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The Impact of Consumer Confidence on Tourism: Evidence from Indonesia

Ar Razy Ridha Maulana ^{1,*} and Hendra Dharmawan ²

¹ Statistics Aceh Besar Regency, Jantho 23951, Indonesia; arrazy.ridha@bps.go.id (A.R.R.M.)

² Statistics Aceh Province, Banda Aceh 23121, Indonesia; hendrad@bps.go.id (H.D.)

* Correspondence: arrazy.ridha@bps.go.id

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Abstract

Understanding the drivers of tourism demand is crucial not only for economic policy but also for business strategy in tourism-related industries. This study investigates the impact of consumer confidence on tourism arrivals in Indonesia, with a specific focus on both short-term and long-term effects. Employing the Autoregressive Distributed Lag (ARDL) model, complemented by robustness checks using FMOLS, DOLS, and CCR methods over the period 2008–2023, the empirical findings reveal that the Consumer Confidence Index (CCI) has a strong, positive, and statistically significant effect on the number of tourist visits, particularly in the long term. The results remain consistent across multiple estimation techniques, confirming the robustness and reliability of the evidence. These findings highlight the strategic importance of consumer sentiment as a forward-looking behavioral indicator in tourism demand modeling. For policymakers and business leaders in the tourism sector, the study underscores the value of monitoring public economic sentiment to anticipate demand shifts and inform responsive strategies.



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1. Introduction

Tourism has become one of the most dynamic and significant contributors to national economic performance, particularly in emerging economies such as Indonesia [1]. As a multifaceted industry, tourism stimulates employment, drives foreign exchange earnings, and fosters infrastructure development [2]. Indonesia, with its vast cultural and natural attractions, has experienced substantial growth in tourist arrivals over the past two decades [3]. However, this growth has not been immune to fluctuations arising from broader economic cycles and shifts in public sentiment [4]. Against this backdrop, understanding the determinants of tourism demand is not only an academic concern but also a practical necessity for sustainable development.

In addition to its macroeconomic importance, tourism is a demand-driven sector that requires close attention from businesses and managers, particularly in the areas of strategy, marketing, and capacity planning [5]. For firms in the tourism and hospitality industries, fluctuations in visitor numbers directly affect revenues, operational efficiency, and investment returns [6]. Yet, many business strategies are still rooted primarily in traditional indicators such as income and prices [7], often overlooking more nuanced behavioral variables. Consumer confidence, as a reflection of the public's economic expectations, offers a forward-looking and actionable indicator that can inform strategic decision-making [8]. By identifying how consumer sentiment influences tourism flows, this study provides insights that bridge economics and management, helping firms

anticipate demand cycles and align their responses with consumer mood and market expectations.

The significance of this issue is particularly visible in Indonesia's recent economic trajectory. Following the COVID-19 pandemic, both tourism and consumer sentiment experienced sharp declines [9]. While international travel restrictions were a direct cause of tourism collapse, the broader recovery has been uneven and closely tied to public confidence in the economy. Consumer confidence in Indonesia has fluctuated in response to global economic uncertainty, inflationary pressures, and shifting employment conditions [10]. Despite macroeconomic stabilization efforts, the return to pre-pandemic levels of travel demand has been gradual, raising questions about what drives tourists' decisions in the post-crisis context. These real-world dynamics highlight the practical relevance of examining how sentiment indicators like the Consumer Confidence Index (CCI) interact with tourism behavior, especially in a country whose tourism sector remains vulnerable to both internal shocks and external volatility.

Much of the existing literature on tourism demand has focused on structural macroeconomic variables such as income levels [11, 12], inflation [13, 14], and exchange rates [15, 16]. While these variables provide valuable insights, they tend to emphasize objective economic conditions while overlooking subjective perceptions that often drive consumer behavior, particularly in relation to non-essential expenditures like travel. Among the relatively underexplored factors is consumer confidence, which serves as a proxy for the public's expectations about future economic conditions. In emerging markets such as Indonesia, where consumption behavior can be highly sensitive to perceived economic stability, incorporating consumer confidence into tourism demand models offers a more comprehensive understanding of demand-side dynamics [17]. This study narrows its focus to this sentiment-based factor, aiming to clarify its relative importance in shaping fluctuations in tourism activity.

Theoretically, the influence of consumer confidence on economic behavior is rooted in behavioral economics. Behavioral economics supports the idea that optimism or pessimism can shape consumer decisions, particularly for discretionary spending [18]. In the context of tourism, this implies that high consumer confidence leads to a greater willingness to allocate income toward travel and leisure, while lower confidence may result in postponed or canceled travel plans [19]. In addition, the expectation theory of consumption posits that individuals base their current spending decisions on anticipated future income and economic conditions [20]. As such, when consumers

expect stable or improving conditions, they are more likely to increase expenditures on non-essential goods and services, including tourism [21]. Given the intangible but powerful nature of sentiment, its inclusion in tourism models is both theoretically sound and practically relevant.

Although some empirical studies in advanced economies have investigated the link between consumer behavior and tourism demand, such as studies by Scarth & Novelli [22], Reyes-Menendez et al. [23], and Li & Cao [24], findings remain mixed and relatively sparse. In developing countries, where consumer sentiment can shift rapidly in response to political and economic events, the role of confidence may be even more pronounced, but is largely under-researched. This is particularly true for Indonesia, where macroeconomic stability has improved over time, but public perceptions and expectations continue to play a critical role in shaping consumer behavior. Moreover, previous studies rarely capture the dynamic nature of this relationship over both short- and long-term horizons, nor do they rigorously test the robustness of their findings.

Given the increasing relevance of behavioral indicators in shaping economic outcomes, particularly in consumption-driven sectors like tourism, this study aims to examine the impact of consumer confidence on the number of tourist visits in Indonesia. Specifically, it investigates how this relationship unfolds over both the short term and long term, using robust time-series econometric methods. By focusing on consumer confidence as a forward-looking behavioral variable, the research fills a gap in the literature that has traditionally emphasized structural macroeconomic factors. The findings offer empirical evidence on the role of sentiment in tourism demand, contributing to the broader discourse on behavioral economics and tourism management. In doing so, this study advances the understanding of tourism demand determinants in developing economies and provides actionable insights for both economic policymakers and business practitioners. Its contributions are especially relevant for scholars and firms seeking to integrate behavioral indicators into forecasting, strategic planning, and market analysis within the tourism sector.

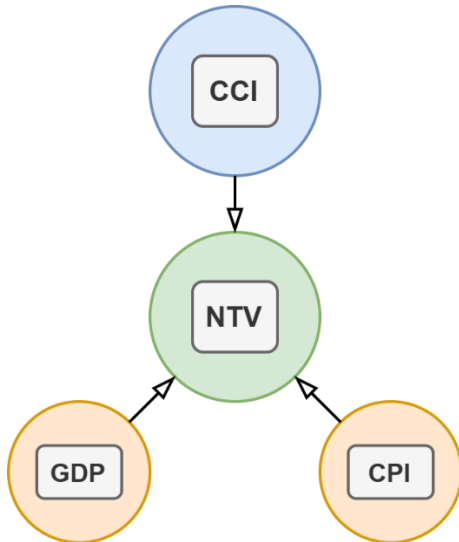
2. Materials and Methods

2.1. Data and Variables

This study uses monthly time series data from January 2008 to December 2023. The justification for choosing this period is that data for the main independent variable, the Consumer Confidence Index (CCI), is only available within this timeframe. The study includes four variables:

Table 1. Details of variables.

Status	Variable	Symbol	Unit Measurement	Source
Dependent	Number of Tourist Visit	NTV	Person	BPS [25]
Main Independent	Consumer Confident Index	CCI	100 as the central point	OECD [26]
Control Independent	Gross Domestic Product	GDP	Constant LCU	WDI [27]
	Consumer Price Index	INF	Index, 2010 = 100%	WDI [27]

**Figure 1.** Conceptual framework of the study.

the number of tourist visits (NTV) as the dependent variable, the Consumer Confidence Index (CCI) as the main independent variable, and Gross Domestic Product (GDP) and the Consumer Price Index (CPI) as additional independent variables. NTV data is sourced from Statistics Indonesia (BPS) [25], CCI data from the Organisation for Economic Co-operation and Development (OECD) [26], and GDP and CPI data from the World Bank's World Development Indicators (WDI) [27]. Details of the variables are presented in Table 1.

2.2. Conceptual Framework

The conceptual framework of this study illustrates the relationship between macroeconomic variables and the number of tourist visits (NTV) in Indonesia, with a central focus on the Consumer Confidence Index (CCI) as the primary explanatory variable (see Figure 1). CCI is positioned in this study not merely as a proxy for individual consumer behavior but as a forward-looking indicator of collective economic sentiment. It captures how optimistic or pessimistic the public is about the overall economic outlook, which, in turn, influences their readiness to engage in discretionary spending such as travel. In this sense, CCI reflects broader economic expectations rather than immediate consumption patterns, making it particularly relevant for anticipating shifts in tourism demand.

To isolate the specific impact of consumer sentiment on tourism, the model also incorporates two control variables: Gross Domestic Product (GDP) and inflation (INF). GDP serves as a proxy for income and purchasing power, indicating the general capacity of consumers to afford travel [28–30]. Inflation, on the other hand, reflects changes in the cost of goods and services, which can affect travel affordability and influence short-term decision-making [31, 32]. Including these variables helps account for the underlying economic environment and enables a more precise estimation of the distinct role that sentiment (CCI) plays in influencing tourism patterns.

This framework is structured to distinguish between structural economic conditions and behavioral expectations, allowing the study to empirically test the effect of CCI while controlling for other macroeconomic influences. Accordingly, the guiding main hypothesis of this study is:

H₀: The Consumer Confidence Index does not have a statistically significant effect on the number of tourist visits in Indonesia.

H₁: The Consumer Confidence Index has a statistically significant positive effect on the number of tourist visits in Indonesia.

By grounding the model in this conceptual structure, the study aims to contribute to a clearer understanding of how sentiment-based indicators interact with real economic activity, particularly within the context of a tourism-dependent emerging economy like Indonesia.

2.3. Model Specification

The main focus of this study is to examine the impact of the Consumer Confidence Index (CCI) on the number of tourist visits (NTV), controlled for Gross Domestic Product (GDP) and the Consumer Price Index (CPI). Equation 1 presents the mathematical function used in this study.

$$NTV = f(CCI, GDP, INF) \quad (1)$$

Where, *NTV* is number of tourist visits, *CCI* is Consumer Confidence Index, *GDP* is the gross domestic product, and *INF* is the inflation. Based on Equation 1, the econometric model on this study is shown in Equation 2.

$$NTV_t = \beta_0 + \beta_1 CCI_t + \beta_2 GDP_t + \beta_3 INF_t + \varepsilon_t \quad (2)$$

Here, t represents the period, β_0 is the constant, $\beta_1 - \beta_3$ are the coefficients, and ε is the error term.

Since this study uses different units of measurement, the original data is converted to natural logarithm (ln) form to facilitate the interpretation of the results in terms of percentage changes rather than absolute changes. The final model of this study is shown in Equation 3.

$$\ln NTV_t = \beta_0 + \beta_1 \ln CCI_t + \beta_2 \ln GDP_t + \beta_3 \ln INF_t + \varepsilon_t \quad (3)$$

2.4. Main Method: Autoregressive Distributed Lag (ARDL)

Autoregressive Distributed Lag (ARDL) is a statistical model used to analyze the relationship between a dependent variable and its own lagged values, as well as the lagged values of independent variables [10]. One of the key advantages of the ARDL model is its ability to estimate both short-term and long-term dynamics in a

single equation, making it particularly useful for examining complex relationships between variables [33]. Additionally, the ARDL model can be applied regardless of whether the underlying variables are stationary at levels or first differences, allowing for greater flexibility when working with time series data [34]. This makes ARDL particularly suitable for time series analysis, as it can handle different types of data patterns, such as non-stationarity, and provide more reliable and interpretable results in examining the long-term equilibrium and short-term adjustments in time-dependent relationships. The specific ARDL model used in this study is shown in Equation 4.

In this equation, t indicates the time period within the study, and Δ signifies the first-difference operator. ECT refers to the error correction term. The coefficients β_1 to β_4 represent the short-term effects, whereas δ_1 to δ_4 capture the long-term dynamics. Lastly, q and p denote the optimal lag lengths selected for the model.

$$\Delta \ln NTV_t = \beta_0 + \sum_{i=1}^q \beta_1 \Delta \ln NTV_{t-i} + \sum_{i=0}^p \beta_2 \Delta \ln CCI_{t-i} + \sum_{i=0}^p \beta_3 \Delta \ln GDP_{t-i} + \sum_{i=0}^p \beta_4 \Delta \ln INF_{t-i} + ECT_{t-1} + \delta_1 \ln NTV_{t-1} + \delta_2 \ln CCI_{t-1} + \delta_3 \ln GDP_{t-1} + \delta_4 \ln INF_{t-1} + \varepsilon_t \quad (4)$$

2.5. Robustness Check Methods

To verify the robustness of the long-run estimation results, three advanced cointegration techniques were employed: Fully-Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Canonical Cointegrating Regression (CCR). These methods are widely used in empirical research to address common econometric issues such as serial correlation, endogeneity, and non-stationarity in time series data. Each technique provides corrections that enhance the reliability of the long-run coefficient estimates derived from cointegrated relationships, making them suitable for validating ARDL-based results.

2.5.1. Fully-Modified Ordinary Least Squares (FMOLS)

FMOLS includes extra lagged values of both the dependent and independent variables to help address issues related to endogeneity and serial correlation. By incorporating these lagged terms, FMOLS reduces problems like autocorrelation and simultaneity bias, resulting in more reliable parameter estimates and stronger conclusions [35, 36]. A major advantage of FMOLS is its ability to deliver consistent estimates even when dealing with non-stationary or endogenous time series data, making it especially valuable for cointegration analysis [37]. As such, FMOLS is well-suited for verifying the reliability of long-term results obtained from the ARDL model.

2.5.2. Dynamic Ordinary Least Squares (DOLS)

Dynamic Ordinary Least Squares (DOLS) is an advanced econometric technique used to estimate long-run relationships among variables in time series data. It addresses potential endogeneity and serial correlation by including both leads and lags of the differenced independent variables in the regression model [18]. This adjustment helps correct for feedback effects and omitted variable bias, resulting in more efficient and unbiased parameter estimates. DOLS is particularly effective when dealing with non-stationary variables that are cointegrated, as it enhances the accuracy of long-run estimations [38]. Therefore, DOLS serves as a reliable method for confirming the robustness of long-term relationships identified by the ARDL model.

2.5.3. Canonical Cointegrating Regression (CCR)

Canonical Cointegrating Regression (CCR) estimates cointegrating vectors directly while accounting for possible endogeneity by including lagged values of the variables. This approach improves resistance to specification errors and allows for more efficient estimation of cointegration relationships [37]. Its main strength lies in producing consistent and dependable estimates of cointegrating vectors, which supports accurate modeling and interpretation of long-run equilibrium relationships among variables [10]. As a result, CCR, like FMOLS, is a suitable method for

Table 2. Descriptive statistics of raw data.

Variable	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis
NTV	749146.7	721532.5	1547231	105788	354858.5	0.101520	2.552.872
CCI	1.005.170	1.007.203	1.016.958	9.827.685	0.887183	-0.857842	2.857.448
GDP	9.17E+15	9.21E+15	1.23E+16	6.18E+15	1.88E+15	-0.041688	1.761.146
INF	1.309.251	1.346.333	1.690.567	9.111.964	2.463.749	-0.151517	1.693.215

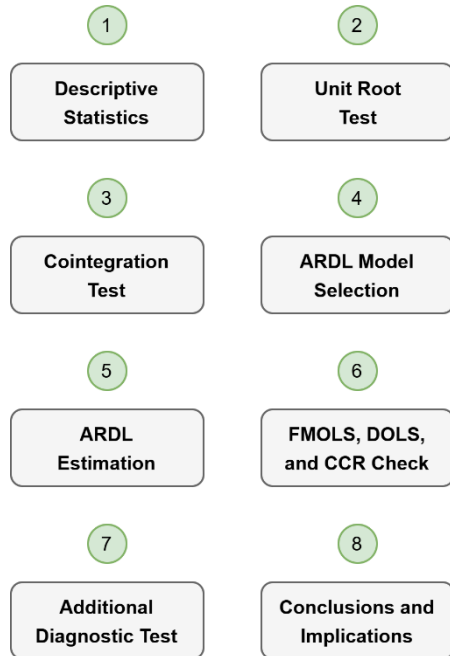


Figure 2. Study's flow analysis.

validating the robustness of long-term estimates obtained from the ARDL model.

2.6. Flow Analysis of the Study

The structured analysis of the study, as illustrated in Figure 2, begins with the presentation of descriptive statistics, followed by unit root testing using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) methods. Subsequently, the Johansen and bounds cointegration tests are conducted to determine the presence of long-term equilibrium relationships. Upon confirmation of cointegration, the optimal ARDL model is selected based on the Akaike Information Criterion (AIC). The cointegrating equation parameters are then estimated using the ARDL approach, with further validation through robustness checks employing the FMOLS, DOLS, and CCR methods. Additional diagnostic tests are conducted to assess classical assumption issues, including the CUSUM test for model stability, the ARCH test for heteroskedasticity, and the Ramsey RESET test for model specification. The analysis then moves on to discuss the empirical results in greater depth and within the context of Indonesia. The study concludes by presenting its main findings, implications for businesses and policymakers, and recommendations for future research.

3. Results and Discussion

3.1. Descriptive Statistics

Table 2 provides descriptive statistics for the key variables used in the analysis: the Number of Tourist Visits (NTV), Consumer Confidence Index (CCI), Gross Domestic Product (GDP), and Inflation (INF). The mean value for NTV is approximately 749,147, with a relatively high standard deviation of 354,858.5, indicating substantial variability in tourism levels over time. The median (721,532.5) being close to the mean suggests a fairly symmetric distribution, which is confirmed by a low skewness value of 0.1015. The kurtosis of 2.55 indicates a distribution that is slightly less peaked than a normal distribution.

For the CCI, the average value is 1,005.17, with a standard deviation of 0.887, indicating relatively low variability. The negative skewness (-0.8578) suggests a longer tail on the left side of the distribution, while the kurtosis of 2.86 is close to normal, implying a modest peak. GDP shows the highest magnitude with a mean of approximately 917 trillion and a standard deviation of 1.88 quadrillion, reflecting its large scale and substantial variability. Its skewness and kurtosis values indicate a near-normal distribution. Lastly, the inflation variable (INF) has a mean of 1,309.25 and a high standard deviation of 2,463.75, implying significant fluctuations. With low skewness and a kurtosis of 1.69, INF also appears to be fairly normally distributed but slightly flatter than a normal curve. Overall, the descriptive statistics suggest that the data is generally well-behaved, with most variables showing moderate skewness and kurtosis.

3.2. Preliminary Test

3.2.1. Unit Root Test

Unit root test aims to determine the stationarity of each variable to ensure the suitability of the data for time series analysis [39]. As shown in Table 3, the results from both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (P-P) tests indicate that all variables (NTV, CCI, GDP, and CPI) are non-stationary in their level form, as their p-values exceed the 5% significance level in most cases. However, after first differencing, all variables become stationary, with p-values less than 0.05 in both the ADF and P-P tests. This suggests that the data series

Table 3. Results of unit root test.

Variable	ADF		P-P	
	Level	1 st Difference	Level	1 st Difference
NTV	0.3827	0.0000*	0.3523	0.0000*
CCI	0.0003*	0.0000*	0.1556	0.0031*
GDP	0.7536	0.0000*	0.6926	0.0000*
CPI	0.6904	0.0000*	0.5448	0.0000*

Note: * indicates significance level at 1%.

Table 4. Results of cointegration test.

Hypothesized No. of CE(s)	Eigenvalue	Trace Stat.	0.05 Critical Value	Prob.
None	0.1811	53.556	47.856	0.0133**
At most 1	0.0507	16.197	29.797	0.6984
At most 2	0.0240	6.4689	15.495	0.6401
At most 3	0.0102	1.9176	3.8415	0.1661

Note: ** indicates significance level at 5%.

Table 5. Results of ARDL bounds cointegration test.

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Stat.	Value	Signif.	I(0)	I(1)
F-statistic	3.9328**	10%	2.37	3.2
K	3	5%	2.79	3.67
		1%	3.65	4.66

Note: ** indicates significance level at 5%.

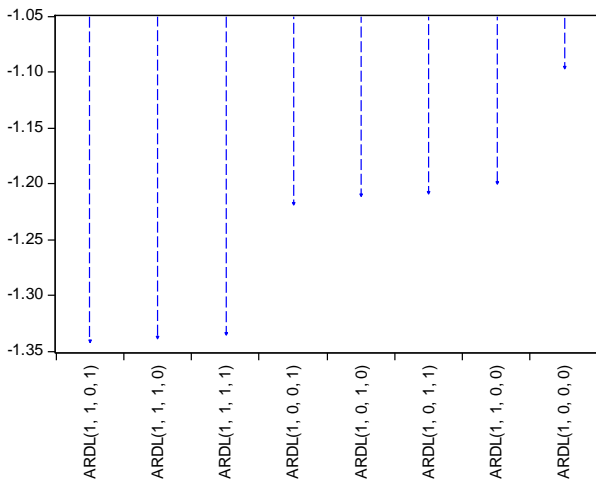


Figure 3. ARDL model selection with Akaike Information Criterion (AIC).

are integrated of order one, I(1), and are suitable for further time series analysis. Accordingly, this study employs the ARDL method as the primary analytical approach, with FMOLS, DOLS, and CCR used for robustness checks.

3.2.2. Cointegration Test

Cointegration test is conducted to examine whether a long-term equilibrium relationship exists among the variables [40]. The results in Table 4 from the Johansen cointegration test indicate the presence of at least one cointegrating relationship among the variables. The trace statistic for the null hypothesis of no cointegration (None) is 53.56, which exceeds the 5% critical value of 47.86, with

a corresponding p-value of 0.0133, indicating statistical significance at the 5% level. This suggests that there is a cointegrating vector, implying a long-run equilibrium relationship exists among the variables in the model.

Moreover, the ARDL bounds cointegration test in Table 5 yields an F-statistic of 3.9328, which is significant at the 5% level. This further confirms the existence of a long-term relationship among the variables, as the F-statistic exceeds the upper bound critical value. Together, the Johansen and ARDL test results provide robust evidence of cointegration, justifying the use of models that account for both short-run dynamics and long-run equilibrium.

3.2.3. ARDL Model Selection

This step identifies the most appropriate ARDL model specification based on model fit and parsimony, using the Akaike Information Criterion (AIC) [41]. The AIC graph in Figure 3 illustrates the model selection process for various ARDL specifications based on their goodness of fit. Among the evaluated models, the ARDL(1,1,0,1) configuration yields the lowest AIC value, indicating it is the most preferred model in terms of minimizing information loss while balancing model complexity and fit. This suggests that including one lag of the dependent variable, one lag of the main independent variable, and one lag of one of the control variables provides the best specification for capturing the dynamics among the variables in the model. The selected specification will be used in subsequent estimation and diagnostic testing to ensure the robustness and validity of the model results.

Table 6. Results of the ARDL estimations.

Independent Variable	Dependent Variable: NTV					
	Long-term			Short-term		
	Coeff.	t-stat.	Prob.	Coeff.	t-stat.	Prob.
InCCI	97.797***	5.1527	0.0000	31.535***	7.2826	0.0000
InGDP	-0.6145	-0.0646	0.9486	-1.5731	-0.8375	0.4034
InINF	-1.2673	-0.1235	0.9018	-2.5731	-1.1995	0.2319
ECT(-1)	n/a	n/a	n/a	-0.0719***	-4.4826	0.0000
C	-408.57	-1.3930	0.1653	n/a	n/a	n/a

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; 'n/a' indicates not applicable.

Table 7. Results of the FMOLS, DOLS, and CCR estimations.

Independent Variable	Dependent Variable: NTV								
	FMOLS			DOLS			CCR		
	Coeff.	t-stat.	Prob.	Coeff.	t-stat.	Prob.	Coeff.	t-stat.	Prob.
InCCI	75.307***	9.6244	0.0000	75.084***	8.9369	0.0000	74.806***	9.9407	0.0000
InGDP	-8.9673**	-2.0628	0.0405	-8.1452*	-1.8022	0.0732	-8.9154**	-2.0283	0.0439
InINF	8.1773*	1.7498	0.0818	7.2936	1.5042	0.1343	8.1305*	1.7209	0.0869
C	-44.097	-0.3438	0.7314	-68.981	-0.5218	0.6024	-43.462	-0.3348	0.7382

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

3.3. ARDL Estimation

The ARDL estimation results presented in Table 6 reveal significant short-term and long-term relationships between the Consumer Confidence Index (CCI) and the number of tourist visits (NTV) in Indonesia. In the long term, the InCCI has a positive and statistically significant effect on InNTV, with a coefficient of 97.80 and a p-value of 0.0000, indicating that a 1% increase in consumer confidence is associated with an approximately 97.8% increase in tourist visits. These results imply that consumer sentiment has a powerful and lasting influence on tourism activity in Indonesia, far exceeding the impact of traditional macroeconomic indicators. In contrast, the coefficients for both the InGDP and InINF are negative and statistically insignificant, suggesting that these control variables do not have a meaningful long-term impact on tourist arrivals in this model.

In the short term, the positive influence of consumer confidence remains significant, with a coefficient of 31.54 and a p-value of 0.0000, reinforcing the robustness of InCCI's impact on tourism activity. The error correction term (ECT) is negative and significant at the 1% level, with a coefficient of -0.0719, indicating that any short-term deviation from the long-term equilibrium is corrected at a speed of approximately 7.2% per period. This supports the existence of a stable long-run relationship among the variables. The significant short-term effect of consumer confidence and the negative, significant error correction term confirm not only the immediate impact of sentiment on tourism demand but also the stability of the long-run equilibrium relationship over time. On the other hand, the short-term effects of InGDP and InINF remain

statistically insignificant, emphasizing that fluctuations in consumer confidence are more influential on tourist activity than traditional macroeconomic indicators in this context.

3.4. Robustness Check with FMOLS, DOLS, and CCR

The robustness check results using the FMOLS, DOLS, and CCR methods consistently confirm the significant positive effect of the Consumer Confidence Index (CCI) on the number of tourist visits (NTV), as presented in Table 7. Across all three estimation techniques, the coefficient of InCCI is positive and statistically significant at the 1% level, with values ranging from 74.81 (CCR) to 75.31 (FMOLS). This consistent pattern strengthens the reliability of the main ARDL model's findings, underscoring the critical role of consumer confidence in influencing tourism demand over the long run. The magnitude of the coefficients indicates that a 1% increase in consumer confidence is associated with approximately a 74.8% to 75.3% increase in tourist visits, which highlights a substantial elasticity and implies that changes in consumer sentiment can lead to large shifts in tourism activity.

Similarly, the coefficients for InGDP and InINF demonstrate a consistent negative relationship. In all models, InGDP carries a negative coefficient and is statistically significant in FMOLS and CCR, further validating the ARDL finding that GDP does not contribute positively to tourist arrivals in this context. Meanwhile, InINF, although positively signed in all three models, does not achieve conventional levels of significance, supporting its limited explanatory power seen in the ARDL results. Overall, the alignment of coefficient signs

Table 8. Results of additional diagnostic test.

Test	Coeff.	Prob.	Decision
R ²	> 0.9673	n/a	The model is well fitted.
R ² Adj.	> 0.9662	n/a	The model is well fitted.
CUSUM	n/a	< 0.05	The model is stable.
ARCH test	2.0719	0.0709	No serial correlation exists.
Ramsey test	2.5094	0.0603	The model is properly specified.

Note: 'n/a' indicates not applicable.

and significance across FMOLS, DOLS, and CCR affirms the robustness and consistency of the empirical findings.

3.5. Additional Diagnostic Test

The results of the additional diagnostic tests, as shown in [Table 8](#), indicate that the ARDL model is statistically robust and reliable. The R² and adjusted R² values exceed 0.9673 and 0.9662 respectively, suggesting a very good fit between the model and the observed data. The CUSUM test reveals a stable model as the test statistic falls within the 5% significance boundary. Furthermore, the ARCH test shows a p-value of 0.0709, indicating no significant evidence of serial correlation in the residuals. The outcome of the Ramsey RESET test, with a p-value of 0.0603, confirms that the model is properly specified and does not suffer from omitted variable bias. Collectively, these diagnostics affirm the validity and stability of the estimated model.

3.6. Discussion

The empirical findings of this study clearly demonstrate that consumer confidence plays a decisive role in shaping tourism demand in Indonesia. The Consumer Confidence Index (CCI) shows a positive and statistically significant relationship with the number of tourist visits (NTV), both in the short-run and long-run estimations. Notably, the magnitude of this relationship is much stronger in the long term than in the short term. In the long run, a one percent increase in consumer confidence is associated with approximately a 97.8% increase in tourist visits, whereas the short-run effect is around 31.5%. This considerable difference highlights that the influence of consumer sentiment accumulates over time, with lasting optimism contributing more substantially to tourism flows than transient changes. Such a result confirms that confidence-driven consumption decisions extend well beyond immediate behavior and are deeply embedded in the economic planning of individuals and households.

The consistency of results across robustness checks using FMOLS, DOLS, and CCR further strengthens the credibility of the main ARDL estimates. Despite their methodological differences, all three techniques confirm the central finding: consumer sentiment exerts a stable, positive, and significant influence on tourism activity. This triangulation of results reduces concerns about model

dependence or estimation bias and reinforces the reliability of the conclusions drawn from the primary model.

This dynamic aligns with theoretical perspectives in behavioral economics, where rising consumer confidence often signals forward-looking behavior and willingness to engage in discretionary spending [42]. As consumers become more secure in their financial outlook, their propensity to allocate resources toward leisure activities like travel increases [43]. Over time, this optimistic outlook reinforces habits of consumption that feed into broader tourism growth [44]. The enduring effect of consumer confidence captured in this study affirms its role not just as a psychological signal but as a substantive determinant of macroeconomic activity, especially in sectors like tourism that are sensitive to perception, optimism, and lifestyle orientation. This study findings also align with previous studies such as by Choudhry & Wohar [45], Belias et al. [46], and Suhartanto et al. [47].

In the Indonesian context, the importance of consumer sentiment is amplified by the country's unique economic and social conditions. Indonesia's tourism sector, which plays a key role in employment and regional development, experienced severe disruptions during the COVID-19 pandemic [48], leading to sharp declines in both international arrivals and domestic travel. Since then, recovery has been gradual and uneven, with consumer confidence fluctuating in response to inflationary pressures, labor market uncertainty, and global economic instability [49]. These fluctuations have had tangible impacts on tourism behavior, particularly among middle-income domestic travelers who account for a large share of national tourism activity [50]. Additionally, with the government's increasing reliance on domestic tourism to cushion external shocks, shifts in national sentiment have become an especially relevant indicator of tourism resilience [51]. Thus, the Indonesian case reinforces the broader conclusion that consumer confidence is not only a theoretical construct but also a practical tool for understanding and forecasting tourism dynamics in emerging economies.

Beyond its academic contribution to the economics of tourism, this study offers insights that are relevant for the

field of management. For businesses operating in the tourism and hospitality industries, fluctuations in consumer confidence can serve as a leading indicator of market behavior. Understanding the link between sentiment and travel decisions allows firms to anticipate demand shifts more effectively and align their strategies accordingly. Marketing campaigns, inventory planning, staffing levels, and investment timing can all be better informed when consumer sentiment trends are closely monitored and incorporated into business intelligence systems. The strong responsiveness of tourism demand to CCI suggests that businesses may benefit from integrating macro-sentiment data into their strategic forecasting processes.

In sum, this research contributes not only to economic modeling of tourism demand but also to the broader understanding of how consumer psychology intersects with market behavior. It positions consumer confidence as a dual-purpose variable: a macroeconomic indicator and a strategic input for business and management decisions. The Indonesian case highlights the potential of sentiment indicators to inform both public and private sector decision-making in tourism-related domains. Future research may explore these themes further by disaggregating consumer confidence into more granular dimensions or by examining firm-level responses to changing sentiment patterns within the tourism sector.

4. Conclusions and Implications

This study concludes that consumer confidence plays a significant and measurable role in shaping tourism demand in Indonesia over the period 2008–2023. By employing the ARDL model along with FMOLS, DOLS, and CCR robustness checks, the analysis demonstrates that the Consumer Confidence Index (CCI) exerts a strong and statistically significant influence on the number of tourist visits, particularly in the long term. The findings show that a 1% increase in consumer confidence is associated with a substantial rise in tourist arrivals, reinforcing the relevance of sentiment as a forward-looking driver of tourism behavior. While traditional macroeconomic variables such as GDP and inflation showed limited explanatory power, consumer sentiment consistently emerged as the dominant factor. These results underscore the importance of integrating behavioral indicators into both economic analysis and tourism management strategies.

For businesses in the tourism and hospitality sectors, these findings highlight the strategic value of monitoring consumer confidence as part of demand forecasting and market planning. High levels of consumer optimism can signal growth opportunities, prompting firms to adjust

operational capacity, staffing levels, pricing strategies, and promotional efforts to capture anticipated increases in demand. Businesses are encouraged to integrate consumer sentiment indices, such as the Consumer Confidence Index (CCI), into their analytics dashboards and decision-making cycles to enhance responsiveness to market shifts. For policymakers, the results suggest that maintaining an environment conducive to public economic optimism, through transparent communication, stable inflation management, employment support programs, and pro-growth fiscal measures, can indirectly stimulate tourism demand. Although formal recommendations are addressed separately, it is evident that sentiment should be recognized alongside structural indicators such as infrastructure, income levels, and exchange rates in both business strategy and macroeconomic policy. By incorporating sentiment dynamics into planning, both sectors can better anticipate shifts, reduce vulnerability to shocks, and foster a more resilient and adaptive tourism sector.

Despite its contributions, this study has several limitations that warrant consideration. First, the analysis focuses solely on Indonesia, which may limit the generalizability of the findings to other countries with different economic structures or tourism dynamics. Future studies could adopt a comparative or panel data approach to explore cross-country variations. Second, the model includes only a limited set of control variables (GDP and inflation) due to data availability constraints over the 2008–2023 period. Incorporating additional macroeconomic or institutional variables such as exchange rates, political stability, or employment rates could provide a more comprehensive understanding of tourism demand drivers. Third, while the ARDL approach is well-suited for analyzing both short- and long-term effects, future research could consider alternative dynamic models such as the Generalized Method of Moments (GMM) or Vector Error Correction Model (VECM) to account for potential endogeneity and deeper lag structures. Addressing these limitations would enhance the robustness and applicability of the findings, and further strengthen the role of sentiment-based indicators in tourism economics and management research.

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