QUANTIFYING THE ECONOMIC EFFECTS OF CIRCULAR ECONOMY PRACTICES IN MANUFACTURING: A CASE STUDY OF BRIDGESTONE'S TATABÁNYA PLANT

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Abstract

Manufacturing firms face increasing pressure to decouple growth from resource consumption, prompting the adaptation of circular economy practices that offer environmental and economic benefits. Nonetheless, limited studies connect these efforts to real cost outcomes, leaving questions about which efficiency strategies promote savings, how performance aligns with strategic goals, and whether sustainability initiatives provide lasting financial benefits. To address this gap, the study uses a 111-month panel (January 2016-March 2025) of production, environmental, and cost data from Bridgestone's Tatabánya plant. It then applies three methods within one analysis: log-difference ordinary least squares regressions to assess cost sensitivities, seasonal time-series forecasting to benchmark carbon dioxide and waste-recovery trends, and interrupted time series with local projections to isolate the impacts of four major initiatives. The findings show that increases in throughput consistently reduce material and consumables costs, and higher carbon dioxide intensity and electricity use increase operating and maintenance expenses. First-pass yield has a minor positive influence on material cost, while waste recovery shows no impact. The plant also surpassed its carbon dioxide intensity and waste-recovery targets years ahead of schedule, with only the EXAMATION rollout and carbon dioxide reduction milestone producing significant slowdowns in cost growth. In identifying which circular initiatives reduce expenses, this work emphasizes their impact on operations and underlines the importance of tracking these measures in standard production and financial reviews.

Author's Declaration

I, the undersigned, **Mervó-Kovács Naomi**, candidate for the BA/BSc degree in Data Science and Society declare herewith that the present thesis is exclusively my own work, based on my research and only such external information as properly credited in notes and bibliography. I declare that no unidentified and illegitimate use was made of the work of others, and no part of the thesis infringes on any person's or institution's copyright.

I also declare that no part of the thesis has been submitted in this form to any other institution of higher education for an academic degree.

Vienna, 21 May 2025

Naomi Mervó-Kovács

Table of Contents

List of Figures

List of Abbreviations

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller test
AI	Artificial Intelligence
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA	Autoregressive Moving Average
BIC	Bayesian Information Criterion
BP	Breusch-Pagan test
CE	Circular Economy
CO_2	Carbon Dioxide
DW	Durbin-Watson statistic
HC3	Heteroskedasticity-consistent (Type 3) robust standard errors
H1-H5	Hypotheses 1 through 5
HUF	Hungarian Forint
ITS	Interrupted-Time-Series analysis
JB	Jarque-Bera test
KPI(s)	Key Performance Indicator(s)
KPSS	Kwiatkowski-Phillips-Schmidt-Shin test
LB	Ljung-Box test
MAE	Mean Absolute Error
OLS	Ordinary Least Squares
PACF	Partial Autocorrelation Function
Q-Q	Quantile-Quantile plot
RRT	Reference Rubber Tonne

RMSE	Root-Mean-Square Error
ROCV	Rolling-Origin Cross-Validation
SARIMA	Seasonal Autoregressive Integrated Moving Average
SARIMAX	Seasonal ARIMA with eXogenous variables
SUV	Sport Utility Vehicle
VIF(s)	Variance-Inflation Factor(s)

Introduction

Under growing pressure to 'do more with less'[2], manufacturers are rethinking linear "take-make-dispose" models in favor of circular economy (CE) strategies that narrow inputs, slow product turnover, and close resource loops (Blomsma & Brennan 2017). Nowhere is this shift more urgent than in the tire industry, where volatile raw material prices and increasing environmental liabilities intersect to threaten both profitability and reputation. Bridgestone's Tatabánya plant in Hungary, operational since 2008, has steadily adopted such CE innovations. Their artificial intelligence (AI) driven process optimization system (EXAMATION) calibrates mixing and curing operations in real time, the lightweight ENLITEN compounds reduce the amount of rubber and filler needed per tire, and on-site renewable energy sourcing decreases the plant's carbon dioxide (CO_2) footprint (Bridgestone 2024). Together, these initiatives support the annual production of over 7.2 million passenger, sport utility vehicle (SUV), and van tires, demonstrating how digital and material-efficiency projects can coexist on a heavy manufacturing production floor (Denys 2019; Bridgestone 2024).

This thesis focuses solely on the Tatabánya facility to explore how its internal performance metrics map onto actual cost outcomes. Based on 111 monthly observations (January 2016-March 2025) from Bridgestone's Operational Excellence scorecards and its SAP S/4HANA enterprise resource planning ledger, the study examines three cost categories, including direct materials, consumables and process inputs, and maintenance, and eight key performance indicators (KPI): CO_2 intensity, energy consumption, fuel use, water use, waste-recovery rate, first-pass yield, total incident rate, and monthly tire output. To ensure consistent comparisons, every variable is normalized per reference-rubber tonne (RRT), a unit that converts mixed tire

[2] Widely used circular economy slogan, not taken from Blomsma & Brennan (2017).

outputs into equivalent tonnes of rubber processed and transformed using log or logit differences so that trends and relationships remain statistically robust over time.

Although CE scholarship now offers numerous distinct "circular" indicators, it rarely connects those metrics to real cost or revenue data at the plant level (Harris et al. 2021). Similarly, Leipold et al. (2021) show that most studies only list environmental, economic, and social KPIs without connecting them to real financial results at the plant, leaving practitioners uncertain about the actual cost or revenue impact. Furthermore, most empirical investigations rely on short-term, retrospective datasets that are too brief to reveal rebound effects or assess the durability of any gains (Harris et al. 2021). Findings across the literature are scattered and uneven: indicator frameworks are inconsistent, study windows are short, data sources lack clarity, and the geographic focus is narrow, skewing heavily toward Western Europe and East Asia despite the global nature of manufacturing (Aljamal et al. 2024). This thesis addresses these four gaps by analyzing a long, paired panel of KPI and ledger data from a single, high-volume plant, offering a clear view of how circular interventions affect cost and revenues in practice.

To frame the analysis, the dissertation poses five research questions. The first three explore how Tatabánya's operational and environmental KPIs influence its cost structure: the first focuses on direct-material cost per RRT, the second on consumables and process-input expenses per RRT, and the third on maintenance outlays per RRT. The fourth projects CO_2 intensity and waste-recovery trends through 2030 to evaluate whether they will meet Bridgestone's Milestone 2030 targets: a 50% reduction in CO_2 intensity from the 2011 baseline and a 40% waste-recovery rate. The fifth question examines the causal cost impacts of four CE-promoting initiatives, including the 2017 rollout of EXAMATION, the 2019 introduction of ENLITEN compounds, and the fulfillment of Milestone 2030 targets.

The thesis is organized into five main sections. Section 1 reviews how CE ideas have moved beyond traditional linear models and then considers the benchmarks used to track progress. It links resource-focused KPIs to financial outcomes, uses the Bridgestone Tatabánya plant as a detailed case study, and concludes by identifying gaps in the existing literature. Section 2 outlines the research design, describing how operational KPIs and financial variables were defined and constructed. It then presents the analytical framework that links monthly KPI changes to cost outcomes, projects future performance targets, and assesses the impact of CE-promoting initiatives, with diagnostic checks ensuring the validity of each method. Section 3 presents the empirical findings, beginning with the regressions that connect KPIs to cost outcomes, then moving to the forecasts of CO_2 intensity and waste recovery through 2030, and concluding with the analysis of CE-promoting initiatives' impacts on costs, all supported by robustness checks. Section 4 discusses the results in light of CE theory and practice, shows how scale, energy use, and loop-closing actions influence cost, explores policies that could accelerate adoption, and then describes the study's limitations and paths for future research. Section 5 combines the findings into a conclusion, turning them into actionable steps, and presents the Tatabánya method as a practical template for embedding circular metrics into day-to-day decisions.

1 Literature Review

1.1 From Linear Logic to Circular Thinking

Linear "take-make-dispose" systems are increasingly challenged for relying on finite resources and generating growing amounts of waste. In response, CE models emerged, aiming to keep materials in use at their highest possible value for as long as feasible (Blomsma & Brennan, 2017). CE thought is far from homogenous, as shown by Kircherr et al. (2023), who identified 221 distinct definitions, demonstrating the concept's consolidation and ongoing dispersion. However, most definitions share a common focus on designing out waste across the entire life cycle by reducing resource inputs, extending product lifetimes, and looping materials back through reuse, remanufacturing, and recycling, thereby decoupling value creation from virgin extraction (Morseletto 2020). Therefore, rather than framing CE as a minor efficiency adjustment, scholars present it as a systemic, regenerative option that relates environmental responsibility with economic value creation.

For manufacturers, implementing this concept involves three strategies: reducing inputs, extending product life, slowing turnover, and reusing and recycling materials. Delivering these strategies requires coordinated innovation in product design, supply logistics, and the business model itself (Bocken et al. 2016). In practical terms, this can involve selecting wear-resistant materials, designing modular parts for easy repair or replacement, and testing durability to ensure long product lifespans (Sakao et al. 2024). Put simply, moving from linear to circular manufacturing is about rethinking how value is created, delivered, and recaptured across the industrial system.

1.2 Benchmarks for Circular Progress

Reliable measurement turns circular rhetoric into operational change. A scoping review of dozens of "circular" metrics across company reports, academic papers, and policy dashboards found that most remain limited to a single scale and overlook ripple effects beyond the factory gate (Harris et al. 2021). To reduce complexity, researchers call for more streamlined indicator sets or key performance indicators (KPIs) that capture what matters: how materials flow through the system, whether those flows reduce environmental footprints, and how trade-offs unfold over time (Aljamal et al. 2024). Nevertheless, critics note that a dashboard can show rising recycling percentages even as total material use keeps climbing, defeating the purpose of circularity (Leipold et al. 2021). A clear takeaway is that benchmarks must monitor material flows across life cycles, connect them to environmental outcomes, and guarantee transparency around system boundaries.

1.3 From Resource KPIs to Financial Results

The organizational value of CE efforts lies in their ability to generate economic returns. Aljamal et al.'s (2024) social network analysis groups circular metrics into five main clusters, including material efficiency, remanufacturing productivity, technology investment, eco-innovation, and strategies/initiatives, showing these as the most influential for advancing circularity at the plant level. Sakao et al. (2024) then frame CE within the 'narrow, slow, close' logic, stressing that measurement should account for environmental and economic outcomes to support balanced decision-making. These elements align directly with a tire factory's profit drivers, including avoided raw material purchases through CE practices, lower utility costs enabled by energy efficiency projects minimized environmental liabilities through comprehensive waste management and zero landfill initiatives, and more affordable sustainability-linked financing supported by strong performance and alignment with recognized international standards (Brisa 2024).

Evidence from the industry supports this perspective. Across 241 Tire Industry Project sites, water intensity has decreased by 41 % between 2009 and 2021, energy intensity fell from 10.8 to 9.4 gigajoules per ton (a 13 % reduction), and CO_2 intensity declined by approximately 30%, despite a rebound in production after the COVID-19 pandemic (Tire Industry Project 2022). These operational gains coincide with stronger financial performance. Brisa (2024) reported a 38% increase in operating profit in 2023, driven by production and commercial efficiency, while ongoing circular economy efforts such as waste reduction, energy savings, and zero landfill practices, along with a sustainability-linked loan, support longer-term financial resilience and operational value creation. This reinforces that KPIs reflect more than operational progress, thus demonstrating how resource strategies translate into measurable financial outcomes across production systems.

1.4 Case Context: Bridgestone Tatabánya Plant

Bridgestone Tatabánya was approved in 2005, broke ground in 2006, and produced its first Turanza tire in 2008 (Bridgestone Tatabánya Plant 2023). The plant covers 659,000 square meters and combines automated BIRD cells, each able to build several sizes simultaneously, with a newer BIRD X line that supports premium small-lot orders (Bridgestone Tatabánya Plant 2023). A 2016 upgrade installed the EXAMATION AI system (June 2017), which tracks hundreds of process variables in real-time and applies big-data analytics to lift uniformity and cut energy use (Bridgestone 2016; Bridgestone Tatabánya Plant 2023). Together with successive smart-factory investments, these technologies have increased annual production to over 7.2 million passenger, sport utility vehicle (SUV), and van tires, produced by a workforce of roughly 1,300 (Denys 2019). Tatabánya also serves as Bridgestone's European launch site for ENLITEN (July 2019) lightweight construction, which relieves raw material demand and rolling resistance so vehicles emit less carbon without sacrificing performance (Bridgestone 2024; Bridgestone Tatabánya Plant 2023).

Corporate climate and circularity milestones give Tatabánya a clear direction. Bridgestone's Milestone 2030 requires a 50% absolute reduction in carbon emissions from the 2011 baseline and a 40% share of recycled materials by 2030, setting the course toward net-zero emissions and fully sustainable materials in 2050 (Bridgestone 2020; Bridgestone Tatabánya Plant 2023). These targets sit within the broader E8 Commitment, an eight-pillar pledge that ties energy, ecology, efficiency, extension, economy, emotion, ease, and empowerment to long-term business value (Bridgestone EMEA 2022).

Tatabánya is already on track. The plant switched to certified renewable electricity in 2020, has reported a double-digit decrease in carbon intensity and water withdrawal, and now recycles more than three-quarters of its production waste (Japan Times 2021; Bridgestone Tatabánya Plant 2023). High output, detailed production data, and circular objectives make the site ideal for testing whether resource KPIs translate into measurable financial gains, a topic explored in the following sections.

1.5 Limitations of Existing Studies

Although CE research is expanding quickly, four gaps remain. First, the field is conceptually fragmented. Even after Kirchherr et al. (2023) identified 221 competing CE definitions, many empirical papers continue to apply custom boundaries, making it difficult to compare findings across studies. Second, the time depth of studies is limited. Harris et al. (2021) find that most research is retrospective and rarely tracks indicators over time, which limits understanding of whether early gains persist or are later offset by unintended consequences. Third, transparency is insufficient. Leipold et al. (2021) show that self-selected indicators often obscure trade-offs between physical flows and financial outcomes, while Aljamal et al. (2024) note that most plant-level metrics stop at reporting physical changes and rarely show how these translate into concrete financial outcomes. Fourth, geographic coverage is not globally representative. Most macro and meso level frameworks originate in China, the first country to adopt CE in national policy, or in European countries such as Sweden, the Netherlands, the United Kingdom and France, resulting in a strong regional bias toward East Asia and Western Europe despite the global nature of manufacturing (Aljamal et al. 2024).

This thesis responds by using a monthly panel drawn from Bridgestone Tatabánya's internal operational and financial records covering January 2016 to March 2025. More than nine years of continuous observations provides the time depth that earlier studies lack, while direct access to the plant's data infrastructure allows for consistent and verifiable insights. The Hungarian case also introduces Central-European evidence into a debate still dominated by Western and East-Asian examples. Consequently, the study can assess how resource efficiency influences the plant's cost structure, an area that has not been thoroughly explored in many CE studies.

2 Methodology

2.1 Research Design

The analysis begins with almost a decade of monthly metrics collected from Bridgestone's Tatabánya factory. Since 2016, the factory has layered digital and resource efficiency projects onto a steady premium tire portfolio, bringing the EXAMATION AI online in 2017, phasing in ENLITEN lightweight compounds from 2021, and switching to certified renewable electricity in 2020 (Bridgestone Tatabánya Plant 2023). Each month, an internal scorecard logs operational and environmental KPIs, and the SAP ledger records matching cost figures on the same calendar. Combining the two sources gives 111 monthly observations, enough time depth to follow learning effects and rebound patterns while avoiding the variability a multi-plant sample would introduce. All output and cost variables are normalized per RRT, a unit that converts any mix of tire sizes into the equivalent of one tonne of rubber processed.

This study presents five research questions to address the gaps identified in the literature review. The first three test how KPIs affect Tatabánya's current cost structure, while the final two explore progress toward Bridgestone's Milestone 2030 targets and the financial impacts of CE-promoting initiatives.

Hypothesis 1 (H1) questions whether stronger resource efficiency, measured in higher first-pass yield, lower scrap, more waste recovered, a lighter carbon footprint, and the scale effect of volume growth, reduces direct material cost per RRT. The expectation is a cost decline for every efficiency gain, whereas the statistical null maintains that material cost remains unchanged.

Hypothesis 2 (H2) moves to consumable and process spending. It inserts electricity use, fuel use, water use, and the material cost alongside the efficiency measures from H1 to see whether these inputs lower Tatabánya's monthly outlays on steam, solvents, and auxiliary materials.

The expectation is a downward cost response, whereas the statistical null predicts no systematic effect.

Hypothesis 3 (H3) examines maintenance cost. It combines safety performance, waste recovery, carbon intensity, and throughput to evaluate whether safer and more circular operations shorten unplanned downtime and parts usage. The expectation is lower maintenance expenditure, whereas the statistical null rules out any consistent link.

Hypothesis 4 (H4) asks whether Tatabánya's month-by-month record of carbon intensity and waste recovery since 2016 is steep enough to hit Bridgestone's Milestone 2030 pledges of a 50% reduction from a 2011 carbon baseline and a 40% waste-recovery rate (Bridgestone Tatabánya Plant 2023). The expectation is that forecasts will hit or exceed both thresholds, while the statistical null states that at least one target will be missed.

Building on H4's projection that Tatabánya will meet its 2030 carbon-reduction and waste-recovery targets, Hypothesis 5 (H5) tests whether these achievements and two earlier interventions (EXAMATION and the ENLITEN technologies) have generated causal declines in material, consumables, and maintenance costs. The expectation is that each cost category exhibits a sustained downward shift in its growth trajectory following the attainment of these milestones, whereas the statistical null states that none of these events produces a measurable impact on costs.

These questions form the primary focus of the thesis, using Tatabánya as a case study to explore the financial viability of circular approaches.

2.2 Data and Confidentiality

This study's data are internal to Bridgestone's Tatabánya plant and covered by a non-disclosure agreement. Official currency amounts and vendor identifiers are withheld. All variables presented are natural-log or logit transformations of those ratios, or their first differences.

2.2.1 Operational KPIs

Tatabánya's monthly scorecards are organized around Bridgestone's six operational excellence pillars: Safety, Environment, Quality, Cost, Delivery, and People. They translate high-level ambitions (for example, "Be the industry benchmark for Safety", "Achieve a climate-neutral footprint", "Serve customers with superior quality," and "Build an empowered workforce") into line-level metrics. Although each scorecard records dozens of indicators, this analysis focuses on eight core KPIs chosen for their strategic relevance. These include CO_2 emissions, energy, fuel, and water intensities, waste recovery (Environment), first-pass yield (Quality), total incident rate (Safety), and monthly output (Cost / Delivery). All eight have uninterrupted monthly observations from January 2016 through March 2025, yielding a 111-month panel.

The KPI selection aligns with the CE literature's emphasis on reducing inputs, slowing turnover, and closing loops through metrics like energy and carbon intensity, waste recovery, and material efficiency (Bocken et al. 2016; Sakao et al. 2024). These priorities are reinforced by Aljamal et al. (2024), who group plant-level indicators around resource productivity drivers and reflect Bridgestone's Milestone 2030 targets for halving emissions and increasing recycled content.

2.2.2 Financial Variables

Finance closes the SAP S/4HANA ledger on the same day the operational scorecard is finalized and allocates all spending into its internal cost center categories before exporting the results. To align with resource efficiency hypotheses, this analysis focuses on three cost series all expressed in Hungarian Forint (HUF): direct material cost (raw material expenditures), consumables and process input expenses (utilities and auxiliary inputs such as electricity, fuel, and water), and direct maintenance cost (labor and parts required to keep equipment operating).

The selected cost metrics correspond to flows CE frameworks consistently identify as relevant for decoupling resource use from value creation. These include material inputs, energy and water consumption, and the operational strain linked to equipment wear and failure (Bocken et al. 2016; Sakao et al. 2024). They align with CE strategies that target input reduction, lifespan extension, and system-wide reuse with benchmark recommendations that emphasize tracking resource flows and trade-offs over time (Aljamal et al. 2024). Each indicator is recorded monthly from January 2016 through March 2025 with no missing values, yielding a 111-month panel suitable for longitudinal analysis.

2.2.3 Variable Construction

All KPI and cost series were normalized on a per-unit-of-production basis by dividing each monthly observation by the total output in RRT. Metrics expressed per unit and percentage ratios were left unchanged, except that waste-recovery rates reported as whole numbers were rescaled to percentages (divided by 100).

Visual inspection of the per-unit intensity and cost distributions showed pronounced skewness and clustering. To correct this, all strictly positive series were transformed with natural logarithms, reducing skewness and stabilizing variance. The two bounded percentage indicators (first-pass yield and waste-recovery rate) were first winsorized to the 0.01%-99.99 % range, converted to proportions, and then logit-transformed to map their values onto the full real line.

Stationarity was evaluated using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, both of which indicated that none of the level series was stationary (ADF $p > 0.05$, KPSS $p < 0.05$). Thus, the first differences between the log-transformed and logit-transformed series were taken. All level series retained 111 observations, and every differenced series had 110, confirming that only one observation per series was lost to differencing. The resulting regressors all satisfied stationarity criteria (ADF $p < 0.05$, KPSS $p > 0.05$) and were retained for econometric modeling.

An initial multicollinearity check on the percentage change in monthly output revealed strong correlations with the percentage change in direct material cost and the percentage change in CO_2 intensity. Variance-inflation factors (VIFs) were 9.8 for output growth and 6.7 for the CO_2-intensity growth series. To remove this overlap, CO_2 intensity was first regressed on output growth, and the residuals were retained as the de-correlated CO_2 measure. When VIFs were recomputed, the CO_2 series dropped below the threshold (VIF < 5), but output growth still registered a VIF of 7.2. Accordingly, output growth was regressed on changes in electricity use and maintenance cost to yield a residualized output series. After these adjustments, every pairwise correlation fell below 0.8, and all VIFs dropped under 5. Figure 1 shows the final correlation matrix of the regressors, confirming that they are well conditioned for the modeling approaches in Section 2.3.

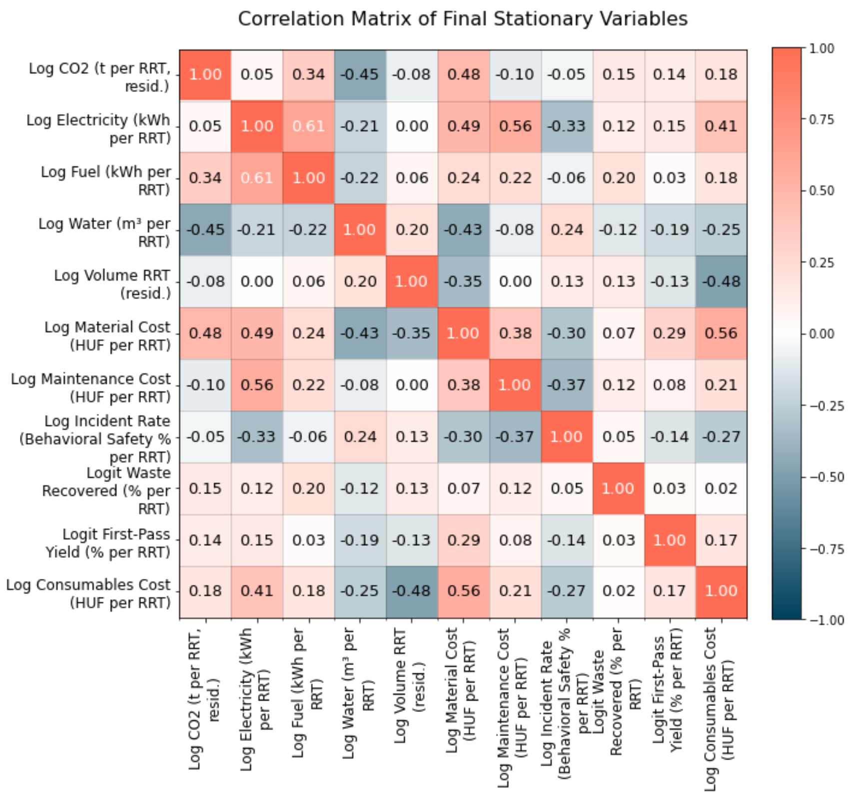

Figure 1: Correlation matrix of final stationary log-difference and logit-difference regressors

2.3 Analytical Framework

The empirical analysis proceeds in three phases. First, ordinary least squares (OLS) regressions identify the monthly cost drivers for material, consumables, and maintenance at the Tatabánya plant (H1-H3). Second, seasonal autoregressive integrated moving average with exogenous variables (SARIMAX) models generate month-by-month forecasts of CO_2 intensity per RRT and waste recovery percentage through December 2030 (H4). Third, interrupted time series (ITS) intervention models and local projection regressions quantify the cost impact of four CE initiatives relative to the counterfactual trend (H5).

2.3.1 Cost-Driver Regressions

The first phase applies OLS regressions to a panel of 110 monthly observations. Each model is estimated in log-differenced form, so the data are covariance-stationary, and the coefficients can be interpreted as elasticities. Heteroskedasticity-consistent (HC3) standard errors are used to protect inference against unknown variance patterns.

In the direct-material-cost regression (H1), the dependent variable is the monthly percentage change in material costs per RRT, and the independent variables look at four CE mechanisms. Change in residualized volume captures the narrowing of material loops through scale effects, in line with the resource-efficiency or "narrowing" strategy that seeks to use fewer inputs per unit output (Blomsma & Brennan 2017). Change in residualized CO_2 emissions reflects minimizing greenhouse-gas impacts alongside material use (Kirchherr et al. 2023). First-pass yield quantifies restorative tactics that extend resource life and reduce scrap (Morseletto 2020). Change in waste recovery measures the closing of material loops through recycling and remanufacturing, aligning loop-closing strategies (Aljamal et al. 2024).

In the consumables-expense regression (H2), the dependent variable is the monthly percentage change in steam, solvent, and auxiliary material spending per RRT, and the independent variables again capture CE factors. Electricity, fuel, and water use per RRT operationalize the narrowing of non-material loops in manufacturing, as reducing energy and water inputs is integral to circular production (Sakao et al. 2024). Controls for volume and CO_2 emissions ensure these process inputs are evaluated net of scale and carbon-intensity effects (Kirchherr et al. 2023). First-pass yield and waste recovery extend material-efficiency logic into auxiliary spending, while the change in direct material cost captures spillover effects in KPI networks, where variations in material use drive changes in steam, solvent, and other consumable requirements (Aljamal et al. 2024).

In the maintenance-cost regression (H3), the dependent variable is the monthly percentage change in maintenance-and-repair-spending per RRT, and the independent variables again reflect CE drivers. Change in total incident rate represents service-and-maintenance loops that extend equipment life and reduce parts usage (Bocken et al. 2016). Change in waste recovery again measures loop-closing benefits in maintenance scrap avoidance (Aljamal et al. 2024). Electricity, fuel, and water use per RRT control for energy- and water-driven wear-and-tear effects in production processes, and volume and CO_2 emissions residuals net out throughput and process-intensity dynamics (Kirchherr et al. 2023).

2.3.2 Milestone 2030 Benchmark Forecasts

The second phase projects Tatabánya's monthly CO_2 intensity and waste-recovery percentage from April 2025 through December 2030 and benchmarks them against Bridgestone's Milestone 2030 targets. Forecasting these KPIs answers calls for longitudinal tracking that connects material-flow indicators to strategic objectives (Harris et al. 2021) and tests the "narrow-close" pillars (Sakao et al. 2024) by focusing on greenhouse-gas intensity (input narrowing) and waste-loop tightening (material recirculation).

The 2011 CO_2 baseline is reconstructed by dividing December 2024's observed CO_2 intensity by 0.36[3], and the 2030 target is set at exactly half of that baseline. CO_2 per RRT is forecast by fitting a SARIMAX on its month-to-month log changes, with nonseasonal and seasonal orders chosen to minimize the corrected Akaike information criterion (AIC). Exogenous drivers confirmed by Granger causality enter the model alongside the log-differenced series. Forecasted log changes are cumulatively applied to the last observed CO_2 level to produce a continuous trajectory.

Waste recovery is modeled in parallel by two. First, a logistic-growth curve is fitted to the logit-transformed recovery percentage (clipped to (0.0001, 0.9999)) with nonlinear least squares, estimating carrying capacity, growth rate, and inflection point, then inverted back to percentage space and extended through 2030. Second, a SARIMAX model is fitted to the month-to-month logit changes, with nonseasonal and seasonal orders selected by minimizing the corrected AIC and exogenous predictors chosen through Granger-causality screening.

2.3.3 Event Effects on Costs

The third phase employs two complementary intervention models that isolate the impact of each CE-promoting event on the cost series while controlling for trend and seasonality. A linear time index captures any underlying trend, and twelve-monthly indicator variables absorb deterministic seasonal effects. For each of the four interventions (EXAMATION in June 2017, ENLITEN launch in July 2019, waste recovery $\geq 40\%$, and CO_2 reduction to $\leq 50\%$ of its 2011 baseline) two exogenous regressors are created; a step dummy activated from the event date, and a ramp variable that counts months since the event.

First, each cost series enters a SARIMAX regression with the step and ramp dummies (plus trend and seasonal indicators) as exogenous inputs. This specification isolates any persistent

[3] Internal non-confidential performance reports from Bridgestone Tatabánya confirm that the plant's December 2024 CO_2-intensity level equals 36 % of the 2011 baseline.

level shifts (from the step) and slope changes (from the ramp) attributable to each intervention. Second, local-projection regressions estimate h-month-ahead log changes on the step dummies (with trend and seasonals), for horizons h = 1…12. The resulting impulse-response coefficients trace the short-run dynamic effects of each event without imposing a fixed autoregressive moving average (ARMA) structure, while the SARIMAX delivers long-run level-and-slope estimates.

This two-stage modeling framework directly addresses literature calls for longitudinal, plant-level evidence that links discrete CE interventions to both immediate and persistent financial outcomes (Harris et al. 2021; Leipold et al. 2021) while explicitly modeling autocorrelation and structural breaks commonly observed in resource-efficiency data. By distinguishing stepwise level shifts from gradual slope changes, the framework also aligns with the "narrow" and "close" levers emphasized in CE strategy research (Bocken et al. 2016; Sakao et al. 2024) and reflects network-propagation effects highlighted by Aljamal et al. (2024).

2.4 Diagnostics and Robustness Plan

2.4.1 Regression Diagnostics

For each of the three log-difference cost-driver models, multicollinearity was assessed by computing VIFs on all two-stage residualized predictors. Potential heteroskedasticity was addressed by estimating every regression with HC3 robust standard errors. Residuals were examined for serial correlation through the Durbin-Watson (DW) statistic and Ljung-Box (LB) tests, as well as heteroskedasticity via Breusch-Pagan (BP) tests. Deviations from normality using omnibus and Jarque-Bera (JB) tests and Quantile-Quantile (Q-Q) plots. Added-variable (partial-regression) plots were generated for each predictor to detect any masked outliers or functional misspecification, and cross-correlation functions (lags 0-12) between each predictor and the dependent series were computed to ensure no relevant lagged relationships were omitted. Autocorrelation (ACF) and partial-autocorrelation (PACF) plots of the residuals (lags up to 24) were also produced for visual confirmation of white-noise behavior. Out-of-sample performance was evaluated with five-fold rolling origin time-series cross-validation (ROCV). In each fold, an OLS model was fit on the training window and used to forecast the next hold-out segment, producing a series of root-mean-square error (RMSE) values.

2.4.2 Forecast Diagnostics

Model selection and forecast performance were assessed first by comparing AIC and Bayesian information criteria (BIC) across candidate specifications. An automated search of nonseasonal and seasonal autoregressive integrated moving-average (SARIMA) orders on the differenced CO_2 and logit-transformed waste series minimized corrected AIC. ROCV with expanding training windows then produced a twelve-month hold-out RMSE and mean absolute error (MAE) to confirm out-of-sample stability and precision.

Residual diagnostics followed, beginning with LB tests at lag 12 to detect any remaining autocorrelation. Corresponding ACF and PACF plots were inspected for overlooked structure. JB tests and Q-Q plots evaluated residual normality, while autoregressive conditional heteroskedasticity (ARCH) tests filtered for conditional heteroskedasticity. Forecast-interval calibration was verified by generating in-sample Gaussian confidence bounds and computing empirical coverage at nominal 50 %, 80 %, and 95 % levels.

Finally, the waste-recovery SARIMAX specification was benchmarked against the logistic-growth alternative by comparing AIC, BIC, and twelve-month ROCV RMSE to evaluate the trade-off between long-term simplicity and short-term accuracy.

2.4.3 Event-Study Diagnostics

Residual dependence is evaluated by inspecting ACF, PACF plots, and LB tests at lags 6 and 12 to verify that serial correlation has been adequately captured. Heteroskedasticity is assessed using BP and White tests, with heteroskedasticity-and-autocorrelation-consistent standard errors (Newey-West) applied where necessary. Anticipatory effects were ruled out with placebo lead tests, introducing one-period leads of each intervention dummy into the ITS and local-projection regressions.

3 Results

3.1 Cost-Driver Regressions

The direct material cost regression explains 36.1% of the month-to-month variation (R-squared value of 0.361). After residualizing for interdependencies, a 1% increase in monthly throughput reduces material cost per RRT by 0.73% ($p = 0.003$), whereas a 1% rise in CO_2 intensity increases cost by 0.91% ($p < 0.001$). By contrast, a 1% improvement in first-pass yield corresponds to a modest 0.18% increase in material cost ($p = 0.012$), perhaps reflecting added process controls, while waste recovery shows no statistically significant effect ($p = 0.588$). Thus, the null hypothesis of no effect is rejected for three of the four efficiency measures.

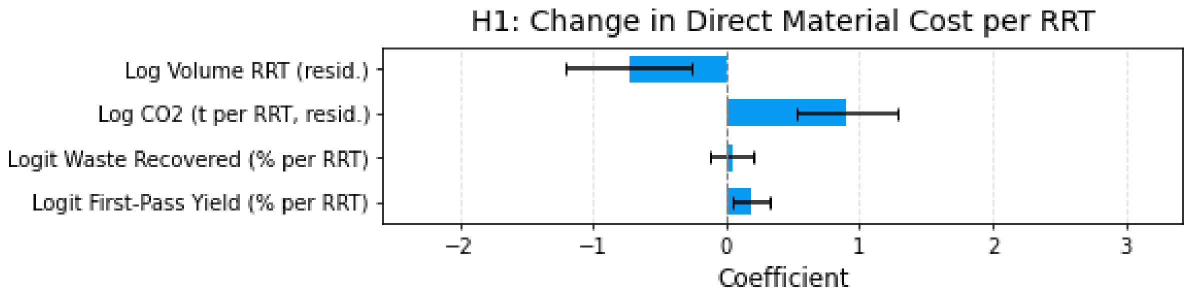

Figure 2: OLS coefficient estimates with 95% confidence intervals for model H1

The consumables expenses regression explains 45.8% of the variation (R-squared value of 0.458). A 1% increase in throughput lowers consumables spending by 1.19% ($p = 0.030$), and a 1% rise in electricity intensity drives a 1.40% cost increase ($p = 0.023$). Fuel use, water use, CO_2, first-pass yield, waste recovery, and direct material cost per RRT all fail to reach statistical significance ($p > 0.05$). Thus, the null hypothesis of no effect is rejected only for throughput and electricity intensity.

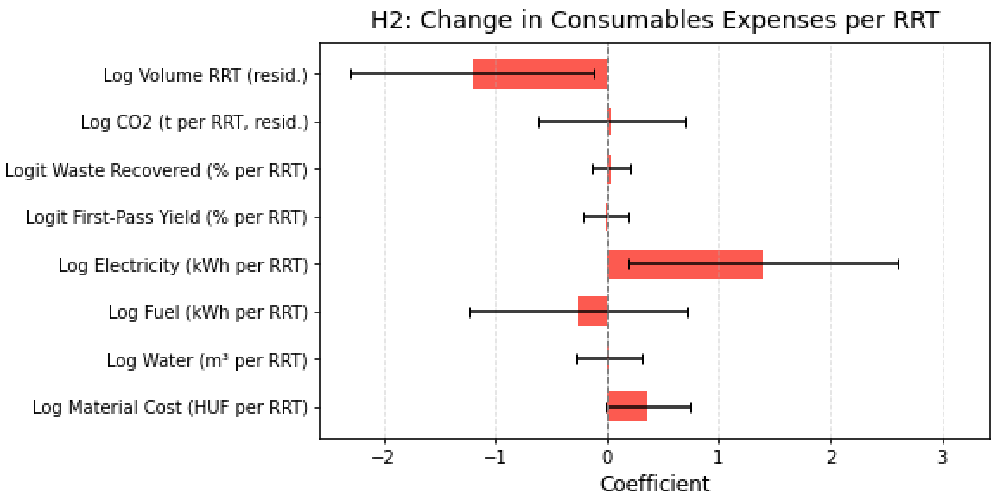

Figure 3: OLS coefficient estimates with 95% confidence intervals for model H2

The maintenance cost regression explains 38.1% of the variation (R-squared value of 0.381). Each 1% uptick in electricity is linked to a 2.21% increase in maintenance spending ($p < 0.001$). However, CO_2, fuel, water use, waste recovery, throughput, and incident rate effects are all statistically indistinguishable from zero ($p > 0.10$). Thus, the null hypothesis of no effect is rejected only for electricity intensity.

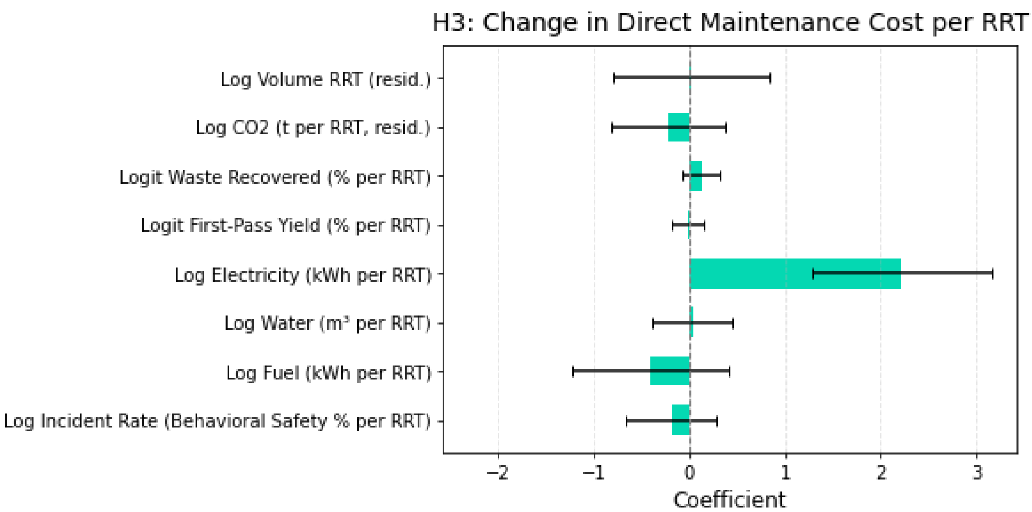

Figure 4: OLS coefficient estimates with 95% confidence intervals for model H3

Overall, scale economies consistently lower costs across material and consumables models, while electricity intensity emerges as the dominant positive cost driver for consumables and maintenance. CO_2 emissions and process yield influence material costs but not operating or maintenance expenses once energy and volume are controlled. Waste recovery has no independent effect in any specification. Full regression tables can be found in the Appendix (Figure A 1 to A 3).

3.1.1 Regression Diagnostics

All VIFs remained below 2, confirming minimal multicollinearity. DW statistics ranged from 2.59 to 3.02, and LB tests at lags up to 24 returned p-values above 0.10 for each model, indicating no meaningful autocorrelation. BP and White tests under HC3 standard errors produced p-values above 0.05, supporting homoscedastic residuals. JB tests and Q-Q plots showed that residuals for H1 ($p = 0.55$) and H3 ($p = 0.29$) adhere closely to normality, while H2 exhibited only minor tail deviation ($p \approx 8 \times 10\text{-}10$). Residual ACF and PACF plots confirmed white-noise behavior. Lastly, five-fold ROCV demonstrated stable out-of-sample accuracy: H1 achieved a mean RMSE of 0.2604 (standard deviation (SD) = 0.0605), H2 0.3837 (SD = 0.1509), and H3 0.3568 (SD = 0.1405).

3.2 Milestone 2030 Benchmark Forecasts

Both CO_2 intensity and waste-recovery forecasts reach Bridgestone's Milestone 2030 thresholds years ahead of schedule, leading to rejection of the null hypothesis that at least one KPI will miss its target.

CO_2 per RRT is projected with a SARIMAX fitted on log-level CO_2 (order (3,0,0), seasonal (2,0,0,12), constant trend). Driver-informed variants were tested, but the pure SARIMAX delivered lower one-step-ahead back-test RMSE (0.762 vs. 0.989) and were therefore adopted. The median forecast first dips below 50 % of the 2011 baseline in July 2016, briefly rebounds each summer (planned plant shutdowns), and remains under the threshold from May 2025 onward, ultimately reaching about 25 % of the 2011 baseline by 2030 (Bridgestone Tatabánya Plant 2023).

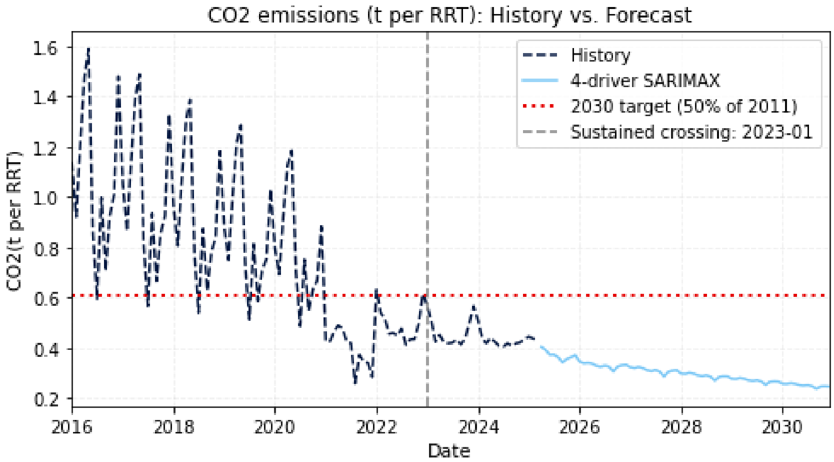

Figure 5: Historical CO_2 and SARIMAX forecast with the 50 %-of-2011 target line and final crossing date

Waste recovery is forecast by a SARIMAX on month-to-month logit changes with order (0,0,0) and seasonal order (0,0,0,12) plus drift, using fuel use change at a 12-month lag as the only exogenous predictor selected through Granger tests. The fuel-augmented SARIMAX model achieves a twelve-month RMSE of 0.015, outperforming both the logistic-growth fit (RMSE 0.178) and the naïve benchmark (RMSE 0.323), and is therefore adopted. The median forecast first crosses the 40% target in April 2019, then dips below during coronavirus-related disruptions in early 2020, reflecting challenges in coordinating with third-party recyclers before rebounding and remaining above the target from April 2020 through December 2030.

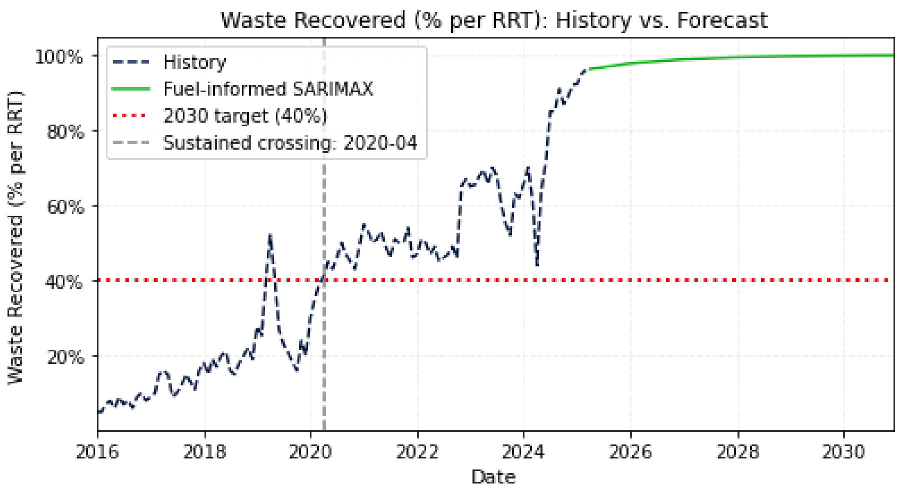

Figure 6: Historical waste-recovery rate and SARIMAX forecast with the 40 % target line and final crossing date

3.2.1 Forecast Diagnostics

Model selection for CO_2 intensity incorporated exogenous predictors confirmed by Granger causality (total incident rate at a 9 month lag, electricity use at a 1 month lag, fuel use at a 5 month lag, and water use at a 9 month lag) while the waste-recovery SARIMAX included only fuel-use change at a twelve month lag. One-step-ahead ROCV yielded an RMSE of 0.36 and MAE of 0.23 for the change in log CO_2 model, and 0.011 and 0.008, respectively, for the change in logit waste model.

Residual diagnostics show no remaining autocorrelation. LB tests at lag 12 returned p of 0.245 for the CO_2 model and p of 0.818 for the waste model. ARCH tests indicated no conditional heteroskedasticity in the CO_2 residuals ($p = 0.909$) and only a modest effect in the waste model ($p = 0.036$). JB tests showed fat tails in the CO_2 residuals ($p < 0.001$) but supported normality in the waste residuals ($p = 0.418$). Autocorrelation and partial autocorrelation plots confirm white noise behavior in both cases.

Forecast interval calibration achieved empirical coverage within two percentage points of nominal levels, capturing 78% of observations in its 80% interval and 94% in its 95% interval for the CO_2 model, and 81% and 96%, respectively, for the waste model.

3.3 Event Effects on Costs

The ITS estimates, illustrated in Figure 6, reveal that only two interventions produced statistically robust changes in cost growth rates. The CO_2 reduction step dummy in January 2023 is associated with an immediate 18.2% decline in the month-over-month growth rate of direct material cost per RRT ($p = 0.001$), and the twelve-month ramp slope is not statistically different from zero. No significant growth-rate shifts are detected at EXAMATION rollout, ENLITEN launch, or waste recovery $\geq 40\%$ events for material costs. Thus, the null hypothesis of no event effect on material cost growth is rejected only for the CO_2 reduction achievement.

For consumables expenses, the EXAMATION step dummy in June 2017 produces an immediate 18.1% slowdown in growth ($p = 0.040$), accompanied by a continuing deceleration of 1.64% per month thereafter ($p = 0.023$). None of the other event dummies or ramp variables achieve significance for consumables growth. Thus, the null hypothesis is rejected for EXAMATION but not for the other interventions in the consumables model.

Maintenance cost growth displays a modest but significant 11.99% drop immediately after the CO_2 target is attained ($p = 0.036$). No level or slope changes at EXAMATION, ENLITEN, or waste recovery ≥ 40% are statistically different from zero at the 5% level. Thus, the null hypothesis is rejected for the CO_2 reduction intervention only.

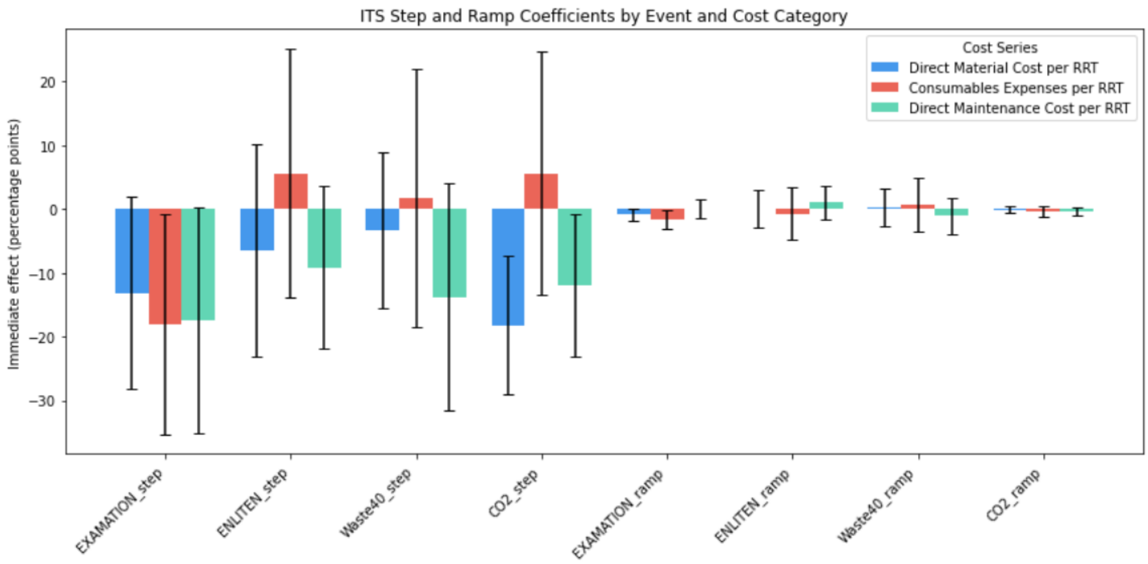

Figure 7: ITS step and ramp coefficients by event and cost category with 95 % confidence intervals

Local-projection impulse responses corroborate these findings. The one-month-ahead response of material-cost growth to the CO_2 policy is -1.25% (95% confidence interval is -15.7 to +13.2), and the one-month impulse on consumables growth after EXAMATION is -8.33% (95% confidence interval is -23.5 to +6.8). Maintenance-cost IRFs show a –6.60% response in the first month after the CO_2 event (95% confidence interval is –20.0 to +6.8). Dynamic effects at ENLITEN and waste recovery ≥ 40% remain statistically indistinguishable from zero at all horizons, confirming failure to reject the null for those events in all series. The complete ITS regression tables are reported in the Appendix (Figures A 4 to A 6).

3.3.1 Event-Study Diagnostics

Autocorrelation was ruled out by LB tests at lags 6 and 12 (all $p > 0.10$) and by inspecting ACF and PACF plots, confirming that the ITS specifications captured serial dependence. Heteroskedasticity checks through BP and White tests returned $p > 0.05$ for all models. Newey-West HAC standard errors (maxlags = 12) were applied in the ITS and local projection models to guard against any remaining autocorrelation. Placebo-led regressions on one-period-ahead step dummies produced non-significant coefficients (all $p > 0.10$), ruling out anticipatory effects. Empirical coverage of the forecast intervals fell within two percentage points of nominal levels (direct material cost model captured 79% in its 80% interval and 95% in its 95% interval; consumables 82% and 96%; maintenance 80% and 94%).

4 Discussion

4.1 Findings and Interpretations

The evidence shows that scale-driven material efficiency is one of the plant's strongest financial levers**.** Every 1% rise in finished-tire output lowered direct-material cost per RRT by 0.73% and consumables spending by 1.19%, confirming that "narrowing" resource flows still yields classical economies of density, despite the factory's digital systems. This mirrors the argument by Bocken et al. (2016) that trimming inputs per functional unit remains the most reliable profit lever in industrial circularity and echoes Kirchherr et al. (2023), who stress that throughput economics (not exotic loop technologies) still account for most industrial CE success.

Energy intensity emerges as the hidden driver of circular performance. A 1% increase in electricity use per RRT raised consumables outlays by 1.40% and maintenance costs by 2.21%. This suggests that the kWh required to power real-time sensing, actuation, and AI optimization can erode part of the material efficiency gained elsewhere. CO_2 intensity shows a similar pattern: each 1% uptick in CO_2 per RRT inflated material cost by 0.91%. These rebound effects reinforce Sakao et al.'s (2024) caution that digitization can shift burdens from matter to energy if the electricity footprint is left unchecked and support Harris et al.'s (2021) call to integrate energy loops explicitly into CE dashboards rather than celebrating recycling metrics in isolation.

Loop-closing activities, by contrast, show little short-run financial traction. Improvements in waste-recovery rates had no measurable effect on any cost line, aligning with the warning that headline recycling indicators can rise even as absolute resource use and expenditure remain unchanged (Harris et al. 2021; Leipold et al. 2021). First-pass yield exerted only a modest 0.18 % upward pressure on material cost, a finding consistent with reports that tighter quality tolerances often demand additional compounds and energy-intensive re-processing (Aljamal et al. 2024).

Only two events generated observable causal step-changes. The roll-out of the EXAMATION AI system in June 2017 produced an immediate 18% deceleration in the growth of consumables spending, with the slope continuing to flatten over the following year. Meanwhile, the plant's formal achievement of Bridgestone's CO_2-reduction target in January 2023 cut the growth rates of material and maintenance costs by 18.2% and 12%, respectively. These turning points illustrate Blomsma & Brennan's (2017) claim that well-timed "catalytic" actions can re-configure resource flows. They also reinforce Kirchherr et al.'s (2023) argument that genuine circularity advances through decisive, system-wide shifts rather than incremental kaizen (small, continuous, bottom-up improvements), and align with Sakao et al.'s (2024) guidance that targeted digital tools and clear carbon milestones can unlock savings beyond routine continuous improvement.

4.2 Theoretical and Practical Implications

The findings tighten the "narrow-slow-close" framework by showing that electricity intensity binds the three loops together: material and carbon efficiencies translate into real savings only when the accompanying energy footprint is kept in check. This adds an energy-systems layer to Bocken et al.'s (2016) resource-efficiency taxonomy and supports Sakao et al.'s (2024) warning that digitalization can trigger rebound effects if extra kilowatt-hours are ignored. It also lends empirical weight to Kirchherr et al.'s (2023) call for decisive, system-wide shifts over marginal adjustments.

For managers, three priorities follow. First, kilowatt-hours per unit must sit on the same dashboard as scrap and yield, as firms that track only material loops risk celebrating "circularity for circularity's sake," as Harris et al. (2021) caution, while rising energy use quietly undermines both environmental and financial gains. Second, ambitious, dated, plant-level targets matter: the 2023 CO_2 milestone at Tatabánya synchronized capital spending across maintenance, utilities, and production, exemplifying Kirchherr et al.'s (2023) argument that systemic shifts, not incremental kaizen, drive meaningful progress. Third, recycling should remain the last lever. Leipold et al. (2021) caution that recycling rates can climb while absolute resource use and cost barely budges, a pattern mirrored by the plant's own null result for waste recovery.

Policy design can reinforce these levers. Price signals that are set at the scale of individual plants rather than corporate averages improve incentives, as evidenced by the sharpest cost break once Tatabánya's own CO_2 baseline became the reference point for internal decision-making, echoing Harris et al.'s (2021) insistence on metrics that match operational decision scopes. As digital optimization magnifies material and energy gains, targeted support for AI-enabled process control would accelerate circular transitions in energy-intensive sectors, aligning with Sakao et al.'s (2024) view of technology as a practical enabler of loop performance.

4.3 Strengths, Limitations, and Future Research Prospects

The primary strength of this research is its longitudinal granularity: 111 consecutive months of paired operational performance and ledger data permit elasticity estimates and event-study identification that snapshot surveys or short panels cannot approach. Using several econometric approaches (first-difference OLS, SARIMAX forecasting, ITS, and local projections) ensures that no single modeling assumption drives the results and that the coherence across methods materially reinforces internal validity. Equally important, the dataset combines all KPIs on a common monthly timeline, filling the gap noted by Harris et al. (2021), who criticize CE studies for tracking resource flows in isolation.

Even with these strengths, the findings are not universally applicable. Evidence from a single Central European tire plant may not carry over to industries that rely on different manufacturing technologies, electricity mixes, or regulatory settings. However, other constraints are methodological and therefore more tractable. Monthly aggregation, adopted to match accounting cycles, smooths shift-level volatility and can blur very short-run shocks, while higher-frequency logging would sharpen causal attribution. Confidentiality rules prevent publishing absolute cost figures, which limits external benchmarking, but releasing anonymized cost indices or arranging pre-registered data-sharing agreements could ease that constraint. Finally, the study records eight operational KPIs but no revenue indicators, such as the price premium that customers might pay for greener products or the interest savings from sustainability-linked loans, so it cannot show the whole financial upside of circular performance, a shortcoming already noted by Kirchherr et al. (2023).

Future work can advance the agenda along three paths. First, replicating this panel framework across multi-plant networks with contrasting grid-carbon intensities and tariff regimes would test whether electricity remains the dominant moderator under varied cost structures. Second, linking operational data to price realization, customer turnover, or financing costs would yield a fuller picture of circular value creation and risk mitigation. Third, coupling the quantitative design with qualitative process tracing could reveal how leadership commitment, workplace norms, and reward systems explain the empirical relationships found in the study, responding to Blomsma & Brennan's (2017) call to connect organizational dynamics with resource outcomes. By pursuing these routes, researchers can move from a single case toward a comparative evidence base that weighs material, energy, carbon, and financial performance with equal robustness.

Conclusion

This thesis set out to discover whether a single factory can turn CE ideals into financial returns. Drawing on 111 consecutive months of matched operations KPI data and cost accounts from Bridgestone's Tatabánya tire plant, it estimated the elasticities between resource-efficiency KPIs and cost categories, projected progress toward the firm's 2030 carbon- and waste-reduction targets, and evaluated the impact of four major operational programs against data-driven counterfactuals.

The analysis makes one point unmistakable. Larger volumes consistently lower unit spending, confirming that scale economics remain a first-order lever even inside a digitally managed facility. Yet, the margin survives only while electricity use per RRT stays flat or falls. Once kilowatt hours increase, consumables and maintenance bills rise quickly enough to absorb much of the margin gained through leaner use of raw materials, and higher carbon intensity amplifies the pressure on material cost. In contrast, actions aiming solely at closing material loops, such as improving first-pass yield or routing more scrap back into the process, produced no near-term relief on any cost line. Therefore, recycling remains valuable for environmental reasons, but did not improve the plant's balance sheet during the study window.

Change followed an episodic rather than gradual path. The mid-2017 launch of the AI control platform EXAMATION slowed the growth of consumables spending, and attaining the carbon milestone in January 2023 bent both material and maintenance trends downward. Forward projections extend those gains, with CO_2 intensity expected to remain below half its 2011 baseline 2023 onward and waste recovery rates surging past 40% by 2020. These overachievements affirm the power of rigorous KPI benchmarking and continuous performance tracking as pillars of sustained improvement. They also challenge skepticism about voluntary corporate pledges by showing that transparent target setting can create a feedback loop in which early wins catalyze further resource-efficiency initiatives.

The Tatabánya case, therefore, offers a clear message for manufacturers facing rising input prices and tightening climate rules: environmental stewardship and cost discipline are not opposing goals but two sides of the same operational dashboard. When kilowatt-hours, tonnes of rubber, and tonnes of carbon appear on the same monthly ledger, and management is willing to back time-bound targets with real investment, circular ambition becomes a durable competitive advantage. That logic travels well beyond one tire plant. In a world of volatile input prices, supply-chain shocks, and tightening climate policy, companies that integrate resource-efficiency KPIs into their financial dashboards surface hidden savings, harden resilience, and earn reputational credit. By acting on such data, firms will be equipped to navigate the resource-constrained economy of the twenty-first century.

Appendix

```
                                OLS Regression Results
==============================================================================
Dep. Variable:     d_log_DirMatCost_per_RRT   R-squared:                       0.361
Model:                                  OLS   Adj. R-squared:                  0.337
Method:                       Least Squares   F-statistic:                     11.26
Date:                      Fri, 16 May 2025   Prob (F-statistic):           1.22e-07
Time:                              12:05:14   Log-Likelihood:                -9.4170
No. Observations:                       110   AIC:                             28.83
Df Residuals:                           105   BIC:                             42.34
Df Model:                                 4
Covariance Type:                        HC3
================================================================================================
                                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------------------
const                          0.0103      0.027      0.386      0.699      -0.042       0.062
d_log_Volume_resid2           -0.7307      0.242     -3.020      0.003      -1.205      -0.257
CO2_resid_vs_Volume            0.9063      0.193      4.692      0.000       0.528       1.285
d_logit_OE_Yield_pct           0.1820      0.072      2.526      0.012       0.041       0.323
d_logit_Waste_Recovered_pct    0.0444      0.082      0.541      0.588      -0.116       0.205
==============================================================================
Omnibus:                        1.641   Durbin-Watson:                   2.593
Prob(Omnibus):                  0.440   Jarque-Bera (JB):                1.189
Skew:                          -0.017   Prob(JB):                        0.552
Kurtosis:                       3.508   Cond. No.                         7.95
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

Figure A 1: OLS regression for H1, change in log direct material cost per RRT

```
                                   OLS Regression Results
=============================================================================================
Dep. Variable:     d_log_ConsumablesExpenses_per_RRT   R-squared:                       0.458
Model:                                           OLS   Adj. R-squared:                  0.415
Method:                                Least Squares   F-statistic:                     17.56
Date:                               Fri, 16 May 2025   Prob (F-statistic):           3.78e-16
Time:                                       12:05:14   Log-Likelihood:                -25.427
No. Observations:                                110   AIC:                             68.85
Df Residuals:                                    101   BIC:                             93.16
Df Model:                                          8
Covariance Type:                                 HC3
================================================================================================
                                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------------------
const                          0.0019      0.032      0.059      0.953      -0.061       0.064
d_logit_Waste_Recovered_pct    0.0360      0.087      0.414      0.679      -0.135       0.207
CO2_resid_vs_Volume            0.0371      0.335      0.111      0.912      -0.619       0.693
d_log_Volume_resid2           -1.2093      0.558     -2.166      0.030      -2.304      -0.115
d_log_Elec_kWh_RRT             1.3963      0.616      2.267      0.023       0.189       2.604
d_log_Fuel_kWh_RRT            -0.2607      0.494     -0.527      0.598      -1.230       0.708
d_log_Water_m3_RRT             0.0144      0.151      0.095      0.924      -0.281       0.310
d_log_DirMatCost_per_RRT       0.3643      0.196      1.860      0.063      -0.019       0.748
d_logit_OE_Yield_pct          -0.0131      0.100     -0.131      0.896      -0.208       0.182
==============================================================================
Omnibus:                       19.274   Durbin-Watson:                   3.023
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               41.894
Skew:                          -0.654   Prob(JB):                     7.99e-10
Kurtosis:                       5.726   Cond. No.                         22.8
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

Figure A 2: OLS regression for H2, change in log consumables expenses per RRT

```
                            OLS Regression Results
=======================================================================================
Dep. Variable:     d_log_DirectMaintCost_per_RRT   R-squared:                       0.381
Model:                                      OLS    Adj. R-squared:                  0.332
Method:                           Least Squares    F-statistic:                     7.270
Date:                          Fri, 16 May 2025    Prob (F-statistic):           1.38e-07
Time:                                  12:05:14    Log-Likelihood:                -17.639
No. Observations:                           110    AIC:                             53.28
Df Residuals:                               101    BIC:                             77.58
Df Model:                                     8
Covariance Type:                            HC3
=============================================================================================
                                 coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------------------
const                          0.0089      0.031      0.291      0.771      -0.051       0.069
d_log_TIR_BS                  -0.1933      0.238     -0.811      0.418      -0.661       0.274
d_logit_Waste_Recovered_pct    0.1297      0.099      1.315      0.189      -0.064       0.323
CO2_resid_vs_Volume           -0.2302      0.304     -0.758      0.449      -0.826       0.365
d_log_Volume_resid2            0.0159      0.417      0.038      0.970      -0.802       0.834
d_logit_OE_Yield_pct          -0.0164      0.086     -0.190      0.849      -0.185       0.152
d_log_Elec_kWh_RRT             2.2214      0.475      4.673      0.000       1.290       3.153
d_log_Water_m3_RRT             0.0347      0.215      0.161      0.872      -0.387       0.456
d_log_Fuel_kWh_RRT            -0.4017      0.417     -0.964      0.335      -1.219       0.415
==============================================================================
Omnibus:                        2.728   Durbin-Watson:                   2.650
Prob(Omnibus):                  0.256   Jarque-Bera (JB):                2.468
Skew:                          -0.124   Prob(JB):                        0.291
Kurtosis:                       3.690   Cond. No.                         19.5
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

Figure A 3: OLS regression for H3, change in log direct maintenance cost per RRT

```
=== ITS: d_log_DirMatCost_per_RRT ===
=====================================================================================
                      coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
Intercept          -0.1126      0.193     -0.583      0.560      -0.491       0.266
M_2[T.True]         0.0811      0.179      0.454      0.650      -0.269       0.431
M_3[T.True]         0.2820      0.211      1.339      0.181      -0.131       0.695
M_4[T.True]         0.1976      0.200      0.985      0.324      -0.195       0.591
M_5[T.True]         0.0865      0.177      0.488      0.626      -0.261       0.434
M_6[T.True]        -0.1439      0.154     -0.933      0.351      -0.446       0.158
M_7[T.True]        -0.2021      0.161     -1.259      0.208      -0.517       0.113
M_8[T.True]         0.3170      0.304      1.041      0.298      -0.280       0.914
M_9[T.True]        -0.0830      0.152     -0.547      0.585      -0.381       0.215
M_10[T.True]        0.0717      0.190      0.378      0.705      -0.300       0.444
M_11[T.True]        0.0126      0.173      0.073      0.942      -0.327       0.352
M_12[T.True]        0.1025      0.298      0.344      0.731      -0.482       0.687
t                   0.0104      0.005      1.889      0.059      -0.000       0.021
EXAMATION_step     -0.1312      0.077     -1.713      0.087      -0.281       0.019
ENLITEN_step       -0.0647      0.085     -0.759      0.448      -0.232       0.102
Waste40_step       -0.0334      0.062     -0.539      0.590      -0.155       0.088
CO2_step           -0.1818      0.056     -3.256      0.001      -0.291      -0.072
EXAMATION_ramp     -0.0087      0.005     -1.670      0.095      -0.019       0.002
ENLITEN_ramp        0.0004      0.015      0.028      0.978      -0.029       0.030
Waste40_ramp        0.0027      0.015      0.180      0.857      -0.027       0.032
CO2_ramp           -0.0007      0.002     -0.307      0.759      -0.005       0.004
=====================================================================================
```

Figure A 4: ITS coefficients and 95% confidence intervals for the change in log direct material cost per RRT

=== ITS: d_log_ConsumablesExpenses_per_RRT ===

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-0.1759	0.192	-0.917	0.359	-0.552	0.200
M_2[T.True]	-0.0350	0.332	-0.105	0.916	-0.685	0.615
M_3[T.True]	0.2316	0.157	1.477	0.140	-0.076	0.539
M_4[T.True]	0.3048	0.217	1.405	0.160	-0.120	0.730
M_5[T.True]	0.0915	0.150	0.610	0.542	-0.203	0.386
M_6[T.True]	-0.1462	0.161	-0.910	0.363	-0.461	0.169
M_7[T.True]	-0.1795	0.182	-0.989	0.323	-0.535	0.176
M_8[T.True]	0.2662	0.265	1.004	0.316	-0.254	0.786
M_9[T.True]	-0.1184	0.160	-0.741	0.459	-0.431	0.195
M_10[T.True]	0.2263	0.165	1.375	0.169	-0.096	0.549
M_11[T.True]	-0.0260	0.168	-0.155	0.877	-0.355	0.303
M_12[T.True]	0.1097	0.267	0.411	0.681	-0.414	0.633
t	0.0166	0.007	2.334	0.020	0.003	0.031
EXAMATION_step	-0.1811	0.088	-2.055	0.040	-0.354	-0.008
ENLITEN_step	0.0564	0.100	0.565	0.572	-0.139	0.252
Waste40_step	0.0177	0.103	0.171	0.864	-0.185	0.220
CO2_step	0.0563	0.098	0.576	0.564	-0.135	0.248
EXAMATION_ramp	-0.0164	0.007	-2.274	0.023	-0.030	-0.002
ENLITEN_ramp	-0.0068	0.021	-0.323	0.747	-0.048	0.034
Waste40_ramp	0.0063	0.022	0.290	0.772	-0.036	0.049
CO2_ramp	-0.0030	0.004	-0.716	0.474	-0.011	0.005

Figure A 5: ITS coefficients and 95% confidence intervals for the change in log consumables expenses per RRT

=== ITS: d_log_DirectMaintCost_per_RRT ===

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-0.3864	0.177	-2.177	0.029	-0.734	-0.039
M_2[T.True]	0.5096	0.201	2.531	0.011	0.115	0.904
M_3[T.True]	0.5733	0.137	4.179	0.000	0.304	0.842
M_4[T.True]	0.6358	0.161	3.948	0.000	0.320	0.951
M_5[T.True]	0.4533	0.142	3.185	0.001	0.174	0.732
M_6[T.True]	0.1456	0.169	0.861	0.389	-0.186	0.477
M_7[T.True]	0.5641	0.185	3.051	0.002	0.202	0.926
M_8[T.True]	0.6198	0.240	2.583	0.010	0.150	1.090
M_9[T.True]	0.0844	0.138	0.611	0.541	-0.187	0.355
M_10[T.True]	0.4391	0.186	2.355	0.019	0.074	0.805
M_11[T.True]	0.4541	0.153	2.965	0.003	0.154	0.754
M_12[T.True]	0.8044	0.194	4.152	0.000	0.425	1.184
t	0.0033	0.008	0.418	0.676	-0.012	0.019
EXAMATION_step	-0.1751	0.090	-1.937	0.053	-0.352	0.002
ENLITEN_step	-0.0911	0.065	-1.394	0.163	-0.219	0.037
Waste40_step	-0.1375	0.091	-1.506	0.132	-0.317	0.041
CO2_step	-0.1199	0.057	-2.102	0.036	-0.232	-0.008
EXAMATION_ramp	0.0009	0.007	0.114	0.910	-0.014	0.016
ENLITEN_ramp	0.0108	0.013	0.803	0.422	-0.016	0.037
Waste40_ramp	-0.0105	0.015	-0.725	0.469	-0.039	0.018
CO2_ramp	-0.0032	0.003	-0.999	0.318	-0.010	0.003

Figure A 6: ITS coefficients and 95% confidence intervals for the change in log direct maintenance cost per RRT

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