparison subsample denotes the analytical enterprise group, whereas EU ETS refers exclusively to the European Union Emissions Trading System.

The dataset was constructed from annual financial statements, company filings, integrated and sustainability reports, ESG and management disclosures, and regulatory filings for 2013–2023. Financial values were obtained from company reports and, where available, cross-checked against Bloomberg (n.d.) and LSEG (n.d.) company data. Greenhouse-gas information was harmonized using the GHG Protocol Corporate Standard (GHG Protocol, n.d.), while circularity variables were derived from corporate disclosures, including materials prepared under GRI and CDP frameworks (Global Reporting Initiative, n.d.; CDP, n.d.). Annual EU ETS allowance prices were obtained from EEX (n.d.) and the European Commission (n.d.), and sectors were classified according to NACE Rev. 2 (Eurostat, 2008).

To improve comparability, reporting boundaries were aligned, absolute quantities were converted into relative indicators where required, and values were documented as directly reported, transparently reconstructed, or imputed. Directly reported values were accepted when their definition, unit, and reporting boundary matched the study protocol. Reconstructed values were accepted only when their numerator, denominator, and calculation could be reproduced from disclosed quantitative components. Imputed values were retained in the full panel and identified by the firm-year *IMP* indicator. Under the study protocol, *M3* is defined solely as the *IMP* = 0 subsample and is therefore described as non-imputed rather than independently verified. Table A2 reports the operational definitions and harmonization rules for *WR*, *RI*, and *ECS*. Available source references, reporting-boundary information, transformations, and data-status records were retained where recoverable.

Candidate *ECS* investment items were assessed using these inclusion and exclusion criteria. Items without an identifiable operational link to circular resource flows, an isolable circularity-related component, or sufficient quantitative support were excluded from the *ECS* numerator. The archived materials retain the final item classifications but not independent first-pass coder labels; inter-coder agreement is therefore not reported retrospectively.

The firm-year *IMP* indicator equals one when at least one non-financial input was imputed. It identifies 55 observations: 50 for the 10 Ukrainian enterprises in 2013–2017, three for Befesa S.A. in 2013–2015, and two for Covestro AG in 2013–2014. Because *IMP* is a firm-year rather than variable-specific indicator, it does not identify which input was imputed. The archive does not retain variable-specific flags or the original cell-level calculation log; exact variable-level counts and algorithms are therefore not reconstructed retrospectively. Table B1 summarizes *WR*, *RI*, and *ECS* data status for the 220 observations with *IMP* = 0 and reports the 55 *IMP* = 1 observations separately at the firm-year level. *M3* excludes all *IMP* = 1 observations and retains all 25 enterprises, including 60 of 110 Ukrainian and 160 of 165 European comparison observations. Annual coverage ranges from 13 to 15 enterprises in 2013–2017 and reaches all 25 enterprises from 2018 onward. Because exclusions are concentrated by country and period, differences between *M2* and *M3* may reflect both imputation status and country-time composition. *M3* is therefore treated as a non-imputed sensitivity specification rather than an independent validation sample.

Because sample inclusion depended on sufficiently detailed financial and non-financial disclosure, the findings should be interpreted as applicable to comparable large industrial enterprises with similar reporting characteristics rather than to the entire industrial population. Reporting-related selection bias therefore remains possible.

Enterprise operating performance is measured by EBITDA margin

$$EBITDAm_{i,t} = 100 \cdot \left(\frac{EBITDA_{i,t}}{Revenue_{i,t}} \right), \quad (1)$$

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because it captures core operating profitability while being less sensitive than net profit to taxation, financing structure, depreciation policies, and non-operating items. Net profit margin, is retained only for descriptive comparisons.

$$NetMargin_{i,t} = 100 \cdot \left(\frac{NetProfit_{i,t}}{Revenue_{i,t}} \right), \quad (2)$$

Organizational circularity is operationalized as the aggregate *CI* and three component indicators. *WR* measures the share of generated production waste returned to economic circulation through reuse, recovery, recycling, or another disclosed recovery route. *RI* measures the share of secondary materials used as substitutes for primary production inputs. *ECS* measures the share of total annual capital expenditure attributable to identifiable circularity-related investment and serves as a proxy for a circularity-related investment-modernization channel. In the empirical analysis, *CI* is interpreted as a proxy based on observable material-flow and investment manifestations of organizational circularity rather than as a complete measure of its managerial, coordination, and capability dimensions. Exact component formulas and verification rules are reported in Table A2.

Raw *ECS* enters the decomposed regressions. Only its contribution to the aggregate index is bounded:

$$ECSN_{i,t} = 100 \cdot \min\left(\frac{ECS_{i,t}}{\tau}, 1 \right), \quad \tau = 15. \quad (3)$$

The saturation threshold corresponds to the empirical 75th percentile of raw *ECS* and is used only to limit the influence of upper-tail observations when constructing *ECSN* and *CI*; decomposed regressions use uncapped *ECS*. At thresholds of 10, 15, 20, and 25 percentage points, the *CI* coefficients are –0.0061, +0.0222, +0.0057, and –0.0103, with *p*-values of 0.970, 0.894, 0.972, and 0.953. Alternative equal, material-flow-oriented, and *ECS*-oriented weights, together with observed-maximum, min-max, percentile-rank, and log-maximum normalizations, also produce statistically insignificant *CI* coefficients; the smallest *p*-value across these alternatives is 0.206. Thus, the absence of a statistically identifiable aggregate association is not specific to the selected threshold, weights, or normalization, although the coefficient direction is not stable. The aggregate index is calculated as follows:

$$CI_{i,t} = 0.40WR_{i,t} + 0.35RI_{i,t} + 0.25ECSN_{i,t}. \quad (4)$$

The main *CI* uses weights of 0.40 for *WR*, 0.35 for *RI*, and 0.25 for *ECSN*, specified on conceptual grounds rather than statistically estimated. *WR* and *RI* receive 75% of the total weight because they represent realized material-flow practices, whereas *ECSN* represents an investment input. Because weighting involves modeling judgement and alternative index constructions do not produce a stable coefficient direction, the main interpretation relies on the decomposed regressions.

Greenhouse gas intensity,

$$GHGint_{i,t} = \frac{\left(GHGScope1_{i,t} + GHGScope2_{i,t} \right)}{Revenue_{i,t}}, \quad (5)$$

expressed in kt CO_2-eq. per USD million of revenue, is included as a time-varying environmental and technological control. Energy intensity,

$$Eint_{i,t} = \frac{Energy_{i,t}}{Revenue_{i,t}}, \quad (6)$$

is used only descriptively. *ETS* captures the annual EU carbon-price environment. *WAR* equals one for Ukrainian enterprises in 2022–2023, *CRISIS* equals one for Ukrainian enterprises in 2014–2015, and *COVID* equals one in 2020; these variables enter only when separately identifiable from enterprise and year effects. *IMP* identifies the legacy firm-year imputation flag, while *ResInt* equals one for enterprises in steel, mining, energy, and chemicals. Additional robustness models include log revenue, log employment, and capital-expenditure intensity measured as *CAPEX* relative to revenue.

The principal econometric specification is:

$$\begin{aligned} EBITDAm_{i,t} &= \alpha + \beta' X_{i,t} + \gamma' Z_{i,t} \\ &+ \mu_i + \lambda_t + \varepsilon_{i,t}, \end{aligned} \quad (7)$$

where $X_{i,t}$ contains *CI* or the decomposed circularity components, $Z_{i,t}$ contains the relevant controls, μ_i denotes enterprise fixed effects, λ_t denotes year fixed effects where included, and $\varepsilon_{i,t}$ is the idiosyncratic error term. Fixed effects are retained as the prespecified within-enterprise estimator because the analysis focuses on within-firm variation and time-invariant enterprise characteristics may be correlated with circularity indicators. The Hausman test is used as a diagnostic comparison rather than as the sole estimator-selection rule.

Standard errors are clustered by enterprise using the *CR1* covariance estimator with the finite-sample factor

$$\left[\frac{G}{G-1}\right]\cdot\left[\frac{N-1}{N-K}\right], \tag{8}$$

where G is the number of enterprise clusters, N is the number of observations, and K is the rank of the estimable model matrix after collinear regressors have been removed. Hypothesis tests use a t reference distribution with $(G - 1)$ degrees of freedom. In *M3*, *CRISIS* is identically zero because the non-imputed subsample contains no Ukrainian observations from 2014–2015; it is therefore omitted before the *CR1* correction is calculated. Unless explicitly labelled otherwise, reported standard errors, p-values, and significance symbols are based on *CR1* inference. Because some specifications contained only 9 to 15 enterprise clusters, *CR1* inference was supplemented with restricted null-imposed wild-cluster-bootstrap-t tests. The tests were clustered by enterprise and used Webb six-point weights, 9,999 replications, *CR1* studentization, two-sided p-values, and a fixed reproducibility seed of 20260727. *WCB* p-values are reported without multiple-testing adjustment and separately from Holm-adjusted *CR1* p-values. The executable code and complete machine-readable bootstrap output are provided in the replication supplement.

The nine principal models comprise the aggregate *CI* specification (*M1*); decomposed full-panel, non-imputed, and one-period lag-only specifications (*M2–M4*); European comparison and Ukrainian operating subsamples (*M5–M6*); resource-intensive and non-resource-intensive sectors (*M7–M8*); and the Ukrainian operating subsample in 2013–2021 (*M9*). Additional robustness analyses examined a combined current-and-lag model; pooled country, sector, and *IMP* interactions; subgroup models with year fixed effects and without subgroup-common variables; additional time-varying controls; sector × year fixed effects; the balanced 2018–2023 common-support sample; leave-one-enterprise-out checks for the Ukrainian and sectoral subsamples; and alternative *CI* constructions.

Country-context and sectoral heterogeneity are evaluated using the pooled interaction model:

$$\begin{aligned}
&EBITDAm_{i,t} = \alpha + \beta_1 WR_{i,t} + \beta_2 RI_{i,t} \\
&+\beta_3 ECS_{i,t} + \theta_1\left(WR_{i,t}\cdot D_i\right) \\
&+\theta_2\left(RI_{i,t}\cdot D_i\right) + \theta_3\left(ECS_{i,t}\cdot D_i\right) \\
&+\gamma' Z_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t},
\end{aligned} \tag{9}$$

where D_i denotes Ukrainian operating status or resource-intensive sector status. Because D_i is time invariant, its main effect is absorbed by enterprise fixed effects. In the *IMP*-interaction model, D_i is replaced by the time-varying *IMP* indicator and its main effect is included. The joint current-and-lag specification separately tests whether the lagged circularity block is jointly equal to zero and whether the current and lagged coefficients are equal.

Formal tests distinguish joint relevance, component equality, and contextual heterogeneity. Coefficient-equality tests compare marginal associations corresponding to a one-percentage-point change in *WR*, *RI*, and *ECS* on their original scales. Because the components have different denominators, distributions, and economic meanings, these tests do not compare standardized effect sizes or establish differences in overall economic importance. The combined current-and-lag model additionally tests whether the lagged component block is jointly zero and whether current coefficients equal their corresponding lagged coefficients.

Descriptive statistics and pairwise correlations were calculated before model estimation. Differences between the Ukrainian operating and European comparison subsamples were assessed using Welch tests based on enterprise-level means, thereby avoiding treatment of repeated firm-year observations as independent. Diagnostic procedures included Hausman comparisons, a residual

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AR(1) diagnostic, the Pesaran CD test of residual cross-sectional dependence, and the Wald restrictions described above.

3. RESULTS

Results are presented in five stages: descriptive statistics, firm-level Welch comparisons, correlations, key estimates from *M1–M9* and robustness analyses, and formal tests and diagnostics. For compactness, EU denotes the European comparison subsample defined in the Method section.

Table 1 reports descriptive statistics for the key financial, circularity, and environmental variables in the full panel of 275 firm-year observations.

The full-panel mean EBITDA margin is 18.677%, and the mean *CI* is 56.562 points. The Ukrainian operating subsample has a higher mean EBITDA margin than the European comparison subsample (24.172% versus 15.015%), whereas the European comparison subsample has higher mean values of *CI*, *WR*, *RI*, and *ECS*.

Because firm-year observations are repeated within enterprises, between-group differences were assessed using Welch tests based on enterprise-level means (Table 2).

The full-panel Welch comparisons show nominal descriptive differences in *EBITDAm*, *CI*, *WR*, *RI*, and *ECS*. Because the Ukrainian circularity means include *IMP*-flagged early-year observations, these comparisons are not used as formal evidence for *H3*.

The annual dynamics of the aggregate circularity index are presented in Figure 1.

The European comparison subsample maintains a higher annual mean *CI* throughout 2013–2023.

Table 3 presents the Pearson correlation matrix for the main variables. *CI* is strongly correlated with *WR* (r = 0.805) and *RI* (r = 0.844) and moderately correlated with *ECS* (r = 0.573). Its correlation with *EBITDAm* is negative (r = −0.249); *RI* and *ECS* are also negatively correlated with *EBITDAm*, whereas the *WR* correlation is weak.

Table 1. Descriptive statistics of key variables, full panel, 2013–2023

Variable	Mean	SD	Min	Max	$Mean_{UA}$	$Mean_{EU}$
EBITDAm	18.677	8.358	3.110	51.040	24.172	15.015
Net margin	5.902	7.849	–35.900	36.870	7.961	4.529
CI	56.562	15.386	25.150	97.450	44.428	64.652
WR	68.357	16.670	31.900	98.000	59.362	74.354
RI	29.843	19.781	4.500	95.000	19.274	36.889
ECS	13.685	7.875	4.550	37.840	8.432	17.188
GHGint	1.721	1.993	0.080	10.143	2.132	1.448
Energy intensity	20.084	37.552	0.633	201.414	38.993	7.478

Note: N = 275 firm-year observations. MeanUA and MeanEU denote the mean values for the Ukrainian operating and European comparison subsamples, respectively. CI denotes the aggregate organizational circularity index.

Table 2. Welch t-test results for differences between Ukrainian operating and European comparison subsamples

Variable	SD_{UA}	N_{UA} firms	SD_{EU}	N_{EU} firms	Mean difference UA–EU	Welch t-test	df	*p*-value
EBITDAm	8.594	10	4.896	15	9.157	3.055	12.93	0.009
Net margin	7.063	10	2.623	15	3.432	1.470	10.67	0.170
CI	8.250	10	12.551	15	–20.224	–4.861	23.00	<0.001
WR	17.922	10	12.433	15	–14.992	–2.302	14.73	0.036
RI	9.910	10	21.652	15	–17.615	–2.749	20.96	0.012
ECS	1.736	10	8.310	15	–8.756	–3.953	15.79	0.001
GHGint	2.367	10	1.720	15	0.684	0.786	15.24	0.444
Energy intensity	54.862	10	7.167	15	31.515	1.806	9.21	0.104

Note: Welch tests are calculated using enterprise-level averages. CI denotes the aggregate organizational circularity index.

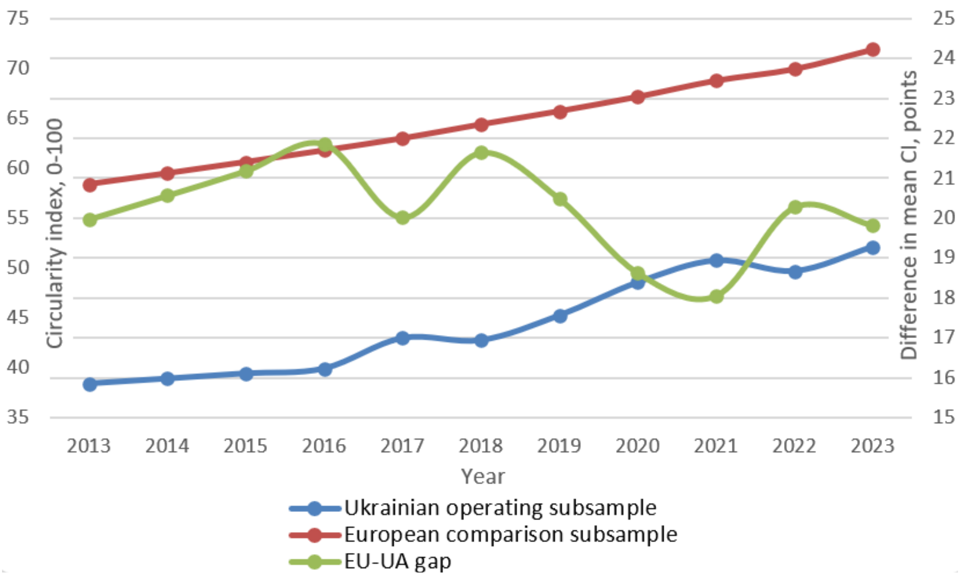

Figure 1. Dynamics of the aggregate circularity index (*CI*) in the Ukrainian operating and European comparison subsamples, 2013–2023

Table 3. Pearson correlations among core variables

Variable	EBITDAm	CI	WR	RI	ECS	GHGint
EBITDAm	1.000	–0.249	–0.045	–0.231	–0.255	0.056
CI	–0.249	1.000	0.805	0.844	0.573	–0.375
WR	–0.045	0.805	1.000	0.515	0.155	–0.313
RI	–0.231	0.844	0.515	1.000	0.498	–0.431
ECS	–0.255	0.573	0.155	0.498	1.000	–0.143
GHGint	0.056	–0.375	–0.313	–0.431	–0.143	1.000

Note: CI denotes the aggregate organizational circularity index.

The main panel regression results are reported in Table C1.

Model *M1* estimates a positive but statistically insignificant coefficient on *CI* (*CI* = +0.0222; *p* = 0.894).

In the full-panel decomposed model *M2, WR, RI,* and *ECS* have different coefficient signs, but none of the three circularity components is statistically significant after enterprise-clustered correction. *RI* is negative (*RI* = –0.3021; *p* = 0.152), *ECS* is positive (*ECS* = +0.2302; *p* = 0.256), and *WR* is negative but statistically insignificant.

In the non-imputed subsample *M3*, the estimated coefficients are –0.1749 for *WR* (*CR1 SE* = 0.2464), –0.2359 for *RI* (*CR1 SE* = 0.2679), and +0.4397 for *ECS* (*CR1 SE* = 0.1733). Only *ECS* is nominally significant under *CR1* inference (*p* = 0.0181). The joint null that all three component coefficients equal zero is rejected, *F*(3, 24) = 5.663, *p* = 0.0044, and coefficient equality is also rejected, *F*(2, 24) = 8.133, *p* = 0.0020. *CRISIS* is omitted because it is not identifiable in this subsample.

In the decomposed lagged model *M4*, RI_{t-1} has a negative and nominally statistically significant coefficient (RI_{t-1} = –0.5109; *p* = 0.046), whereas ECS_{t-1} is positive but statistically insignificant (ECS_{t-1} = +0.2974; *p* = 0.192).

For the European comparison subsample in *M5*, *ECS* has a positive coefficient of +0.4581, with *CR1 p* = 0.0011 and an unadjusted *WCB p*-value of 0.0198. *RI* is positive but statistically insignificant, whereas *WR* is negative and statistically insignificant.

In the Ukrainian operating subsample *M6, RI* has a negative coefficient of –1.3716 (*CR1 p* = 0.0048; unadjusted *WCB p* = 0.017), whereas *WR* has a

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positive coefficient of +0.9425 (*CR1* p = 0.0078; unadjusted *WCB* p = 0.020). ECS is close to zero and statistically insignificant (β = +0.0183; p = 0.958). The *WR* and *RI* coefficients are supported by unadjusted *WCB* inference but do not survive Holm adjustment of the *CR1*-based p-values.

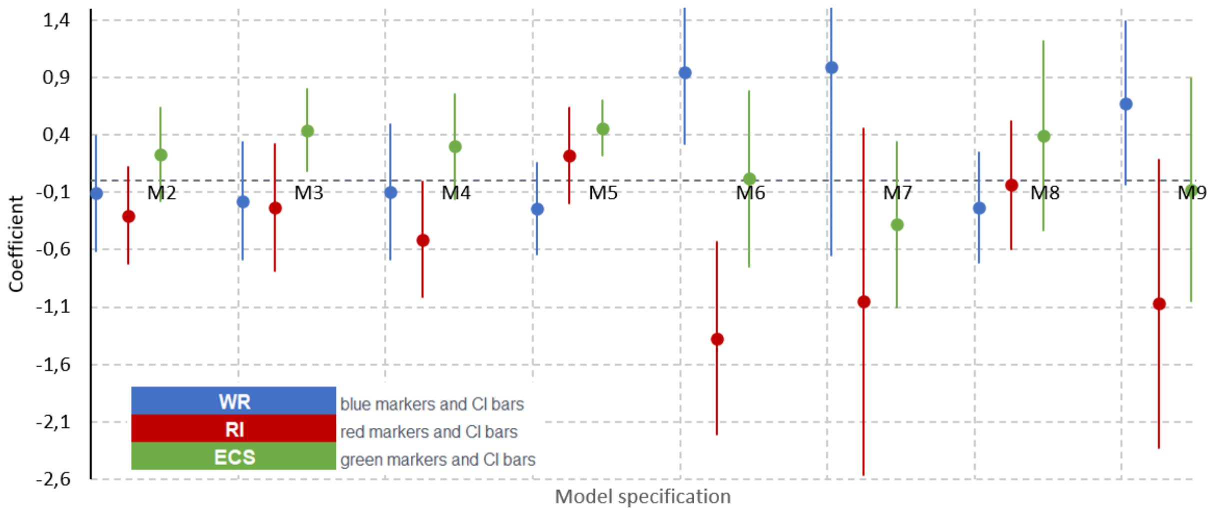
Models *M7* to *M9* report additional subsample estimates. In resource-intensive sectors (*M7*), *RI* is negative but statistically insignificant after enterprise-clustered correction (*RI* = –1.0515; p = 0.146), while *ECS* is also insignificant. In non-resource-intensive sectors (*M8*), *RI* is close to zero and statistically insignificant, and *ECS* is positive but statistically insignificant (*ECS* = +0.3935; p = 0.324). In the Ukrainian operating subsample excluding 2022–2023 (*M9*), *WR* is positive and marginally significant (*WR* = +0.6760; p = 0.061), *RI* is negative and marginally significant (*RI* = –1.0700; p = 0.085), and ECS is statistically insignificant. Neither *WR* nor *RI* is supported by wild-cluster-bootstrap inference in *M9*.

For specifications with 9-15 enterprise clusters, unadjusted wild-cluster-bootstrap inference supports the *ECS* coefficient in *M5* and the *WR* and *RI* coefficients in *M6*, but not the component coefficients in *M7* or *M9*. Separately, after Holm adjustment of the 25 CR1-based circularity-coefficient tests in *M1* to *M9*, only *ECS* in *M5* remains statistically significant: *CR1* p = 0.0011 and Holm-adjusted p = 0.0273. Its unadjusted *WCB* p-value is 0.0198. The *M5 ECS* result is therefore supported by two distinct robustness checks, whereas the remaining nominally significant coefficients are interpreted as model-specific or context-dependent.

Figure 2 provides a visual summary of the circularity component coefficients across model specifications *M2* to *M9*.

The formal tests and model diagnostics are summarized in Table D1.

Joint relevance is established in *M2* to *M6* but not in *M7* to *M9*. These tests assess whether the component coefficients are jointly zero and do not by themselves establish heterogeneity. Coefficient equality is not rejected in *M2* (p = 0.101) but is rejected in *M3* (p = 0.002); formal component heterogeneity is therefore sample-sensitive. The country-context interaction block is jointly significant (p = 0.042). *RI* × *UA* is the only individually significant interaction (β = –1.566; p = 0.038), whereas *WR* × *UA* is marginal and *ECS* × *UA* is insignificant. Equality among the three interaction shifts is not rejected (p = 0.138); therefore, the analysis does not establish that the *RI* shift is larger than



Note: Points show the estimated coefficients of WR, RI, and ECS. Vertical bars represent 95% confidence intervals calculated as $\beta \pm t_{0.975,G-1} SE_{CR1}$, where SECR1 is the enterprise-clustered standard error with the CR1 finite-sample correction. M4 reports one-period-lagged coefficients. Visual differences across separately estimated models are descriptive and should be interpreted together with the pooled interaction tests. WR denotes waste recovery and recycling share; RI, recycled input share; ECS, circularity-related eco-capex share.

Figure 2. Circularity component coefficients with 95% confidence intervals

the *WR* or *ECS* shifts. Resource-intensity interactions are not jointly significant (p = 0.179).

First, *ECS* remains positive and statistically significant in the balanced 2018–2023 common-support sample (β = +0.5396; p = 0.0251). This result shows that the positive association persists when all 25 enterprises are observed over the same six-year window; it does not demonstrate that the difference between *M2* and *M3* is caused solely by imputation status. The *IMP* interactions further indicate overlap with sample composition: *RI* × *IMP* is significant (β = +0.1015; p = 0.011), *ECS* × *IMP* is marginally significant (β = −0.4385; p = 0.063), and *WR* × *IMP* is insignificant. Imputation status and country-time composition therefore cannot be separated completely.

Second, when current and lagged components enter jointly, the lagged block is not jointly different from zero (p = 0.4073), and the restriction equating each current coefficient to its corresponding lagged coefficient is not rejected (p = 0.9655). These non-rejections do not demonstrate the absence or equality of dynamic associations because current-lag correlations are extremely high for *WR* (0.9980), *RI* (0.9989), and *ECS* (0.9917), limiting separate identification. The nominally significant lag-only *RI* estimate in *M4* is therefore treated as exploratory, and the analysis does not provide independently identified evidence of a delayed component effect.

The Hausman diagnostics do not reject the random-effects alternative in the two baseline comparisons: for *M1*, χ^2 = 4.437, df = 4, p = 0.350; for *M2*, χ^2 = 6.016, df = 6, p = 0.421. Fixed effects are nevertheless retained as the prespecified within-enterprise estimator. The residual *AR(1)* diagnostic indicates within-enterprise serial correlation, ρ = 0.371, p < 0.001. The Pesaran CD test does not indicate residual cross-sectional dependence, *CD* = −0.463, p = 0.643.

Table E1 reports the hypothesis-verification matrix. *H1* is rejected because *CI* is statistically insignificant. *H2* receives partial and sample-sensitive support, while *H2a* is context-dependent and its lag-only *RI* evidence is exploratory. The contemporaneous part of *H2b* receives partial support, whereas its delayed component is rejected. *H3* receives partial support from the jointly significant country-context interaction block. *RI* × *UA* is the only individually significant interaction, but equality among the three interaction shifts is not rejected; therefore, the analysis does not establish a statistically dominant component shift.

4. DISCUSSION

The aggregate organizational circularity index does not show a statistically identifiable short-term association with EBITDA margin, whereas *WR*, *RI*, and *ECS* display different coefficient profiles. This is consistent with evidence that aggregate indicators may combine practices, outcomes, and organizational capabilities with different purposes and implementation horizons (Elia et al., 2017; Moraga et al., 2019; Kristensen & Mosgaard, 2020; Vinante et al., 2021). Component equality is not rejected in *M2* but is rejected in non-imputed *M3*. Because these tests compare one-percentage-point changes on the original component scales, they do not establish differences in standardized effects or overall economic importance. *H2* therefore receives partial and sample-sensitive support.

RI has a predominantly negative coefficient profile, particularly in the lag-only and Ukrainian operating specifications, but its statistical support is not uniform. The *M4* result is exploratory because the lagged *RI* coefficient is not reproduced when current and lagged components enter simultaneously. In *M6*, *RI* is supported by unadjusted wild-cluster-bootstrap inference but does not survive Holm adjustment of the *CR1*-based p-values. The evidence therefore indicates a context-dependent association rather than a general negative effect of recycled-material use. Greater reliance on secondary inputs may coincide with sorting, quality-control, logistics, process-adaptation, and supplier-coordination costs. These mechanisms are consistent with evidence that circularity-performance associations vary by practice and implementation context (Yin et al., 2023; Pan et al., 2024; Mazzucchelli et al., 2022), but they are not identified here as causal channels.

ECS shows the most favorable coefficient profile. It is positive and nominally significant in the non-imputed model *M3* and statistically supported in the European comparison model *M5*. In *M5*, the coef-

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ficient remains significant under unadjusted wild-cluster-bootstrap inference and after Holm adjustment of the *CR1 p*-value, making it the strongest circularity-related result across *M1* to *M9*. This profile is consistent with interpreting *ECS* as a proxy for a circularity-related investment-modernization channel associated with technological renewal, process improvement, and production resilience (Bocken et al., 2016; Geissdoerfer et al., 2020; Fernandez de Arroyabe et al., 2021). However, *ECS* measures the circularity-related share of total capital expenditure rather than the absolute volume of circular investment. A higher *ECS* value may reflect an increase in circularity-related capex, a reduction in other capital expenditure, or both. Its coefficient is therefore interpreted as an association with the composition of capital expenditure. Reverse causality cannot be excluded because enterprises with stronger operating performance or financing capacity may be better able to allocate a larger share of their capital expenditure to circularity-related projects. *ECS* may also overlap with broader production-modernization expenditure, including technology and energy-efficiency upgrades that improve material use, process reliability, or production efficiency. The coefficients therefore represent conditional associations rather than identified causal effects of circular investment. Lagged *ECS* is insignificant, and the lagged component block is not jointly significant in the combined current-and-lag model. The contemporaneous part of *H2b* therefore receives partial support, whereas its delayed component is unsupported.

WR is insignificant in the full panel and non-imputed subsample but positive in the Ukrainian operating model. Although the *M6* coefficient is supported by unadjusted wild-cluster-bootstrap inference, it does not survive Holm adjustment and is therefore interpreted as context-specific. Waste recovery may be relevant where recovered streams reduce disposal requirements, substitute internal material demand, or are integrated into production and supply-chain routines (Zhu et al., 2011; Calzolari et al., 2021). The pooled country-context interaction block is jointly significant, providing partial support for *H3*. *RI* × *UA* is the only individually significant interaction, but equality among the three interaction shifts is not rejected. The results therefore identify a joint contextual difference without establishing that the *RI* shift is statistically larger than the *WR* or *ECS* shifts or that all three components differ between the subsamples. Formal sectoral heterogeneity remains unsupported.

The full-panel versus non-imputed comparison does not isolate a pure imputation-status effect. Excluding *IMP* = 1 observations strengthens the positive *ECS* coefficient, but these records are concentrated in the early years and mainly concern Ukrainian enterprises. The common-support and *IMP*-interaction results indicate that the difference between *M2* and *M3* reflects both imputation status and country-time composition. Because these dimensions overlap, their contributions cannot be separated completely. *M3* should therefore be interpreted as a combined imputation-status and sample-composition sensitivity finding, consistent with evidence that corporate circularity disclosures differ in completeness and comparability (Heras-Saizarbitoria et al., 2023; Vitolla et al., 2023).

Overall, the findings support analyzing organizational circularity through distinct recovery, material-substitution, and investment-modernization channels rather than relying solely on a composite indicator. Nevertheless, only *ECS* in the European comparison model survives the family-wise multiple-testing adjustment; the remaining results constitute model-specific or context-dependent evidence. The study is limited by its purposive sample of 25 large industrial enterprises, reporting-related selection, differences in corporate definitions and reporting boundaries, and the overlap between imputation status, country, and period. A one-period lag may not capture longer investment horizons, and the estimates should therefore be interpreted as conditional associations rather than causal effects.

CONCLUSION

This study examined whether organizational circularity and its individual components are associated with the operating performance of industrial enterprises in the Ukrainian operating and European comparison subsamples over 2013–2023. The aggregate circularity index has no statistically identifiable short-term association with EBITDA margin, so *H1* is rejected. Component equality is not rejected in the full-panel model *M2* but is rejected in the non-imputed model *M3. H2* therefore receives partial and sample-sensitive support and should not be interpreted as stable across alternative sample definitions.

The component-level findings differ in statistical strength. *RI* has a predominantly negative profile, but its Ukrainian association does not survive Holm adjustment, and the lag-only result is not reproduced in the combined current-and-lag specification. *ECS* is positive in *M3* and *M5*. The European comparison result is the strongest finding because it is supported separately by unadjusted *WCB* inference (p = 0.0198) and Holm-adjusted *CR1* inference (p = 0.0273). The analysis does not support an independently identified delayed *ECS* association. *WR* is positive in the Ukrainian model but remains specification-sensitive and is not Holm-robust. The jointly significant country-context interaction block provides partial support for *H3*. *RI* × *UA* is the only individually significant interaction, but the tests do not establish that its shift is statistically larger than those of *WR* or *ECS*.

The findings indicate that recovery, material-substitution, and investment-modernization measures should be assessed separately rather than assumed to have equivalent performance-related associations. The estimates nevertheless represent conditional associations rather than causal effects. *ECS* may partly capture broader technological modernization, more profitable enterprises may have greater capacity to finance circular investment, and differences between the full panel and non-imputed subsample reflect both imputation status and country-time composition. Further research should use larger and more representative samples, more granular source data, longer observation periods, and stronger causal-identification designs.

AUTHOR CONTRIBUTIONS

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APPENDIX A

Table A1. Sample selection and panel construction algorithm

Selection stage	Screening criterion	Enterprises remaining
Initial search frame	Large industrial enterprises with potentially relevant circular transformation practices	126
Reporting availability	Publicly available financial and sustainability / ESG / integrated / regulatory disclosures	74
Circularity-data availability	Data allowing *WR, RI*, and *ECS* to be constructed, reconstructed, or classified under the study protocol	39
Boundary and consistency check	Financial and non-financial reporting boundaries could be reconciled or reasonably matched	31
Final analytical panel	Balanced panel suitable for model estimation over 2013–2023	25

Table A2. Operational harmonization and data-status rules for circularity components

Component / Included in the indicator	Excluded from the indicator	Data-status rule and *M3* eligibility
WR – waste recovery and recycling share. $$WR_{i,t}=\frac{WasteRecovered_{i,t}}{WasteTotal_{i,t}}\cdot 100$$ Reused, recycled, recovered, or diverted-from-disposal production waste when a recovery route was disclosed	Waste sent to landfill or disposal; wastewater; emissions; qualitative waste-management statements without quantitative evidence; by-products not clearly classified as recovered or reused waste	Directly reported or transparently reconstructed values were accepted under the component protocol. *M3* eligibility was determined by *IMP* = 0
RI – recycled input share. $$RI_{i,t}=\frac{SecondaryInput_{i,t}}{MaterialInput_{i,t}}\cdot 100.$$ Secondary raw materials, recycled feedstock, scrap, recovered materials, or recycled input materials used as substitutes for primary material inputs	Internal waste recovery that did not substitute production input; qualitative references to circularity without a material-input denominator; fuel substitution unless explicitly reported as material input; by-products reused without evidence of primary material substitution	Direct percentages or transparent material-input reconstructions were accepted under the component protocol. *M3* eligibility was determined by *IMP* = 0
ECS – circularity-related eco-capex share. $$ECS_{i,t}=\frac{EcoCapex_{i,t}}{Capex_{i,t}}\cdot 100.$$ Capital expenditure linked to resource saving, recycling or recovery infrastructure, waste reduction, material-efficiency improvement, secondary material utilization, resource-loop closure, or process modernization reducing material or production losses. Energy-efficiency investments were included only when directly connected to circular resource flows	General environmental administration, reporting costs, philanthropy, routine compliance costs, compensation payments, non-production environmental activities, broad environmental spending without identifiable circularity-related content, and general energy-efficiency investments unrelated to circular resource flows	Circularity-related capex was accepted when it could be isolated or transparently reconstructed. *M3* eligibility was determined by *IMP* = 0

Note: WasteRecovered$_{i,t}$ denotes the quantity of production waste reused, recovered, recycled, or otherwise returned to economic circulation by enterprise i in year *t*; *WasteTotal*$_{i,t}$ is total production waste generated; *SecondaryInput*$_{i,t}$ is the quantity of secondary materials used as substitutes for primary inputs; *MaterialInput*$_{i,t}$ is total material input; *EcoCapex*$_{i,t}$ is identifiable circularity-related capital expenditure; and *Capex*$_{i,t}$ is total capital expenditure. All formulas are expressed as percentages. *M3* comprises the 220 firm-year observations with *IMP* = 0. *IMP* is a firm-year indicator and does not identify the specific variable affected by imputation.

APPENDIX B

Table B1. Enterprise-level provenance of circularity components in the non-imputed subsample, 2013–2023

Enterprise	Main sources: financial / circularity	*WR*, *IMP* = 0	*RI*, *IMP* = 0	*ECS*, *IMP* = 0	*IMP* = 1 firm-years	*IMP* = 0 firm-years
Metinvest Group	AR; audited CFS / SR; GRI	V(3), R(3)	V(2), R(4)	V(1), R(5)	5	6
Ferrexpo Plc	AR&A / RB; GRI	V(4), R(2)	V(2), R(4)	V(1), R(5)	5	6
Kernel Holding S.A.	AR; IFRS FS / SR; ESG	V(3), R(3)	V(2), R(4)	V(1), R(5)	5	6
DTEK Energy	AR; CFS / SR; ESG	V(2), R(4)	V(1), R(5)	V(2), R(4)	5	6
MHP SE	AR; IFRS FS / SR; ESG	V(3), R(3)	V(2), R(4)	V(1), R(5)	5	6
Astarta Holding PLC	AR; IFRS FS / SR; ESG	V(3), R(3)	V(2), R(4)	V(1), R(5)	5	6
Ukrnafta PJSC	AR; audited FS / ER; SR	V(2), R(4)	V(1), R(5)	V(2), R(4)	5	6
Farmak JSC	AR; FS / SR; ESG	V(3), R(3)	V(1), R(5)	V(1), R(5)	5	6
IMC Agro SA	AR; IFRS FS / SR; ESG	V(2), R(4)	V(1), R(5)	V(1), R(5)	5	6
Energoatom SE	AR; FS / NFR; ER	V(3), R(3)	V(1), R(5)	V(2), R(4)	5	6
ArcelorMittal S.A.	AR; FS / SR; climate; GRI	V(7), R(4)	V(8), R(3)	V(2), R(9)	0	11
Holcim AG	AR; FS / SR; ESG	V(7), R(4)	V(7), R(4)	V(2), R(9)	0	11
HeidelbergMaterials AG	AR; FS / SR; ESG	V(6), R(5)	V(6), R(5)	V(2), R(9)	0	11
Veolia Environnement	URD / URD; ESG annexes	V(8), R(3)	V(4), R(7)	V(3), R(8)	0	11
Umicore NV/SA	AR; IR / IR; SR	V(7), R(4)	V(8), R(3)	V(3), R(8)	0	11
Renewi Plc	AR&A / SR; ESG	V(9), R(2)	V(5), R(6)	V(2), R(9)	0	11
Stora Enso Oyj	AR; FS / SR; GRI	V(7), R(4)	V(8), R(3)	V(2), R(9)	0	11
BASF SE	AR; FS / AR; SR; NFS	V(6), R(5)	V(5), R(6)	V(3), R(8)	0	11
Enel SpA	AR; FS / SR; ESG	V(6), R(5)	V(3), R(8)	V(3), R(8)	0	11
UPM-Kymmene Oyj	AR; FS / AR; SR; GRI	V(7), R(4)	V(8), R(3)	V(2), R(9)	0	11
Covestro AG	AR; FS / SR; NFR	V(5), R(4)	V(5), R(4)	V(2), R(7)	2	9
Befesa S.A.	AR; FS / SR; ESG	V(6), R(2)	V(6), R(2)	V(2), R(6)	3	8
Plastic Omnium SE	URD / URD; CSR; ESG	V(5), R(6)	V(6), R(5)	V(2), R(9)	0	11
LANXESS AG	AR; FS / SR; GRI	V(6), R(5)	V(4), R(7)	V(3), R(8)	0	11
ENGIE SA	URD / IR; SR; ESG annexes	V(6), R(5)	V(3), R(8)	V(3), R(8)	0	11
Total		V(126), R(94)	V(101), R(119)	V(49), R(171)	55	220

Note: Sources before and after the slash refer to financial and circularity-related data, respectively. V denotes directly reported values, and R denotes values transparently reconstructed from disclosed quantitative components. These counts refer to the 220 firm-year observations with IMP = 0. IMP = 1 indicates that at least one non-financial input was imputed. Because variable-specific imputation flags are unavailable, the 55 IMP = 1 observations are reported only at the firm-year level and are not allocated to WR, RI, or ECS. AR – annual report; AR&A – annual report and accounts; FS – financial statements; CFS – consolidated financial statements; SR – sustainability report; RB – Responsible Business report; ER – environmental report; IR – integrated report; NFR/NFS – non-financial report or statement; URD – Universal Registration Document. Exact source or page references were not recoverable for all observations.

APPENDIX C

Table C1. Main panel regression results (M1 to M9)

Variable	M1	M2	M3	M4	M5	M6	M7	M8	M9
CI	+0.022								
	(0.165)								
WR		–0.111	–0.175		–0.243	+0.942**	+0.989	–0.234	+0.676
		(0.243)	(0.246)		(0.184)	(0.277)	(0.711)	(0.224)	(0.315)
RI		–0.302	–0.236		+0.221	–1.372**	–1.051	–0.037	–1.070
		(0.204)	(0.268)		(0.195)	(0.370)	(0.653)	(0.261)	(0.554)
ECS		+0.230 (0.198)	+0.440* (0.173)		+0.458** (0.112)	+0.018 (0.338)	–0.382 (0.313)	+0.393 (0.386)	–0.077 (0.429)
WR_{t-1}				–0.098					
				(0.284)					

Table C1 (cont.). Main panel regression results (M1 to M9)

Variable	M1	M2	M3	M4	M5	M6	M7	M8	M9
RI_{t-1}				−0.511*					
				(0.243)					
ECS_{t-1}				+0.297					
				(0.222)					
GHGint	−0.744	−0.365	−0.068	−0.255	+0.524	−1.271	−1.235	+0.601	−2.265
	(0.750)	(0.612)	(0.965)	(0.787)	(1.064)	(0.930)	(0.911)	(1.707)	(1.626)
ETS					+0.004				
					(0.028)				
WAR	−5.411**	−7.231**	−7.180**	−7.506**		−6.565**	−10.530*	−5.957**	
	(1.892)	(2.114)	(2.009)	(2.171)		(2.011)	(4.138)	(1.621)	
CRISIS	−2.556*	-1.247	omitted	+0.058		−2.085*	−1.322	−1.376	−2.452***
	(0.926)	(0.814)		(1.164)		(0.646)	(1.557)	(0.820)	(0.480)
COVID					−0.341	−0.077			+0.211
					(0.467)	(1.510)			(1.661)
Enterprise FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No	No	Yes	Yes	No
N	275	275	220	250	165	110	99	176	90
Firms / clusters	25	25	25	25	15	10	9	16	10
Total R^2	0.9037	0.9100	0.9019	0.9104	0.8249	0.8982	0.8947	0.9302	0.9242
Adjusted R^2	0.8882	0.8946	0.8806	0.8937	0.8006	0.8807	0.8605	0.9152	0.9089

Note: Coefficients are reported with enterprise-clustered CR1 standard errors in parentheses. CI – aggregate organizational circularity index; WR – waste recovery and recycling share; RI – recycled input share; ECS – circularity-related eco-capex share; WRt-1, and ECSt−1 – one-period-lagged circularity components; GHGint – greenhouse-gas intensity; ETS – EU ETS allowance price; WAR – indicator for Ukrainian enterprises in 2022–2023; CRISIS – indicator for Ukrainian enterprises in 2014–2015; COVID – pandemic-period indicator. M1 – aggregate CI model; M2 – full-panel decomposed model; M3 – non-imputed subsample (IMP = 0); M4 – lag-only specification; M5 – European comparison subsample; M6 – Ukrainian operating subsample; M7 – resource-intensive sectors; M8 – non-resource-intensive sectors; M9 – Ukrainian operating subsample excluding 2022–2023. CRISIS is omitted from M3 before calculation of the CR1 finite-sample correction. Significance symbols refer to CR1 p-values: *** p < 0.001; ** p < 0.01; * p < 0.05; p < 0.10. WCB p-values are based on restricted null-imposed wild-cluster-bootstrap-t inference with enterprise clustering, Webb six-point weights, 9,999 replications, CR1 studentisation, and seed 20260727.

APPENDIX D

Table D1. Formal tests and model diagnostics

Test group	Model / test	Statistic or coefficient	df / SE	*p*-value
Joint relevance	*M2: WR, RI, ECS* jointly zero	4.312	3, 24	0.014
Joint relevance	*M3: WR, RI, ECS* jointly zero	5.663	3, 24	0.0044
Joint relevance	*M4:* lagged *WR, RI, ECS* jointly zero	5.502	3, 24	0.005
Joint relevance	*M5: WR, RI, ECS* jointly zero	7.026	3, 14	0.004
Joint relevance	*M6: WR, RI, ECS* jointly zero	4.806	3, 9	0.029
Joint relevance	*M7: WR, RI, ECS* jointly zero	1.560	3, 8	0.273
Joint relevance	*M8: WR, RI, ECS* jointly zero	1.296	3, 15	0.312
Joint relevance	*M9: WR, RI, ECS* jointly zero	1.660	3, 9	0.244
Coefficient equality	M2: WR = RI = ECS	2.522	2, 24	0.101
Coefficient equality	M3: WR = RI = ECS	8.133	2, 24	0.0020
Country-context interactions	Ukrainian interactions jointly zero	3.174	3, 24	0.042
Country-context interactions	RI × UA	–1.566	0.712	0.038
Country-context interactions	WR × UA = RI × UA = ECS × UA	2.154	2, 24	0.138
Sectoral interactions	Resource-intensity interactions jointly zero	1.774	3, 24	0.179
Temporal current-lag tests	Combined current-and-lag model: lagged block jointly zero	1.006	3, 24	0.407

Table D1 (cont.). Formal tests and model diagnostics

Test group	Model / test	Statistic or coefficient	df / SE	*p*-value
Temporal current-lag tests	Combined current-and-lag model: current coefficients equal corresponding lagged coefficients	0.089	3, 24	0.965
Residual serial correlation	AR(1), H0: ρ = 0	0.371	0.092	<0.001
Cross-sectional dependence	Pesaran *CD, H0:* cross-sectional independence	–0.463	–	0.643
Hausman diagnostic	*M1 CI* model	4.437	4	0.350
Hausman diagnostic	*M2* components model	6.016	6	0.421

Note: For F-tests, the df / SE column reports numerator and denominator degrees of freedom. For individual coefficient rows, the df / SE column reports the corresponding CR1 standard error. M3 statistics are based on the estimable model after CRISIS is omitted. The M4 joint-relevance test refers to the lag-only specification, whereas the temporal current-and-lag tests refer to the combined specification including current and lagged circularity components simultaneously. Hausman diagnostics are reported as chi-square statistics.

APPENDIX E

Table E1. Hypothesis verification based on panel model estimates and formal tests

Hypothesis	Empirical result	Model specifications / Decision
H1: The aggregate index of organizational circularity has a statistically identifiable association with enterprise economic performance	In *M1, CI* is positive but insignificant: *β* = +0.0222, *CR1 SE* = 0.1651, *p* = 0.894	*M1*. Not supported in the short term
H2: The associations between organizational circularity components and the economic performance of an industrial enterprise are heterogeneous, since individual components differ in the direction and magnitude of their coefficients	Coefficient equality is not rejected in *M2, F*(2, 24) = 2.522, *p* = 0.101, but is rejected in non-imputed *M3, F*(2, 24) = 8.133, *p* = 0.0020	*M2-M3*. Partially supported; heterogeneity is sample-sensitive
H2a: An increase in the share of secondary inputs in the enterprise's resource structure is associated with a decline in its short-term economic performance	*RI* is negative and nominally significant in *M4* (*p* = 0.046) and supported by *CR1* and *WCB* in *M6 (CR1 p* = 0.0048; *WCB p* = 0.0166), but neither result survives Holm adjustment. The *M4* result is not reproduced in the combined current-and-lag model	*M2-–M9*; current-and-lag robustness. Limited context-specific support; not family-wise robust
H2b: A higher share of circularity-related eco-capex is positively associated with enterprise economic performance, with a possible delayed profile	*ECS* is nominally significant in non-imputed *M3* (*p* = 0.0181). *M5* is supported by *CR1, WCB*, and Holm inference (*β* = +0.4581; *WCB p* = 0.0198; Holm *p* = 0.0273). Lagged *ECS* and the lagged block are insignificant (*p* = 0.407)	*M3, M5* and current-and-lag robustness. Contemporaneous association partially supported; delayed component unsupported
H3: The associations between organizational circularity components and enterprise economic performance differ between enterprises in the Ukrainian operating and European comparison subsamples	The country-context interaction block is jointly significant, *F*(3, 24) = 3.174, *p* = 0.042. *RI × UA* is the only individually significant interaction (*β* = –1.566; *p* = 0.038), but equality among the three interaction shifts is not rejected (*p* = 0.138)	*M5-M6*; pooled interaction model. Partially supported; a joint contextual difference is identified, without a statistically dominant component shift
Sectoral heterogeneity check	Resource-intensity interactions are not jointly significant, *F*(3, 24) = 1.774, *p* = 0.179	*M7-M8*; pooled sector-interaction model. Not supported

Note: Enterprise economic performance is operationalized through EBITDA margin. M3 is the non-imputed subsample with IMP = 0. CR1 provides the main inference; WCB is an unadjusted small-cluster robustness check, and Holm adjustment addresses multiple testing across M1 – M9. Coefficient-equality tests compare one-percentage-point changes in WR, RI, and ECS on their original scales.

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