Manufacturing Resilience in Indonesia: Fiscal Intervention under Law No. 2/2020

Endi Muhammad Akbar AS[1]*, Marselina[2]
Department of Development Economics, Faculty of Economics and Business, Universitas Lampung, Bandar Lampung, Indonesia [1,2]
2311021026@students.unila.ac.id[1]; marselina@feb.unila.ac.id[2]*

Abstract
Purpose: This study examines changes in Indonesia's large and medium manufacturing production around the period associated with the COVID-19 shock and the extraordinary fiscal response under Law No. 2 of 2020.
Methodology/approach: The analysis uses 192 monthly observations of the Industrial Production Index (IPI) from January 2010 to December 2025. The main Interrupted Time Series model separates the initial level shift and the within-window trend during May 2020–June 2023 from the additional level and trend changes beginning in July 2023. Monthly indicators control for seasonality, and Newey–West standard errors with 12 lags support statistical inference.
Results/findings: The pre-window trend is positive at 0.444 IPI points per month. The average IPI deviation during the intervention window is −16.782 points relative to the continuation of the pre-window path ($p < .001$). The resulting slope is positive during the window (0.708 points per month, $p < .001$) and after the window (0.414 points per month, $p < .001$). Nevertheless, the post-window level remains 15.311 points below the baseline trajectory ($p < .001$). The post-window slope-change coefficient is not statistically significant. These findings indicate a persistent level gap alongside continued positive production growth, rather than a declining post-window trajectory. Unit-root tests, alternative endpoints, HAC lag lengths, a log specification, a quadratic trend, and an AR(1)-error model are reported as robustness checks.
Limitations: The analysis describes temporal changes in manufacturing production; it does not identify the isolated causal effect or effectiveness of Law No. 2 of 2020.

Keywords: Industrial Production Index; manufacturing production; fiscal response; COVID-19; Interrupted Time Series

1. Introduction

Economic resilience is a dynamic feature of development. It concerns how an economy absorbs a shock, how production responds while the shock is active, and whether activity later returns to its previous path or follows a different trajectory. Martin (2012) explains that recessionary shocks can leave persistent effects on an economy's development path, while Martin and Sunley (2015) distinguish recovery toward an earlier trajectory from adjustment to a new one. These perspectives make the time path of production important: a positive growth rate after a crisis does not necessarily mean that the level of production has returned to its pre-crisis trajectory.

The COVID-19 pandemic disrupted production through simultaneous supply- and demand-side channels. Restrictions on mobility and business operations interrupted production schedules and the movement of inputs, while uncertainty and lower household and business income weakened demand. International supply-chain disruption added further pressure to firms that relied on imported inputs or external markets (Demirgüç-Kunt et al., 2021; International Monetary Fund [IMF], 2022). Indonesia's national economy contracted by 2.07% in 2020 and expanded by 3.69% in 2021 (Badan Pusat Statistik [BPS], 2021, 2022). The aggregate recovery, however, does not establish whether manufacturing production returned to its earlier path.

Manufacturing is a central component of Indonesia's production structure. BPS reported that manufacturing accounted for 19.87% of gross domestic product in 2020, while its share was 18.98% in

2024 (BPS, 2020, 2025a). The sector's scale makes changes in manufacturing production relevant to employment, intermediate-input demand, exports, and the performance of connected industries. The monthly IPI for large and medium manufacturing industries provides a high-frequency indicator of production activity. BPS describes the IPI as an index of manufacturing production relative to a base period and compiles it from the Monthly Survey of Large and Medium Manufacturing Industries (BPS, 2024, 2025b).

The pandemic also prompted an exceptional fiscal response. Law No. 2 of 2020 established a legal framework for state financial policy and financial-system stability during the pandemic. The law was enacted on 16 May 2020 and promulgated on 18 May 2020 (Indonesia, 2020). The Ministry of Finance reported that the National Economic Recovery programme disbursed IDR 579.78 trillion in 2020, equivalent to 83.4% of its IDR 695.2 trillion allocation (Directorate General of Treasury, 2021). This figure describes the scale of the national response; it is not a measure of the amount received by manufacturing firms and is not included as an explanatory variable in the present model.

The policy timeline contains two distinct institutional reference points. Law No. 2 of 2020 allowed the budget deficit to exceed 3% of GDP until the end of fiscal year 2022, after which the statutory ceiling returned to 3% from fiscal year 2023 (Indonesia, 2020). Separately, Presidential Decree No. 17 of 2023 declared the end of Indonesia's COVID-19 pandemic status, effective 21 June 2023 (Indonesia, 2023). The main analytical window therefore runs from May 2020 to June 2023 because it covers the period from the enactment of the law to the formal end of pandemic status. The alternative endpoint of December 2022 is also tested because it corresponds more closely to the temporary fiscal-deficit flexibility under the law. The analytical window is not presented as the legal duration of every provision of the statute.

The empirical gap is specific. Existing Indonesian studies have examined the fiscal response, manufacturing performance, and structural change, while methodological studies have established segmented regression for intervention analysis. However, the evidence assembled here does not provide a monthly assessment of the national large-and-medium manufacturing IPI through December 2025 that separates (1) the initial level shift and trend within the pandemic-response window from (2) a further level adjustment and trend change after that window. A model that omits the second level shift can incorrectly assign a persistent level gap to the post-window slope. The revised specification addresses this problem and tests alternative endpoints and error structures.

The study has three objectives. First, it measures the level deviation and production slope during May 2020–June 2023 relative to the pre-window trajectory. Second, it tests the additional level difference and the resulting production slope from July 2023, including whether that slope differs from zero. Third, it evaluates whether the central findings remain consistent across alternative window endpoints, HAC lag lengths, functional forms, and an AR (1)-error specification. These objectives concern the observed production path. Because the model contains no direct fiscal-spending variable, comparison series, or untreated control group, it does not identify the causal effect of Law No. 2 of 2020.

2. Literature Review and Hypothesis Development

2.1 Economic Resilience and Production Trajectories

Economic resilience is more than the avoidance of an initial decline. Martin (2012) links recessionary shocks to possible hysteresis, through which a temporary disturbance can affect subsequent economic performance. Martin and Sunley (2015) describe resilience as a process of response, recovery, and adaptation. An economy may return toward its previous path, or it may settle on a different path after the shock. Martin et al. (2016) further show that the structure of economic activity influences how places respond to recessions. The implication for manufacturing is that the level of production and its subsequent slope should be assessed separately.

This study uses resilience as an interpretive framework rather than as a separate index. The IPI records manufacturing production, not the whole real sector and not the full capacity of an economy to absorb shocks. A negative level gap combined with a positive subsequent slope indicates that production is growing while remaining below the path implied by the earlier trend. Such a pattern is consistent with partial recovery and a persistent level gap; it is not a direct measure of national economic resilience.

2.2 Fiscal Policy as an Instrument of Stabilisation

Keynes (1936) argues that output and employment can remain below potential when private expenditure is insufficient. Public expenditure and other fiscal instruments can support aggregate demand when households and firms reduce spending. Musgrave (1959) places economic stabilisation among the main functions of public finance, alongside allocation and distribution. During a large shock, fiscal support may help sustain household demand, business liquidity, and the provision of essential services. Its transmission to manufacturing production depends on policy design, implementation, timing, firms' access to support, and the conditions facing domestic and external markets.

In Indonesia, Law No. 2 of 2020 provided the legal basis for extraordinary state-finance and financial-system measures. The PEN programme included health spending, social protection, support for micro, small, and medium enterprises, corporate financing, and business incentives (Directorate General of Treasury, 2021). These programmes formed part of the national response, but the aggregate disbursement cannot be interpreted as manufacturing-specific assistance. The law is therefore treated as the institutional context for the study period rather than as a direct numerical regressor. The regression does not test whether the law or the PEN programme caused the observed changes in IPI.

2.3 The Industrial Production Index as a Manufacturing Indicator

BPS defines the monthly IPI as an index that describes manufacturing production in a given month relative to the base period. The national index is compiled from the Monthly Survey of Large and Medium Manufacturing Industries and is reported by two-digit KBLI classification. BPS documents the use of the Discrete Divisia method to aggregate monthly production ratios and identifies 2010 as the index base in its manufacturing production publication (BPS, 2024, 2025b). An index above 100 indicates production above the base-period level; an index below 100 indicates production below that level (BPS, 2024).

The IPI is appropriate for a monthly time-series analysis because it records production activity at a higher frequency than annual national accounts. Its scope must nevertheless remain explicit. The series used here covers large and medium manufacturing industries. It does not directly measure micro and small manufacturing, agriculture, construction, services, employment, or household welfare. The results should therefore be interpreted as evidence about one production-side component of Indonesia's real sector.

2.4 Empirical Evidence on the Pandemic and Manufacturing Activity

Official Indonesian statistics document substantial heterogeneity across firms and sectors during the pandemic. BPS reported that micro and small manufacturing production growth contracted year on year in each quarter of 2020, with the deepest contraction, 21.31%, recorded in the second quarter. The same publication reported positive quarter-on-quarter growth in the third and fourth quarters of 2020 (BPS, 2021). These figures refer to micro and small manufacturing and are not the same population as the large and medium manufacturing IPI used in this study. They nevertheless show that production conditions differed by firm scale and by quarter.

The IMF's assessment of Indonesia's pandemic experience emphasises the uneven sectoral effects of the shock and the importance of fiscal buffers in supporting domestic demand (IMF, 2022). Krisnawati

(2023), using quarterly Indonesian data from 2010 Q1 to 2021 Q4, finds that inflation significantly affected manufacturing output in the short run, while broad money, inflation, and the policy interest rate were significant in the long run. This evidence reinforces the importance of macroeconomic conditions beyond the fiscal response. In its 2024 manufacturing production publication, BPS reported positive year-on-year growth in large and medium manufacturing production in all four quarters of 2024: 2.82% in the first quarter, 2.86% in the second, 0.90% in the third, and 3.89% in the fourth (BPS, 2025b). These observations provide context for interpreting the positive post-window slope in the present analysis, but they do not replace the monthly regression results.

The empirical literature also shows why the policy context should not be treated as a single explanatory factor. Sholihah et al. (2022) discuss fiscal policy as part of the effort to strengthen national economic resilience, while Sopanah and Haikal (2022) examine Law No. 2 of 2020 as a fiscal-policy strategy. Neither study supplies the monthly manufacturing IPI series used here. Galdi et al. (2023) demonstrate the value of industrial production indicators for tracking economic activity, and Khairunnisa et al. (2025) examine manufacturing growth and the trade balance in Indonesia. The present study complements these contributions with monthly national IPI evidence through December 2025.

2.5 Structural Change and Interrupted Time Series

A structural change can involve a shift in the level of a series, a change in its trend, or both. Perron (1989) demonstrates that major economic events can alter the behaviour of macroeconomic time series, while Bai and Perron (2003) develop methods for identifying multiple structural changes. The present study differs from endogenous-break procedures because its intervention dates are specified in advance from the institutional timeline.

Interrupted Time Series analysis uses observations before and after a defined event to test whether an outcome's level or trend changed. Segmented regression can distinguish the baseline trend, a level shift, and a subsequent slope change (Lopez Bernal et al., 2017; Wagner et al., 2002). Model specification matters because a missing level term can cause the trend coefficient to absorb a persistent level difference. Lopez Bernal et al. (2018) and Turner et al. (2021) emphasise the need to match the model to the intervention structure and to examine alternative specifications. Schaffer et al. (2021) discuss ARIMA-based ITS methods as one way to address serial dependence in intervention time series. These considerations motivate the additional post-window level term, the within-window trend term, and the AR(1)-error robustness model used below.

2.6 Research Gap and Contribution

The contribution is an empirical one. The analysis covers 192 monthly observations through December 2025 and specifies the intervention window before examining the regression results. It distinguishes an initial level shift and trend change during the pandemic-response window from a further level adjustment and trend change after June 2023. This distinction directly addresses a limitation in the earlier specification, which returned the window dummy to zero in July 2023 without a separate post-window level term. The study also reports linear-combination and joint Wald tests, unit-root diagnostics, alternative endpoints, HAC lag sensitivity, a log specification, a quadratic trend check, and an AR(1)-error model.

The paper does not claim that the IPI is a comprehensive resilience index or that the regression isolates the causal effect of Law No. 2 of 2020. Its contribution concerns the temporal behaviour of large and medium manufacturing production around the period of the pandemic and the government's fiscal response.

2.7 Hypothesis Development

The first hypothesis follows from the disruption to production operations, supply chains, and demand during the initial pandemic period. The initial level shift at the beginning of the analytical window is expected to be negative ($\beta_2 < 0$).

The second hypothesis follows from the possibility of production adjustment as firms adapt and demand recovers. The within-window slope change is expected to be positive ($\beta_3 > 0$), indicating that the monthly trajectory improves relative to the baseline trend. This hypothesis concerns the slope change, while the resulting within-window slope is $\beta_1 + \beta_3$.

The third hypothesis reflects the possibility of persistent output scarring. The level gap at the start of the post-window period, measured as $\beta_4 + 38\beta_3$, is expected to remain negative if production has not returned to the no-break baseline path.

The fourth hypothesis concerns the post-window trajectory. The resulting post-window slope, $\beta_1 + \beta_5$, is expected to be positive as production continues to expand after the formal end of pandemic status. A separate test of β_5 determines whether the post-window slope differs from the pre-window slope. Finally, a joint Wald test evaluates whether the intervention-window and post-window level and trend terms are jointly equal to zero.

Table 1. Testable hypotheses and regression parameters

Hypothesis	Expected pattern	Statistical test
H1: Initial window level shift	$\beta_2 < 0$	Coefficient test for β_2
H2: Within-window trend adjustment	$\beta_3 > 0$	Coefficient test for β_3; total slope $\beta_1 + \beta_3$
H3: Post-window level gap	$\beta_4 + 38\beta_3 < 0$	Linear-combination test for $\beta_4 + 38\beta_3$
H4: Positive post-window slope	$\beta_1 + \beta_5 > 0$	Linear-combination test for $\beta_1 + \beta_5$
Joint structural change	At least one level or trend term differs from zero	Wald test of $\beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$

3. Research Methodology

3.1 Research Design

The study applies a quantitative monthly time-series design using segmented regression within an Interrupted Time Series framework. The unit of analysis is one monthly observation of the national IPI for large and medium manufacturing industries. The sample covers January 2010 to December 2025, giving 192 observations. The event dates are defined before the regression analysis: May 2020 marks the enactment of Law No. 2 of 2020, and July 2023 begins the period after the formal end of pandemic status under Presidential Decree No. 17 of 2023 (Indonesia, 2020, 2023).

The analysis is observational. It examines changes in the IPI around the predefined time structure and does not identify a separate causal effect of the law. The model contains no direct measure of PEN expenditure allocated to manufacturing, no untreated comparison group, and no control series. Other contemporaneous factors, including public-health restrictions, monetary conditions, global demand, and supply-chain disruption, may have influenced production.

3.2 Data Source, Coverage, and Continuity

The dependent variable is the monthly IPI from the workbook supplied for this study. The workbook identifies the series as "Indeks Produksi Bulanan Industri Besar dan Sedang Menurut KBLI 2 Digit [KBLI 2020] (2010=100)." The title and classification correspond to the BPS statistical table and to the BPS publication on manufacturing production for large and medium industries (BPS, 2025b, 2026). The BPS statistical table was last updated on 28 September 2026 when checked for this revision. The workbook was processed on 11 November 2026; the original download date was not recorded in the workbook.

The workbook contains 192 consecutive monthly observations from January 2010 through December 2025, with no missing IPI values. It labels the supplied observations as one 2010=100 series using KBLI 2020. The workbook does not include a historical revision log or a methodological note documenting any backcasting across classification changes. The analysis therefore uses the BPS-supplied series without splicing a separate series, while recognising that the workbook alone does not independently verify the full historical classification bridge. The BPS publication confirms that the large-and-medium monthly survey reports manufacturing indices by two-digit KBLI and uses the 2010=100 base (BPS, 2025b).

The BPS metadata defines the IPI as a monthly indicator of manufacturing production relative to the base period and documents the Discrete Divisia calculation based on monthly production ratios (BPS, 2024). Since the index is reported in index points, the coefficients in the level model are interpreted as index-point changes and index points per month. A log specification is included as a robustness check so that its coefficients can be interpreted in proportional terms.

Table 2. Descriptive statistics of the monthly IPI

Period	Observations	Mean	Std. dev.	Minimum	Maximum
Pre-window (Jan 2010–Apr 2020)	124	123.98	16.63	92.32	158.00
Intervention window (May 2020–Jun 2023)	38	143.10	11.46	104.02	158.82
Post-window (Jul 2023–Dec 2025)	30	159.67	6.95	138.78	172.43
Full sample	192	133.34	19.89	92.32	172.43

Note. The source series is the national large-and-medium manufacturing IPI, not a measure of all real-sector activities. The descriptive statistics are calculated directly from the 192 observations in the supplied workbook.

3.3 Intervention Period and Variable Construction

The main intervention window covers May 2020 through June 2023, a total of 38 months. The pre-window period contains 124 months, while the post-window period from July 2023 through December 2025 contains 30 months. The main endpoint follows the effective date of Presidential Decree No. 17 of 2023, which ended the formal pandemic status on 21 June 2023. The December 2022 endpoint is tested separately because the temporary permission for a budget deficit above 3% of GDP under Law No. 2 of 2020 applied no later than the end of fiscal year 2022 (Indonesia, 2020, 2023).

The variables are coded from calendar dates rather than relying on the pre-existing dummy columns in the workbook. Time increases sequentially from 1 in January 2010 to 192 in December 2025.

WindowLevel equals one from May 2020 to June 2023 and zero elsewhere. WindowTrend is zero before May 2020, increases from 1 to 38 during the window, and remains at 38 after June 2023. PostLevel equals one from July 2023 onward. PostTrend equals zero before July 2023 and increases from 1 to 30 during the post-window period. Monthly indicators for February through December are included, with January as the reference month.

Table 3. Operational definitions of variables

Variable	Construction	Interpretation
IPI_t	Monthly IPI, January 2010–December 2025	Manufacturing production index in index points
$Time_t$	1, 2, …, 192	Pre-window monthly trend, β_1
$WindowLevel_t$	1 during May 2020–June 2023; otherwise 0	Initial level shift at the beginning of the window, β_2
$WindowTrend_t$	0 before May 2020; 1–38 during the window; held at 38 after June 2023	Within-window slope change, β_3
$PostLevel_t$	1 from July 2023 onward; otherwise 0	Additional level adjustment from July 2023, β_4
$PostTrend_t$	0 before July 2023; 1–30 from July 2023 onward	Post-window slope change, β_5
$Month_{mt}$	Monthly indicators for February–December	Controls recurring seasonal differences

3.4 Main Model Specification

The enhanced segmented regression is specified as follows:

$$\mathbf{IPI_t = \beta_0 + \beta_1 Time_t + \beta_2 WindowLevel_t + \beta_3 WindowTrend_t + \beta_4 PostLevel_t + \beta_5 PostTrend_t + \Sigma \delta_m Month_{mt} + \varepsilon_t}$$

The coefficient β_1 represents the baseline monthly trend before May 2020. The coefficient β_2 represents the initial level shift at the beginning of the intervention window. The coefficient β_3 captures the change in slope during the window, so the total within-window slope is $\beta_1 + \beta_3$. The WindowTrend variable is held at 38 after June 2023 rather than returning to zero. This coding preserves the cumulative within-window trend when the model moves into the post-window period.

The coefficient β_4 represents the additional level adjustment beginning in July 2023, conditional on the accumulated WindowTrend term. The post-window level difference relative to the no-break baseline at the beginning of July 2023 is therefore $\beta_4 + 38\beta_3$. The coefficient β_5 represents the change in slope after June 2023, and the resulting post-window slope is $\beta_1 + \beta_5$. This specification allows the post-window trajectory to differ in both level and slope. It avoids forcing the IPI series to return mechanically to the pre-window trend when the temporary WindowLevel dummy switches off.

For a summary of the intervention-window deviation, the average level difference across the 38 months is tested as $\beta_2 + 19.5\beta_3$, because the monthly WindowTrend values run from 1 to 38. This linear combination is more informative than interpreting β_2 as a constant average effect throughout the window.

3.5 Regression Procedure and Statistical Inference

The regression models were computed using OLS with Newey–West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. The main specification uses 12 lags to cover a one-year dependence horizon in monthly data. The analysis also reports results with 6 and 18 lags. HAC standard errors affect the covariance matrix and the associated tests; they do not remove serial correlation from the residual series (Newey & West, 1987). All numerical calculations in this revision were carried out using Python with statsmodels 0.14.6 and SciPy 1.17.0. The supplied workbook was used as the source of the 192 monthly IPI observations, and no missing values were imputed or replaced.

The analysis uses a 5% significance level and reports coefficient values, standard errors, test statistics, p-values, and 95% confidence intervals. The resulting within-window and post-window slopes are tested directly as linear combinations. Joint Wald tests assess the intervention-window terms and post-window terms. The combined structural-change test evaluates the null hypothesis that β_2, β_3, β_4, and β_5 are jointly zero.

3.6 Stationarity, Diagnostic Tests, and Model Treatment

The level and log-level series are assessed using the Augmented Dickey–Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The ADF null hypothesis is a unit root, while the KPSS null hypothesis is stationarity. Both constant-only and constant-plus-trend forms are examined. The first differences of IPI and log IPI are also tested. The regression residuals are checked after the trend, seasonal, and intervention terms have been included. These tests are interpreted together because a failure to reject one null does not establish the alternative on its own.

Residual diagnostics include the Breusch–Godfrey test for serial correlation at lags 1 and 12 and the Breusch–Pagan and White tests for heteroskedasticity. Calendar-month indicators control recurring seasonality. Because the residual diagnostics can reject the assumptions of homoskedasticity and no serial correlation, the main OLS results use HAC standard errors. A supplementary SARIMAX model with AR(1) errors evaluates whether the main slope findings remain under an explicit autoregressive error structure (Schaffer et al., 2021).

3.7 Robustness Checks

Five robustness exercises are conducted. First, the endpoint of the intervention window is changed to December 2022 and December 2023, while retaining May 2020 as the start date. Second, the HAC lag length is changed from 12 to 6 and 18. Third, the dependent variable is changed from IPI in levels to the natural logarithm of IPI. Fourth, a quadratic time term is added to evaluate whether the long pre-window trend is inconsistent with a linear form; a separate pre-window-only quadratic regression is also examined. Fifth, a SARIMAX regression with AR(1) errors is fitted as an alternative treatment of serial dependence.

3.8 Scope of Inference

The paper analyses monthly manufacturing production in large and medium industries. The model does not contain direct measures of fiscal spending, tax incentives, transfers, deficit levels, firm-level programme receipt, or a comparison group. Consequently, the coefficients describe changes associated with the predefined periods and cannot be interpreted as the isolated causal effect of Law No. 2 of 2020. The IPI also does not represent the entire real sector or a comprehensive resilience index.

4. Results and Discussion

4.1 Descriptive Pattern of the IPI

The supplied series contains 192 consecutive observations. The mean IPI rises from 123.98 in the pre-window period to 143.10 during the intervention window and 159.67 in the post-window period. The

minimum value in the full sample is 92.32 and the maximum is 172.43. These period means show that the index level increased across the sample; they do not, by themselves, indicate whether production followed the path implied by the pre-window trend. The segmented regression tests that distinction. Figure 1 presents the monthly IPI, the fitted values from the enhanced model, and the no-break baseline trajectory. The model fitted values follow the actual series across the three periods. The counterfactual line extends the pre-window trend and monthly seasonal pattern while setting the intervention and post-window terms to zero. The persistent distance between the fitted series and the no-break baseline illustrates why the post-window level term is necessary.

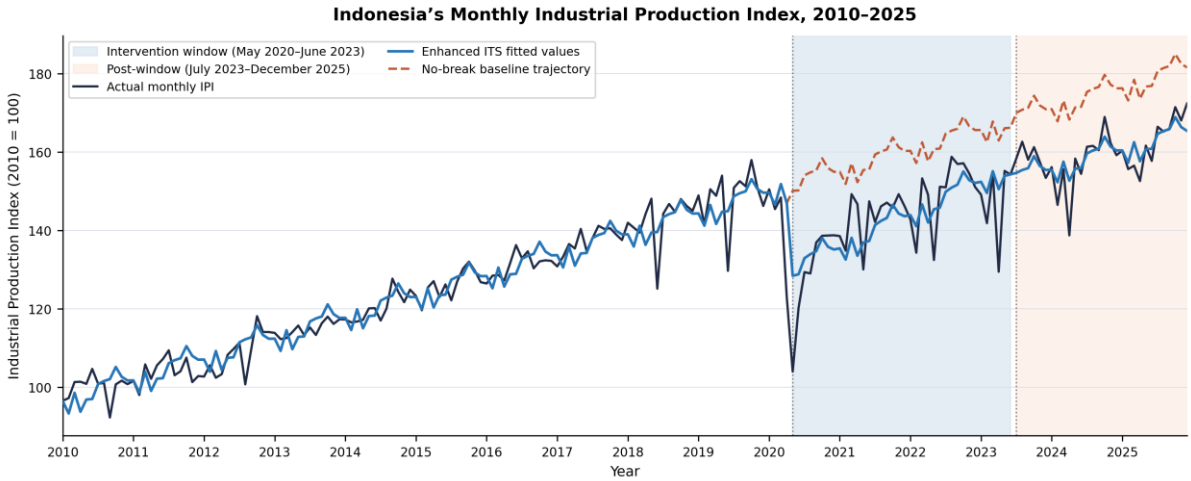

Figure 1. Monthly IPI, enhanced ITS fitted values, and no-break baseline trajectory, 2010–2025
Note. The shaded area from May 2020 to June 2023 denotes the analytical intervention window. The post-window period begins in July 2023. The no-break baseline uses the pre-window trend and seasonal indicators while setting all intervention and post-window terms to zero. Source: Author's calculations using the BPS IPI series supplied in the workbook.

4.2 Unit-Root Tests and Residual Diagnostics

Table 4. ADF and KPSS stationarity tests

Series	ADF statistic (trend)	ADF p	KPSS statistic (trend)	KPSS p	Assessment
IPI level	-2.431	0.363	0.231	0.010	Non-stationary
Log IPI	-2.269	0.451	0.322	0.010	Non-stationary
First difference of IPI	-4.910	< .001	0.048	0.100	Stationary
First difference of log IPI	-4.981	< .001	0.054	0.100	Stationary

Note. ADF uses the AIC-selected lag length; KPSS uses the automatic bandwidth. The reported tests include a constant and linear trend. For IPI levels and log IPI, ADF does not reject a unit root and KPSS rejects trend stationarity. For the first differences, ADF rejects a unit root and KPSS does not reject stationarity at 5%.

The unit-root tests indicate that IPI in levels and log levels is non-stationary under the reported specifications. The first differences of both series are stationary. This result cautions against interpreting a deterministic trend regression without examining its residual behaviour. After the enhanced trend, seasonal, and intervention terms are included, the residual ADF test with a trend rejects the unit-root null (ADF = −4.289, p = .003), while the KPSS test does not reject stationarity (KPSS = 0.030, p =

.100). These residual checks provide supplementary information about the regression residuals, while the non-stationarity of the raw index remains an important qualification. Because the tests are applied to regression-generated residuals, the reported univariate critical values are not treated as a formal Engle–Granger cointegration test.

Table 5. Residual diagnostic tests for the enhanced model

Test	Statistic	p-value	Decision at 5%
Breusch–Godfrey, lag 1	11.000	< .001	Reject no serial correlation
Breusch–Godfrey, lag 12	28.947	0.004	Reject no serial correlation
Breusch–Pagan	44.415	< .001	Reject constant variance
White	128.475	< .001	Reject constant variance

Note. LM statistics are reported. The null hypotheses are no serial correlation at the tested lag order and homoskedasticity. Newey–West HAC standard errors are used for the main regression inference.
The Breusch–Godfrey tests reject the null of no serial correlation at lags 1 and 12. The Breusch–Pagan and White tests also reject constant error variance. These diagnostics support the use of HAC standard errors for the main OLS regression. The adjustment does not remove residual dependence, so the paper also reports an AR(1)-error model and retains caution in interpreting the p-values
.

4.3 Reproduction of the Earlier Specification

The earlier three-term specification was first reproduced using the supplied IPI observations, the May 2020–June 2023 window indicator, post-window time, and monthly controls. The coefficients closely reproduce the values in the submitted paper: the baseline trend is 0.4044, the intervention-window level coefficient is −12.9881, and the post-window trend-change coefficient is −0.5196. The post-window slope must be tested as $\beta_1 + \beta_3$ rather than inferred from β_3 alone. Its value is −0.1152 IPI points per month, but the linear-combination test is not statistically significant ($p = .474$; 95% CI [−0.432, 0.201]).

The earlier model also does not include a separate post-window level term. When the intervention-window dummy switches off in July 2023, the model forces the fitted series back to the pre-window line at that point. A persistent level gap can therefore be absorbed by the post-window trend coefficient. This is the specification problem identified by the reviewer. The earlier model's joint Wald test rejects the null that the window-level and post-window trend terms are both zero, $\chi^2(2) = 15.652$, $p < .001$, but that result does not solve the missing-level-term problem.

4.4 Enhanced ITS Results

The enhanced model separates the temporary window-level shift, the within-window trend change, the additional post-window level adjustment, and the post-window trend change. It is statistically significant overall, with $R^2 = 0.9302$ and adjusted $R^2 = 0.9239$. The HAC-adjusted model test is $F(16, 175) = 490.98$, $p < .001$. Table 6 reports the five central time coefficients. Monthly seasonal indicators are included, with January as the reference month.

Table 6. Enhanced segmented regression results for monthly IPI

Parameter	Coefficient	HAC SE	t	p-value	95% confidence interval
Baseline time trend (β_1)	0.4436	0.0160	27.79	< .001	[0.412, 0.475]

Parameter	Coefficient	HAC SE	t	p-value	95% confidence interval
Initial intervention-window level shift (β_2)	-21.9301	3.8309	-5.72	< .001	[-29.438, -14.422]
Within-window trend change (β_3)	0.2640	0.1871	1.41	0.158	[-0.103, 0.631]
Additional post-window level adjustment (β_4)	-25.3430	7.1354	-3.55	< .001	[-39.328, -11.358]
Post-window trend change (β_5)	-0.0291	0.1031	-0.28	0.777	[-0.231, 0.173]

Note. OLS coefficients with Newey–West HAC standard errors and 12 lags. The model includes monthly indicators. $R^2 = 0.9302$; adjusted $R^2 = 0.9239$; $F(16, 175) = 490.98$, $p < .001$.

The pre-window trend is positive and statistically significant ($\beta_1 = 0.4436$, $p < .001$), indicating an average increase of 0.444 IPI points per month before May 2020, conditional on monthly seasonality. The initial level shift at the beginning of the intervention window is negative and significant ($\beta_2 = -21.930$, $p < .001$). This coefficient refers to the initial shift in May 2020, not to a constant average difference across all 38 months.

The within-window trend-change coefficient is positive ($\beta_3 = 0.2640$) but is not statistically significant at 5% ($p = .158$). The resulting within-window slope, $\beta_1 + \beta_3$, is 0.7076 IPI points per month and is statistically significant ($p < .001$; 95% CI [0.358, 1.057]). The average level deviation across the 38-month window, measured by $\beta_2 + 19.5\beta_3$, is −16.782 points ($p < .001$; 95% CI [−20.231, −13.334]). The combined results indicate that production remained below the no-break baseline during the window while following a positive monthly trajectory.

The additional post-window level adjustment is negative and statistically significant ($\beta_4 = -25.343$, $p < .001$). Since the WindowTrend term is held at 38 after June 2023, the relevant post-window level gap relative to the baseline trajectory is $\beta_4 + 38\beta_3$, not β_4 alone. This linear combination is −15.311 IPI points ($p < .001$; 95% CI [−20.119, −10.503]). The level gap therefore remains negative at the beginning of the post-window period, even though the index itself continues to rise.

The post-window trend-change coefficient is −0.0291 and is not statistically significant ($p = .777$). The resulting post-window slope is $\beta_1 + \beta_5 = 0.4145$ IPI points per month, which is positive and statistically significant ($p < .001$; 95% CI [0.216, 0.613]). The results therefore do not support the earlier interpretation of a declining post-window trajectory. They indicate a positive post-window slope alongside a persistent level gap relative to the pre-window baseline path.

4.5 Linear-Combination and Joint Wald Tests

Table 7. Linear-combination and joint Wald tests

Test	Result	SE / test statistic	p-value	95% CI / conclusion
Within-window slope: $\beta_1 + \beta_3$	0.7076	0.1784	< .001	[0.358, 1.057]
Post-window slope: $\beta_1 + \beta_5$	0.4145	0.1015	< .001	[0.216, 0.613]
Average window gap: $\beta_2 + 19.5\beta_3$	−16.782	1.759	< .001	[−20.231, −13.334]
Post-window gap: $\beta_4 + 38\beta_3$	−15.311	2.453	< .001	[−20.119, −10.503]

Test	Result	SE / test statistic	p-value	95% CI / conclusion
Wald: $\beta_2 = \beta_3 = 0$	$\chi^2(2) = 98.394$	—	< .001	Window terms jointly significant
Wald: $\beta_4 = \beta_5 = 0$	$\chi^2(2) = 21.107$	—	< .001	Post-window terms jointly significant
Wald: $\beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$	$\chi^2(4) = 133.814$	—	< .001	All break terms jointly significant

Note. Linear combinations use the full HAC covariance matrix. Wald tests use the Newey–West robust covariance matrix. Confidence intervals are 95%.

The linear-combination tests answer the questions that cannot be resolved by reading individual coefficients separately. The total within-window slope and the total post-window slope are both positive and statistically different from zero. At the same time, the average window gap and the post-window gap relative to the baseline path are negative and statistically significant. This combination is consistent with rising production that has not fully closed the level gap against the pre-window trajectory.

The joint Wald tests reject the null that the intervention-window level and trend terms are jointly zero, $\chi^2(2) = 98.394$, $p < .001$. They also reject the null that the post-window level and trend terms are jointly zero, $\chi^2(2) = 21.107$, $p < .001$. The combined test rejects the null that all four break terms are jointly zero, $\chi^2(4) = 133.814$, $p < .001$. These tests provide evidence that the series' level and trend structure differs across the predefined periods. They do not establish that the law caused those changes.

4.6 Robustness Checks

4.6.1 Alternative HAC Lag Lengths

Table 8. Sensitivity to Newey–West lag length

HAC lags	Window level β_2	Window trend p	Post level β_4	Post trend p	Post slope $\beta_1+\beta_5$	Post-slope p
6	-21.930	0.200	-25.343	0.818	0.414	< .001
12	-21.930	0.158	-25.343	0.777	0.414	< .001
18	-21.930	0.108	-25.343	0.727	0.414	< .001

Note. The OLS coefficient values are unchanged across HAC lag choices; standard errors and p-values vary. The post-window slope remains positive and significant for 6, 12, and 18 lags.

Changing the HAC lag length from 6 to 18 does not change the regression coefficients. The post-window slope remains 0.4145 points per month and remains statistically significant at each lag choice. The post-window trend-change coefficient remains statistically insignificant. The main conclusion is therefore not driven by choosing 12 lags, although the standard errors vary with the bandwidth.

4.6.2 Alternative Endpoints for the Intervention Window

Table 9. Sensitivity to the intervention-window endpoint

Endpoint	Window months	Window trend β_3	p-value	Post-window level gap	p-value	Post slope	p-value
Dec2022	32	0.481	0.008	-16.834	< .001	0.483	< .001

Endpoint	Window months	Window trend β_3	p-value	Post-window level gap	p-value	Post slope	p-value
Jun2023	38	0.264	0.158	-15.311	< .001	0.414	< .001
Dec2023	44	0.229	0.096	-18.886	< .001	0.638	< .001

Note. The start date remains May 2020. The alternatives end the window in December 2022, June 2023, and December 2023. The level gap column tests the post-window level difference relative to the baseline path.

The December 2022 alternative is important because the law permitted a deficit above 3% of GDP only through fiscal year 2022. Under this endpoint, the within-window trend change is positive and significant ($\beta_3 = 0.481$, $p = .008$), while the resulting post-window slope is 0.483 points per month and significant ($p < .001$). With the June 2023 main endpoint, the post-window slope is 0.4145 and significant; with a December 2023 endpoint, it is 0.638 and significant. The post-window level gap remains negative and significant under all three endpoints. The conclusion of positive post-window production growth alongside an unresolved level gap is therefore robust to the tested endpoint choices.

4.6.3 Logarithmic IPI Specification

The logarithmic model produces a positive post-window slope of 0.002579 log points per month ($p = 0.00002$), equivalent to a monthly growth rate of 0.258%. Its 95% interval corresponds to 0.140% to 0.376% per month. The post-window level gap relative to the baseline path is −13.16% ($p < .001$; 95% CI [−16.21%, −10.00%]). The log specification therefore preserves the main interpretation: the post-window production index rises, while its level remains below the no-break baseline.

4.6.4 Quadratic Trend

The quadratic time term is not statistically significant in the full enhanced model (coefficient = -0.000176, $p = 0.748$). The pre-window-only quadratic term is also not significant (coefficient = -0.000152, $p = 0.755$). These results do not indicate a statistically significant quadratic curvature in the pre-window trend. The linear pre-window trend therefore remains a defensible baseline specification for this dataset, although other unobserved changes may still affect the series.

4.6.5 AR(1)-Error Model

A supplementary SARIMAX regression with AR(1) errors gives an autoregressive coefficient of 0.235 ($p = 0.036$). The resulting post-window slope is 0.457 IPI points per month ($p < .001$; 95% CI [0.255, 0.658]), consistent with the positive slope in the HAC model. However, the Ljung–Box tests still reject no residual autocorrelation at 12 and 24 lags ($p = 0.008$ and $p = 0.0002$). The AR(1) specification therefore provides a useful sensitivity check but does not remove all serial dependence.

Table 10. Summary of robustness checks

Robustness check	Key result	Assessment
HAC lags 6, 12, 18	Post slope = 0.4145 for all; $p < .001$	Main slope finding is stable
Window endpoint Dec 2022	Post slope = 0.4827; $p < .001$	Main result is stable; window-trend shift is positive
Window endpoint Dec 2023	Post slope = 0.6376; $p < .001$	Main result is stable
Log IPI	Post slope = 0.258% monthly; $p < .001$	Positive post-window growth is retained

Robustness check	Key result	Assessment
Quadratic trend	Time-squared p = .748; pre-only p = .755	No evidence against linear pre-window trend
SARIMAX AR(1) errors	Post slope = 0.4569; p < .001	Consistent slope; residual autocorrelation remains

Note. All robustness checks use the same 192-month IPI series. The AR(1) model is supplementary and retains residual dependence at longer Ljung–Box lags.

4.7 Economic Interpretation and Comparison with Prior Evidence

The central empirical pattern is a negative level deviation during the pandemic-response window and a negative level gap at the start of the post-window period, combined with positive production slopes during both periods. This distinction matters. The data do not show that manufacturing production continued to decline after July 2023. Instead, the IPI increased at a positive monthly rate, while the level remained below the trajectory implied by the pre-window trend. This is consistent with a recovery process that restores output growth without fully closing the level gap within the observation period.

The negative initial shift is consistent with the documented disruption to production and demand during the pandemic. BPS reported contractions in micro and small manufacturing output during 2020, with the deepest year-on-year decline in the second quarter. Although that survey covers a different firm-size group, it supports the broader account of substantial pressure on manufacturing activity at the beginning of the crisis (BPS, 2021). The IMF (2022) also emphasises that the pandemic affected Indonesian sectors unevenly, which cautions against treating aggregate GDP recovery as evidence of uniform industrial recovery.

The positive post-window slope is also consistent with BPS's report of positive year-on-year production growth among large and medium manufacturing industries in each quarter of 2024. The quarterly rates ranged from 0.90% in the third quarter to 3.89% in the fourth quarter (BPS, 2025b). The monthly IPI regression extends the observation period through December 2025 and adds a comparison with the pre-window path. Its contribution is not simply that manufacturing production rose; it shows that positive post-window growth coexisted with a statistically significant level gap relative to the pre-window trend.

Several mechanisms may help explain this pattern, but the present model does not identify them individually. The recovery of domestic consumption, the resumption of business operations, changes in export demand, and the restoration of input supply can all influence manufacturing activity. Manufacturing also contains subsectors with different exposure to domestic demand, imported intermediate goods, and external markets. Krisnawati (2023) shows that monetary conditions and inflation are relevant to Indonesian manufacturing output, while the IMF (2022) documents sectoral heterogeneity during the pandemic. These studies support an interpretation that manufacturing production responds to a combination of fiscal, monetary, supply-chain, and demand conditions rather than to one policy event alone.

The scale of fiscal support is relevant context. The government disbursed IDR 579.78 trillion through PEN in 2020, and Law No. 2 of 2020 provided temporary flexibility in the fiscal deficit rule. Keynesian and Musgravian arguments explain why such support can help sustain aggregate demand and stabilisation during a severe contraction (Keynes, 1936; Musgrave, 1959). However, the regression contains no measure of sector-specific fiscal transfers, tax relief, or programme participation. It cannot determine how much of the IPI path reflects fiscal support, nor whether production would have performed differently without the policy response.

The structural-change tests identify statistically significant differences across the predefined periods. They should be understood as evidence of level and trend changes in the observed IPI series, not as a causal test of the law. The positive post-window slope and persistent level gap have practical significance for industrial monitoring: decision-makers should monitor both the direction of monthly production and its distance from the earlier production path. A positive growth rate alone may conceal a continuing gap in production capacity or output relative to the pre-crisis trajectory.

5. Conclusion

This study examined Indonesia's large and medium manufacturing production from January 2010 to December 2025 using 192 monthly IPI observations. The enhanced Interrupted Time Series specification distinguishes the initial level shift and trend during May 2020–June 2023 from the additional level adjustment and trend change beginning in July 2023. The intervention window reflects the enactment of Law No. 2 of 2020 and the formal end of pandemic status in June 2023. A December 2022 endpoint was also tested to reflect the end of the law's temporary fiscal-deficit flexibility.

The pre-window trend is positive at 0.4436 IPI points per month. The average deviation during the intervention window is −16.782 points relative to the continuation of the pre-window path, while the resulting within-window slope is positive at 0.7076 points per month. The post-window level remains 15.311 points below the baseline trajectory, but the resulting post-window slope is positive at 0.4145 points per month and statistically significant. The post-window trend-change coefficient itself is not statistically significant. Therefore, the evidence supports a persistent level gap alongside continued production growth, not a declining post-window trajectory.

The main finding is robust to the tested HAC lag lengths, alternative intervention endpoints, the logarithmic specification, a quadratic trend check, and an AR(1)-error model. The ADF and KPSS tests indicate non-stationarity in IPI levels and stationarity in first differences. The enhanced model residuals pass the reported ADF and KPSS residual checks, while Breusch–Godfrey and heteroskedasticity tests continue to motivate robust inference. The AR(1) model also leaves residual dependence at longer Ljung–Box lags, so the conclusions remain bounded by the time-series specification.

The study's contribution is a more complete description of manufacturing production adjustment around the pandemic-response period. It shows why the post-window level shift must be separated from the subsequent slope. The findings can inform high-frequency monitoring of manufacturing production and the assessment of whether output growth is accompanied by a closing level gap. They do not establish the effectiveness of Law No. 2 of 2020 or the causal contribution of fiscal stimulus to the IPI path

Limitations and Future Research

The study has four main limitations. First, the IPI represents large and medium manufacturing production and does not measure the entire real sector. Second, the intervention is represented by a predetermined time window rather than direct fiscal variables. Third, the pandemic, supply-chain disruption, demand changes, monetary conditions, and other policies occurred at the same time; the model cannot isolate their separate contributions. Fourth, the supplied workbook does not include a historical revision log, so the analysis cannot independently validate every classification-linking decision within the full 2010–2025 series. The supplementary AR(1) model also leaves residual autocorrelation at longer horizons.

Future research can extend this analysis by linking monthly IPI observations to sector-specific fiscal realisations, external demand, exports, imports of intermediate goods, energy prices, and firm-level production or employment records. Researchers can also compare manufacturing with other production

indicators or construct a credible control series. Further work on subsector composition and supply-chain exposure would help explain why the level gap persists even when the overall production slope is positive.

Acknowledgements

The author expresses sincere gratitude to Prof. Dr. Marselina, S.E., M.P.M., PIA, for her supervision and academic guidance. The author also thanks the Department of Development Economics, Faculty of Economics and Business, Universitas Lampung, for providing the academic environment in which this study was developed. All remaining errors and interpretations are the responsibility of the author.

References

Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18(1), 1–22. https://doi.org/10.1002/jae.659

Badan Pusat Statistik. (2020). Distribusi persentase produk domestik bruto atas dasar harga berlaku menurut lapangan usaha (persen), 2020. https://www.bps.go.id/id/statistics-table/3/T0UxS09GQlBTbk5QWTBNdlVWUmxSMjV3Y3l0VWR6MDkjMw%3D%3D/distribusi-persentase-produk-domestik-bruto-atas-dasar-harga-berlaku-menurut-lapangan-usaha--2023.html?year=2020

Badan Pusat Statistik. (2021). Micro and small manufacturing industry during the COVID-19 pandemic, 2020. https://www.bps.go.id/en/publication/2021/08/25/d2ff97cc365e98eedd4fad7f

Badan Pusat Statistik. (2022). Ekonomi Indonesia triwulan IV 2021 tumbuh 5,02 persen (y-on-y). https://www.bps.go.id/id/pressrelease/2022/02/07/1911/ekonomi-indonesia-triwulan-iv-2021-tumbuh-5-02-persen.html

Badan Pusat Statistik. (2024). Indeks produksi bulanan: Metadata indikator statistik. Sistem Rujukan Statistik Terintegrasi. https://sirusa.bps.go.id/metadata/indikator/e900ac05-3d94-4468-8766-916a24237011

Badan Pusat Statistik. (2025a). Distribusi persentase produk domestik bruto atas dasar harga berlaku menurut lapangan usaha (persen), 2024. https://www.bps.go.id/id/statistics-table/3/T0UxS09GQlBTbk5QWTBNdlVWUmxSMjV3Y3l0VWR6MDkjMyMwMDAw/distribusi-persentase-produk-domestik-bruto-atas-dasar-harga-berlaku-menurut-lapangan-usaha--persen-.html?year=2024

Badan Pusat Statistik. (2025b). Perkembangan indeks produksi industri manufaktur 2024 (Vol. 14). https://web-api.bps.go.id/download.php?f=F2CiKaSF3O0HaWeGY2VRc0lqNUcxN2lvSUtTZldvSE4xdEUzSWFxVWdGVWtqWmh4Z3BXdERVL1JLNkVHN2dRNko0bUVtc1hRMXR6TUd2K0tFbHB5Z1g0SThzVXZLelZnL0lwMi9ZRm1ObkZ3Y1hLS3o2QWhJcG80TmFSN2s3S2Q1eUJ4S1JwSHhQOEZPUmcvYVhDN1VlaUNXZGlrTkh0a2hBa3RJejNlc28za05HeTI1cld0Q0NDczM4ckFuVkxGZFUwaktWbVJGd2ZYZTBGMS9KNkxWNFNWazFSNTkwQzgyNElwbnhpM285OVlIb015UjFoeGM1M2JNSTB4VkI2V2dkTXJlZ3drSlFiUThmSnVKUTdBRmgxT1VCTUdCU1pPMHpoajJnPT0%3D

Badan Pusat Statistik. (2026). Indeks produksi bulanan industri besar dan sedang menurut KBLI 2 digit [KBLI 2020] (2010=100). https://www.bps.go.id/assets/statistics-table/2/MjA3NyMy/indeks-produksi-bulanan-industri-besar-dan-sedang-menurut-kbli-2-digit--kbli-2020---2010-100-.html

Demirgüç-Kunt, A., Lokshin, M., & Torre, I. (2021). The global economic impact of COVID-19: Six channels of transmission. World Bank. https://doi.org/10.1596/1813-9450-9211

Directorate General of Treasury. (2021). Paparkan realisasi pelaksanaan APBN 2020, Menkeu ungkap belanja negara berperan penting dalam pemulihan ekonomi nasional. Ministry of Finance of the Republic of Indonesia. https://djpb.kemenkeu.go.id/portal/id/data-publikasi/data/129-berita/nasional/3554-paparkan-realisasi-pelaksanaan-apbn-2020,-menkeu-ungkap-belanja-negara-berperan-penting-dalam-pemulihan-ekonomi-nasional.html

Galdi, G., Casarin, R., Ferrari, D., Fezzi, C., & Ravazzolo, F. (2023). Nowcasting industrial production using linear and non-linear models of electricity demand. Energy Economics, 126, 107006. https://doi.org/10.1016/j.eneco.2023.107006

Handayani, F. (2021). Structural break and the period of Indonesia's post-pandemic economic recovery. Economics Development Analysis Journal, 10(4), 426–435. https://doi.org/10.15294/edaj.v10i4.46897
International Monetary Fund. (2022). Indonesia: Selected issues (IMF Country Report No. 22/85). https://www.imf.org/en/Publications/CR/Issues/2022/03/23/Indonesia-Selected-Issues-515010
Indonesia. (2020). Law No. 2 of 2020 concerning the stipulation of Government Regulation in Lieu of Law No. 1 of 2020 concerning state financial policy and financial system stability for handling the COVID-19 pandemic and/or threats to the national economy and/or financial system into law. State Gazette of the Republic of Indonesia 2020 No. 134. https://peraturan.bpk.go.id/Home/Download/128214/UU%20Nomor%202%20Tahun%202020.pdf
Indonesia. (2023). Presidential Decree No. 17 of 2023 concerning the determination of the end of the COVID-19 pandemic status in Indonesia. https://peraturan.bpk.go.id/Details/253985/keppres-no-17-tahun-2023-penetapan-berakhirnya-status-pandemi-corona-virus-disea
Keynes, J. M. (1936). The general theory of employment, interest and money. Macmillan.
Khairunnisa, F., Siregar, H., & Widyastutik. (2025). The impact of industrial growth on the manufacturing trade balance: An aggregate and industry-level analysis. Buletin Ilmiah Litbang Perdagangan, 19(1), 68–80. https://doi.org/10.29244/bilp.19.1.68-80
Krisnawati, D. (2023). The influence of monetary policies on manufacturing output. Efficient: Indonesian Journal of Development Economics, 6(2), 146–155. https://doi.org/10.15294/efficient.v6i2.60219
Lopez Bernal, J., Cummins, S., & Gasparrini, A. (2017). Interrupted time series regression for the evaluation of public health interventions: A tutorial. International Journal of Epidemiology, 46(1), 348–355. https://doi.org/10.1093/ije/dyw098
Lopez Bernal, J., Soumerai, S., & Gasparrini, A. (2018). A methodological framework for model selection in interrupted time series studies. Journal of Clinical Epidemiology, 103, 82–91. https://doi.org/10.1016/j.jclinepi.2018.05.026
Martin, R. (2012). Regional economic resilience, hysteresis and recessionary shocks. Journal of Economic Geography, 12(1), 1–32. https://doi.org/10.1093/jeg/lbr019
Martin, R., & Sunley, P. (2015). On the notion of regional economic resilience: Conceptualization and explanation. Journal of Economic Geography, 15(1), 1–42. https://doi.org/10.1093/jeg/lbu015
Martin, R., Sunley, P., Gardiner, B., & Tyler, P. (2016). How regions react to recessions: Resilience and the role of economic structure. Regional Studies, 50(4), 561–585. https://doi.org/10.1080/00343404.2015.1136410
Musgrave, R. A. (1959). The theory of public finance: A study in public economy. McGraw-Hill.
Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703–708. https://doi.org/10.2307/1913610
Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. Econometrica, 57(6), 1361–1401. https://doi.org/10.2307/1913712
Schaffer, A. L., Dobbins, T. A., & Pearson, S.-A. (2021). Interrupted time series analysis using autoregressive integrated moving average (ARIMA) models: A guide for evaluating large-scale health interventions. BMC Medical Research Methodology, 21, 172. https://doi.org/10.1186/s12874-021-01235-8
Sholihah, F. A., Ulya, B., Mirzal, H., Rasyida, S. N., & Zubaidah, S. (2022). The role of fiscal policy in strengthening the resilience of the national economy: Fiscal case study during the COVID-19 pandemic. Ijtimā'iyya: Journal of Muslim Society Research, 7(1), 97–106. https://doi.org/10.24090/ijtimaiyya.v7i1.7553
Sopanah, A., & Haikal, M. F. F. (2022). The effectiveness of Law No. 2 of 2020 concerning the fiscal policy strategy of the Government of the Republic of Indonesia in dealing with the impact of the COVID-19 pandemic. Wiga: Jurnal Penelitian Ilmu Ekonomi, 12(1), 46–54. https://doi.org/10.30741/wiga.v12i1.784
Travis-Lumer, Y., Goldberg, Y., & Levine, S. Z. (2022). Effect size quantification for interrupted time series analysis: Implementation in R and analysis for COVID-19 research. Emerging Themes in Epidemiology, 19, 9. https://doi.org/10.1186/s12982-022-00118-7

Turner, S. L., Karahalios, A., Forbes, A. B., Taljaard, M., Grimshaw, J. M., & McKenzie, J. E. (2021). Comparison of six statistical methods for interrupted time series studies: Empirical evaluation of 190 published series. BMC Medical Research Methodology, 21, 134. https://doi.org/10.1186/s12874-021-01306-w

Wagner, A. K., Soumerai, S. B., Zhang, F., & Ross-Degnan, D. (2002). Segmented regression analysis of interrupted time series studies in medication use research. Journal of Clinical Pharmacy and Therapeutics, 27(4), 299–309. https://doi.org/10.1046/j.1365-2710.2002.00430.x

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica, 48(4), 817–838. https://doi.org/10.2307/1912934