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Commodity Cycles, Macroeconomic Conditions, and Marketing Strategy Intervention: Evidence From Monthly Heavy Equipment Sales in Indonesia (2010-2024)

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Abstract

This study examines how commodity price cycles, macroeconomic conditions, and marketing strategy interventions jointly shape heavy equipment sales in Indonesia. Using monthly observations from a major manufacturer (2010-2024; n = 180), we construct a Commodity Conditions Index (CCI) and a Macroeconomic Conditions Index (MCI) via principal component analysis. An ARDL bounds approach indicates a long-run relationship, while an ECM shows partial adjustment. Commodity conditions and the marketing intervention pulse are positive and significant, whereas macro signals exhibit lagged and mixed effects. The error-correction term suggests that roughly one-fifth of short-run disequilibrium is corrected each month, offering practical guidance for campaign timing and demand planning.

Keywords: Commodity cycles, macroeconomic conditions, marketing strategy intervention, principal component analysis, ARDL-ECM, heavy equipment sales

1. Introduction

Heavy equipment sales in Indonesia are highly cyclical because end-user demand is derived from investment activity in commodity extraction and infrastructure development. When coal, nickel, and other commodity prices rise, cash flows and project approvals typically strengthen, triggering purchases of excavators, dump trucks, and supporting equipment. Conversely, downcycles compress budgets and delay replacement cycles. In parallel, macroeconomic conditions such as interest rates, inflation, and exchange rates shape financing costs and import prices, creating additional headwinds or tailwinds for capital goods demand. Against this backdrop, firms deploy marketing strategy interventions (e.g., campaign bursts, trade events, special offers) to smooth demand and capture share during favorable windows. Despite this intuitive triad, empirical evidence that jointly models commodity conditions, macro signals, and marketing intervention pulses at a monthly frequency remains limited, especially for emerging markets where volatility and policy shifts are pronounced.

Research gap. Prior studies typically examine commodity or macroeconomic drivers of capital-goods demand in isolation, and marketing actions are rarely modeled as a measurable, time-stamped intervention in the same monthly framework. In addition, evidence using monthly data for emerging-market capital goods is still limited, which makes it difficult to translate external cycles into actionable campaign timing and demand-planning decisions. To address these gaps, this study integrates composite commodity and macro signals (via PCA) with a marketing intervention pulse and estimates dynamic effects using an ARDL-ECM approach.

This study addresses that gap using monthly data from a major heavy equipment manufacturer operating in Indonesia from 2010 to 2024 (n = 180). To reduce multicollinearity among external drivers and to align measurement with the multi-commodity nature of the Indonesian industrial base, we construct two composite indices: (i) a Commodity Conditions Index (CCI) summarizing key commodity prices, and (ii) a Macroeconomic Conditions Index (MCI) summarizing macro indicators. Both indices are extracted via principal component analysis (PCA) (Jolliffe, 2002; Abdi & Williams, 2010). We then estimate an autoregressive distributed lag (ARDL) model and apply bounds testing to evaluate long-run relationships and short-run dynamics (Pesaran, Shin, & Smith, 2001), complemented by an error-correction model (ECM) representation (Engle & Granger, 1987).

The paper contributes in three ways. First, it provides monthly evidence on how composite commodity conditions translate into heavy equipment sales (Cuddington & Jerrett, 2008; Erten & Ocampo, 2013). Second, it clarifies the role of macro signals when modeled jointly with commodity conditions, highlighting lagged and mixed effects. Third, it quantifies the incremental effect of a marketing intervention pulse, linking marketing-response theory to demand planning for capital goods (Vakratsas & Ambler, 1999).

2. Literature Review

Commodity-driven investment cycles are a central determinant of capital goods demand in resource-based economies. Empirical work on commodity price dynamics documents persistent upswings and downswings that can influence investment decisions over multi-year horizons (Cuddington & Jerrett, 2008; Erten & Ocampo, 2013). In Indonesia, commodity sectors such as coal and minerals also generate spillovers to construction services and logistics, amplifying demand for heavy equipment. Accordingly, a composite commodity signal is expected to capture broad market momentum more reliably than a single commodity series.

Macroeconomic conditions affect heavy equipment demand through financing and cost channels. Interest rates influence the cost of credit and leasing; exchange rate depreciation can raise imported equipment prices; and inflation can erode project purchasing power. However, macro impacts may be delayed because project pipelines and procurement decisions often adjust with lags. Thus, even when macro indicators do not contemporaneously predict sales, they may exert lagged effects once credit conditions and budgets fully transmit to procurement.

Marketing interventions can accelerate purchase timing and improve conversion rates, particularly when external conditions are supportive. Marketing-response research suggests that promotional activity and communication can influence awareness, consideration, and purchase decisions, although effects depend on market context and competitive actions (Vakratsas & Ambler, 1999). For capital goods, interventions such as targeted campaigns, events, and limited-time offers may be especially effective when customers are already in an investment cycle. This implies complementarities between external conditions (commodities, macro) and managerial actions (marketing intervention pulses).

Methodologically, empirical work with monthly time series in emerging markets must address potential mixed integration orders and dynamic adjustments. ARDL models are widely used because they can accommodate regressors integrated of order zero and one and provide a coherent framework for testing long-run relationships through bounds testing (Pesaran et al., 2001). Once cointegration is supported, an ECM representation enables interpretation of short-run impacts and the speed of adjustment back to equilibrium (Engle & Granger, 1987). Composite index construction via PCA further helps summarize correlated indicators into interpretable signals (Jolliffe, 2002; Abdi & Williams, 2010).

3. Hypothesis Development

Based on the above mechanisms, we posit three hypotheses. First, stronger commodity conditions are expected to increase heavy equipment sales by improving project profitability and accelerating investment decisions.

H1: Commodity conditions (CCI) have a positive effect on heavy equipment sales.

Second, macroeconomic conditions may affect sales through financing costs and imported price pressures. Given procurement and investment lags, the effect may be delayed and may vary in sign depending on which macro components dominate during a given period.

H2: Macroeconomic conditions (MCI) affect heavy equipment sales, potentially with lagged and mixed effects.

Third, a marketing strategy intervention is expected to raise sales by stimulating customer engagement and reducing frictions in purchase decisions, especially when aligned with favorable external conditions.

H3: A marketing strategy intervention (MSI_pulse) has a positive effect on heavy equipment sales.

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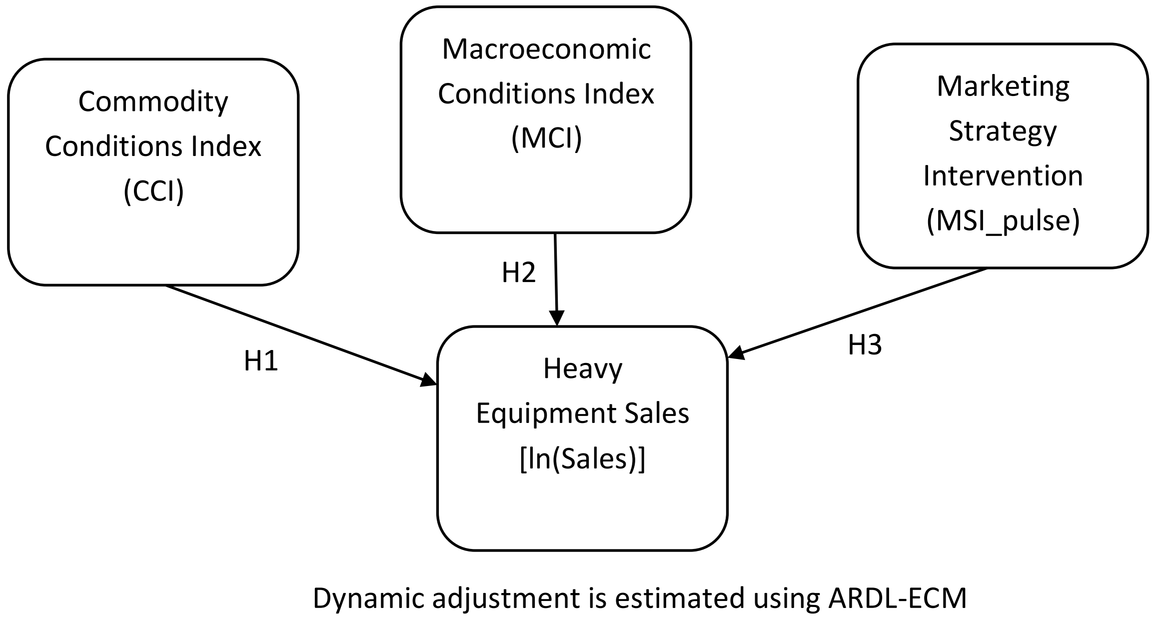

Figure 1. Conceptual framework.

4. Method

4.1 Data and Variables

The dependent variable is monthly heavy equipment sales (units) for January 2010 to December 2024 (n = 180). Sales are analyzed in logarithms to stabilize variance and interpret coefficients as semi-elasticities. Commodity indicators used to build CCI include major commodities relevant to Indonesian investment activity (e.g., coal, nickel, palm oil, and gold). Macroeconomic indicators used to build MCI reflect monetary and external conditions (e.g., interest rate, inflation, exchange rate, and activity proxies). Marketing Strategy Intervention (MSI) is operationalized as a pulse dummy that marks planned campaign periods.

Table 1 summarizes the operational definitions and expected signs for ln(Sales), CCI, MCI, and the marketing intervention pulse.

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Table 1. Variable Definitions and Expected Signs

Variable	**Definition / construction**	**Expected sign**	**Notes**
ln(Sales)	Natural log of monthly unit sales	–	Dependent variable
CCI_z	Commodity Conditions Index: 1st PCA component of standardized monthly commodity prices	+	Scaled as z-score
MCI_z	Macroeconomic Conditions Index: 1st PCA component of standardized macro indicators (rate, inflation, FX, output)	±	Effects may be lagged
MSI_pulse	Marketing intervention dummy: 1 in scheduled campaign months, 0 otherwise	+	Pulse intervention
Controls	Implicit lag structure via ARDL specification	–	Lag length selected by information criteria

4.2 Index Construction (PCA)

We standardize the commodity and macro indicators and extract the first principal component for each block to form CCI and MCI as z-scores. This approach reduces dimensionality and collinearity while preserving the dominant common variation (Jolliffe, 2002; Abdi & Williams, 2010).

As an illustration, Table 2 reports the explained variance for the commodity block, where the first component (PC1) captures the dominant common movement. Table 3 reports the corresponding factor loadings.

Table 2. PCA Explained Variance (Commodity Block)

PC	**ExplainedVar**
PC1	0.659015
PC2	0.16845
PC3	0.117835
PC4	0.0547006

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Table 3. PCA Loadings (Commodity Block)

Variable	Loading_PC1	Loading_PC2
coal_usd_mt	0.498539	0.212373
cpo_usd_mt	0.533347	0.14421
nickel_usd_mt	0.545034	0.346915
gold_usd_oz	0.412236	-0.902082

4.3 Model Specification and Estimation

We estimate an ARDL model of ln(Sales) on lags of ln(Sales), CCI, MCI, and MSI. The bounds test is used to evaluate the existence of a long-run relationship among variables (Pesaran et al., 2001). Conditional on cointegration, we estimate the associated ECM to interpret short-run changes and the speed of adjustment (Engle & Granger, 1987). Standard diagnostic tests evaluate autocorrelation, heteroskedasticity, and normality; stability is assessed using CUSUM and CUSUMSQ.

Model form (ARDL). ln(Sales)_t = c0 + Σ φ_i ln(Sales)_(t-i) + Σ β_j CCI_z_(t-j) + Σ γ_k MCI_z_(t-k) + Σ δ_l MSI_pulse_(t-l) + ε_t, where Σ denotes lagged terms. Lag orders are selected by an information criterion across candidate specifications.
Estimation steps. (1) Standardize input series and build CCI_z and MCI_z from the first PCA component; (2) check integration order using ADF tests; (3) estimate candidate ARDL models and apply the bounds F-test for cointegration; (4) conditional on cointegration, estimate the ECM to interpret short-run changes and the speed of adjustment; (5) run residual diagnostics (serial correlation, heteroskedasticity, normality) and stability checks (CUSUM/CUSUMSQ).

4.4 Variable Validation

To reduce subjectivity in indicator selection, we complement the quantitative approach with a modified Delphi process, in which internal and external experts evaluate candidate variables for relevance and measurability and converge toward a final set (Hsu & Sandford, 2007).

5. Results

5.1 Stationarity testing

We apply the Augmented Dickey-Fuller (ADF) test to assess the integration order of each series. Table 4 indicates that ln(Sales), CCI_z, and MCI_z are non-stationary in levels but become stationary after first differencing, while the MSI_pulse is stationary in levels. This mixed integration pattern supports the use of the ARDL framework (Pesaran et al., 2001).

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Table 4. ADF Unit Root Test (Summary)

Series	Form	Type	ADF stat	CV 1%	CV 5%	CV 10%	Decision (5%)
ln(Sales)	Level	drift	-2.47504	-3.46	-2.88	-2.57	Not stationary
ln(Sales)	FirstDiff	drift	-10.3302	-3.46	-2.88	-2.57	Stationary (I(0))
CCI_z	Level	drift	-1.71585	-3.46	-2.88	-2.57	Not stationary
CCI_z	FirstDiff	drift	-4.6469	-3.46	-2.88	-2.57	Stationary (I(0))
MCI_z	Level	drift	-0.630059	-3.46	-2.88	-2.57	Not stationary
MCI_z	FirstDiff	drift	-3.329	-3.46	-2.88	-2.57	Stationary (I(0))
msi_pulse	Level	drift	-8.72298	-3.46	-2.88	-2.57	Stationary (I(0))
msi_pulse	FirstDiff	drift	-8.28693	-3.46	-2.88	-2.57	Stationary (I(0))

5.2 Bounds testing for long run relationship

We estimate candidate ARDL specifications and conduct the bounds test for cointegration. Table 5 reports the bounds F-statistic and associated p-value, supporting the presence of a long-run relationship among ln(Sales), CCI_z, MCI_z, and MSI_pulse at conventional levels.

Table 5. Bounds Test and Model Fit

Item	Value
Bounds F-statistic	4.7166
Bounds p-value	0.03228
Adjusted R-squared	0.243995
RMSE (in-sample)	0.221105

5.3 ARDL estimation results

In the preferred ARDL specification, selected coefficients indicate that commodity conditions (CCI_z) and the marketing intervention pulse (MSI_pulse) are positive and statistically significant, while the macroeconomic signal enters with a lag (MCI_z at t-3) and exhibits a negative effect (see Table 6).

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Table 6. ARDL Estimation Results (Selected Coefficients)

Term	Estimate	p-value
CCI_z	0.06567	0.00237
MSI_pulse	0.08940	0.029224
MCI_z(t-3)	-0.35754	0.049848

5.4 Error-correction representation

Given evidence of a long-run relationship, we interpret short-run dynamics using the ECM. Table 7 shows a negative and statistically significant error-correction term (ECT_1), implying that deviations from long-run equilibrium are partially corrected each month. This indicates gradual adjustment in capital goods demand, where procurement decisions and project pipelines do not instantly respond to shocks.

Table 7. ECM Estimated Coefficients

Variable	Estimate	Std. Error	t-stat	p-value	Sig.
(Intercept)	1.00612	0.23119	4.352	2.34e-05	***
d_ln(Sales)_l1	-0.32489	0.07433	-4.371	2.16e-05	***
d_ln(Sales)_l2	-0.18598	0.07646	-2.432	0.0161	*
d_ln(Sales)_l3	-0.09120	0.07171	-1.272	0.2052	
d_MCI	-0.30564	0.17830	-1.714	0.0883	.
d_MCI_l1	0.05655	0.17925	0.315	0.7528	
d_MCI_l2	0.35754	0.17865	2.001	0.0470	*
ECT_1	-0.18635	0.04252	-4.383	2.06e-05	***

5.5 Diagnostic and stability checks

To assess model adequacy, we examine residual diagnostics and parameter stability. Table 8 reports formal tests for serial correlation, heteroskedasticity, and normality.

The Breusch-Godfrey/Ljung-Box test suggests no residual autocorrelation ($p = 0.273$), indicating that the dynamic specification captures short-run dependence. By contrast, the Breusch-Pagan test indicates heteroskedasticity ($p = 0.0248$) and the normality test rejects Gaussian residuals ($p = 0.00316$). These features are common in monthly macro time-series; accordingly, inference can be complemented with heteroskedasticity-robust standard errors and forecast uncertainty bands. Stability is assessed using CUSUM and CUSUMSQ; the diagnostic plots do not indicate systematic parameter instability over the sample period (plots available upon request).

Table 8. Residual Diagnostic Tests

Test	Statistic	p-value
Autocorrelation (BG / Ljung-Box)	14.446	0.273141
Heteroskedasticity (Breusch-Pagan)	16.0315	0.0248298
Normality (Jarque-Bera / Shapiro)	11.512	0.00316378

6. Hypothesis Testing

Hypotheses are evaluated based on the sign, magnitude, and statistical significance of the estimated coefficients in the ARDL-ECM framework. We focus on (i) the contemporaneous effect of CCI_z, (ii) the lag structure of MCI_z, and (iii) the MSI_pulse effect.

Table 9. Hypothesis Testing Summary

Hypothesis	Expected sign	Empirical evidence (ARDL/ECM)	Decision
H1: CCI_z -> ln(Sales)	+	CCI_z is positive and significant (p = 0.00237) in Table 6.	Supported
H2: MCI_z -> ln(Sales)	± (lagged)	MCI_z effects vary across lags; one lagged term is significant (Table 7).	Partially supported
H3: MSI_pulse -> ln(Sales)	+	MSI_pulse is positive and significant (p = 0.0288) in Table 6.	Supported

7. Discussion

The results reinforce the view that commodity-driven investment cycles are central to heavy equipment demand in Indonesia. The positive CCI_z coefficient implies that when commodity conditions strengthen, firms accelerate project execution and capital expenditure, increasing equipment purchases. This aligns with the literature on commodity super-cycles and their real-sector transmission to investment and durable goods demand (Cuddington & Jerrett, 2008; Erten & Ocampo, 2013).

The MSI_pulse effect is economically meaningful: after controlling for lagged sales and external conditions, marketing initiatives are associated with higher sales. This supports marketing-response arguments that promotional activities can shift purchase timing and improve conversion, especially in contexts where customers are already considering investment

(Vakratsas & Ambler, 1999). From a planning perspective, MSI can be treated as a controllable lever that complements, rather than replaces, external cycle monitoring.

Macroeconomic impacts appear more nuanced. The lagged significance of macro terms suggests that credit conditions and import-cost pressures may influence procurement with delays. This pattern is plausible in monthly data because project approvals, financing arrangements, and procurement processes often unfold over several months. Therefore, macro indicators may be more useful for medium-term risk management than for short-horizon demand triggering.

8. Implications

Managerial implications. Practitioners can operationalize CCI_z as an early-warning indicator for demand planning, linking commodity market movements to expected pipeline strength. Marketing teams can time MSI_pulses around periods of improving CCI_z to raise lead conversion and shorten sales cycles. Given heteroskedasticity in residuals, planners should embed uncertainty bands in forecasts and update plans dynamically as external conditions change.

Strategic implications. Integrating external indices (CCI_z and MCI_z) with internal activity data (MSI) supports a more transparent and repeatable decision process for budgeting, campaign timing, and inventory positioning. This can reduce the tendency to rely on ad hoc judgments and improve cross-functional alignment between marketing and forecasting teams.

9. Limitations

Several limitations should be considered. First, the analysis uses a single-firm sales series and may not represent the full market. Second, MSI is captured as a pulse dummy and does not measure intensity, spend, or channel mix. Third, diagnostic tests indicate heteroskedasticity and non-normal residuals; while common in macro time-series, these features motivate robust inference and complementary robustness checks. Finally, structural breaks associated with major shocks (e.g., global crises) may require explicit modeling beyond standard stability tests.

10. Future Research

Future research can extend this work by (1) incorporating multi-brand or market-level sales data, (2) enriching marketing measures (spend, event counts, lead-generation metrics) to estimate dose-response relationships, (3) testing nonlinearities or regime-switching behavior across boom and bust periods, and (4) integrating additional external drivers such as global industrial production and domestic infrastructure spending. These extensions could improve forecasting accuracy and deepen understanding of how external cycles interact with marketing strategy in capital goods markets.

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