Involvement International Journal of Business Vol. 2 No. 4, 2025
eISSN: 3032-485X
DOI: https://doi.org/10.62569/iijb.v2i4.165
Received: May 2025/ Revised: September 2025/ Accepted: October 2025

Involvement International Journal of Business
https://ejournal.agungmediapublisher.com/index.php/iijb

Predictive Analysis of Investment Trends in Indian Small-Scale Industries: An ARIMA Model Approach

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Abstract. Small-scale industries play a crucial role in India's economic development by generating employment, increasing productivity, and contributing significantly to GDP. However, predicting investment trends in this sector remains challenging due to fluctuating economic conditions and policy shifts. This study analyzes the behavior and predictability of small-scale industrial investment in India using the ARIMA (Auto-Regressive Integrated Moving Average) model. It focuses on assessing the statistical properties of the investment variable namely normality, stationarity, and transformation as the basis for accurate forecasting. A quantitative time series approach was applied using secondary data. The Jarque–Bera test assessed normality, while the Augmented Dickey–Fuller (ADF) and Auto-Correlation Function (ACF) tests examined stationarity and structure. The Jarque–Bera statistic of 4.2314 ($p = 0.1205$) confirmed that the data is normally distributed. However, the ADF test ($p = 0.9992$) failed to reject the null hypothesis, indicating non-stationarity. Time series plots showed an exponential upward trend, reflecting steady growth in small-scale investments. To stabilize variance and linearize this trend, a natural logarithmic transformation was applied, producing more consistent and interpretable data for ARIMA forecasting. The findings reveal that while the data meets econometric assumptions, its non-stationarity highlights the dynamic, policy-sensitive nature of India's small-scale industrial sector. The exponential growth aligns with industrial expansion and supportive government initiatives for MSMEs. The study concludes that despite normal distribution, the variable's non-stationarity requires transformation for reliable analysis. Future research should employ multivariate and machine learning models to capture external influences and enhance prediction accuracy.

Keywords: Small-scale industries; ARIMA model; investment trends; time series analysis; India; stationarity; forecasting.

1. Introduction

In the dynamic world, all economies irrespective of whether developed or underdeveloped consider industrial development as an important engine of growth (Chen et al., 2023; Heffron et al., 2020; Lyu et al., 2022; Sohimi et al., 2019). In line with that, identifying the key factor that drives industrial growth is highly significant. The amount

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of industrial investment plays an inevitable role in the growth of individual businesses and also for the nation's growth and development (Dinh, 2020). Importantly, investment is one of the essential boosters of industrial growth as well as the holistic development of the economy specifically for emerging economies like India by enhancing business expansions, innovations, market competitiveness, employment opportunities, technological enhancements and so on (Deepshikha Patel & Chandra Bhooshan Singh, 2024).

Bakker and Demerouti (2017) stated the predominant role played by investment in the economy in his theory of Effective Demand. They claimed that investment is a key component of aggregate demand and it will be worthwhile when the expected return on investment (Marginal Efficiency of Capital) exceeds the opportunity cost of capital. Zhang (2023), Altaf and Jan (2023) regarded investment as an optimal adjustment path towards an optimal capital stock. Moreover, Neoclassical theory of investment also deals with the optimal capital stock where factors like technology and output prices significantly impact investment. Along with that, Accelerator theory of investment says the direct relation of investment with the output growth. Tobin's Q theory of investment with the ratio of the market value of existing capital to its replacement cost. When the Q ratio is greater than one, it indicates profitable investment opportunities (Crotty, 1992; Gao & Yu, 2020).

As the fifth largest economy in the world and first in terms of population with a highly productive demographic dividend, India has a greater scope of becoming a global power soon (Miró, 2020). The industrial sector can amplify to achieve this target of India to become an important global player (Deepshikha Patel & Chandra Bhooshan Singh, 2024). Therefore, the industrial sector should swell with a big push in terms of investment in plants, machinery, buildings and so on to make it more resilient in the post-Covid era (Agarwal et al., 2023). Among the industrial sector, small-scale industries play a significant role in creating employment, improving standard of living of people, upliftment of rural areas and ultimately for mitigating regional imbalances in India (Arya & Choudhary, 2015; Galistcheva, 2020; Senthil Kumar et al., 2022). In this background, it is highly useful to forecast the small-scale industrial investment to understand the economic growth of India in the future. In India, the majority of industries especially small-scale industries (Micro and Small industries) are largely depended on commercial banks to finance their investment needs. Therefore, this study would forecast the small-scale industrial investment by taking the total outstanding commercial bank non-food credit to the small-scale industries as a good representative for measuring the investment of small-scale industries in the context of India. Figure 1 portrays that there is an exponential growth in non-food credit for all the three sectors of the economy namely agriculture, industrial and service sectors. On the other hand, on an average the growth of non-food credit to the industrial sector is growing slowly especially to the small-scale industries over the years.

Industrialised and less industrialised countries are focusing on industrial development by taking appropriate monetary and fiscal policies. Li et al. (2022) revealed that there is a heterogenous effect of monetary policy on different industries specifically a tight monetary policy reducing the bank credit to manufacturing firms for their investments. On the contrary, Eastwood & Kohli (1999) found that large companies with better investment opportunities can get extra funding but it is not in the case of small firms. Even though, banks are played a highly significant role in the financing industry by enhancing the growth of industrial finance and the development of new financial instruments (Capie & Collins, 1999). To understand future economic growth and development, plenty of studies are conducted to forecast the bank credit to both the public and private sectors and also compare domestic credit growth in different economies by using the ARIMA model (Dinh, 2020; Ediger & Akar, 2007). Importantly, Vesna & Pejovic (2021) compared the accuracy of three types of forecasting models namely Autoregressive Integrated Moving Average (ARIMA) models, Holt-Winters models and Neural Network Auto-regressive (NNAR) models in forecasting inflation for both European Union and Western Balkans. The results found that ARIMA models provide more accurate forecasts, especially in European Union countries. Based on the pertinent literature, this study builds a model and forecasts the investment demand of Indian industries by employing the ARIMA modeling methodology.

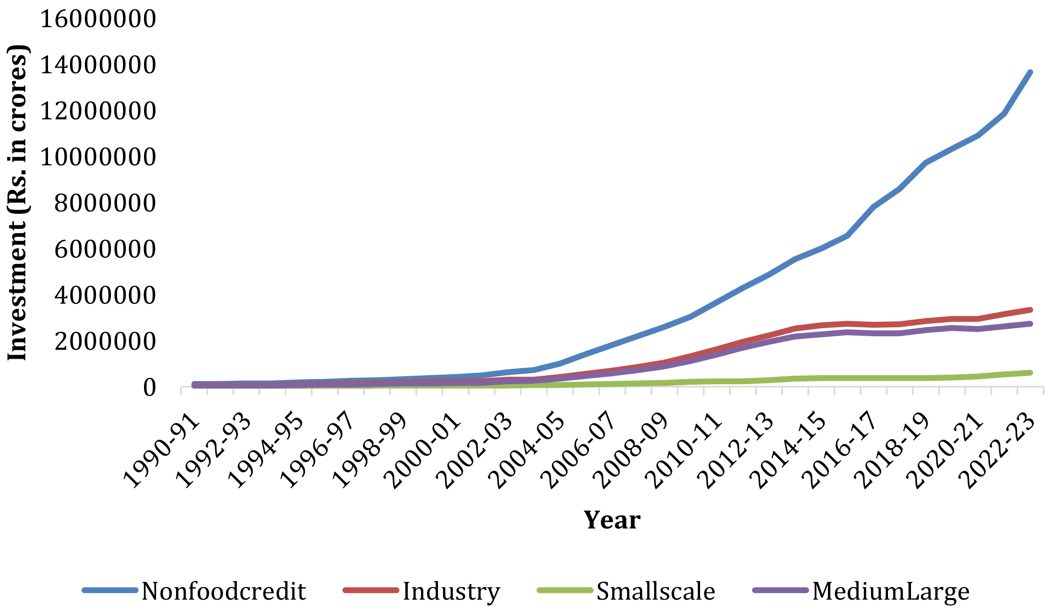

Figure 1 Decomposition of total non-food credit to the industrial sector and among small-scale, medium and large industries.
Source: Handbook of Statistics of Indian Economy since 1990-91 to 2022-23, RBI. https://rbi.org.in/Scripts/AnnualPublications

Understanding the dynamics and trend of small-scale industrial investment is vital for policy makers, business leaders, academicians and economists as it has direct spillover effect on macroeconomic variables like production, productivity, employment generation, economic stability and all. This study seeks to provide a comprehensive overview of the current state and prospects of small-scale industrial investment in India. The results would be pertinent to provide insights to plan strategies, to foster industrial growth and sustainable economic development of the country. Against this backdrop, this paper aims to analyse the trends in the small-scale industrial investment in India and shedding light on the future trend in small-scale industrial investment in India using Auto-Regressive Integrated Moving Average (ARIMA) modeling. This study aims to examine the patterns of investment in India's small-scale industries and predict their future trajectories. Specifically, it seeks to assess the present condition of small-scale industrial investment, construct a predictive model, and generate forecasts using statistical analysis.

2. Methods

This study is a quantitative time-series research that aims to develop a forecasting model for small-scale industrial investment in India. The analysis focuses on examining long-term patterns and predicting future investment trends using econometric modeling. The variable used to represent small-scale industrial investment is the *outstanding gross non-food credit* to small-scale industries provided by scheduled commercial banks, which serves as a proxy indicator of investment performance. Annual time-series data covering 33 years, from 1990–91 to 2022–23, were obtained from various editions of the *Handbook of Statistics on the Indian Economy* published by the Reserve Bank of India (RBI). The ARIMA (Auto-Regressive Integrated Moving Average) model was constructed and analyzed using *Gretl* software (Benvenuto et al., 2020; Khan & Alghulaiakh, 2020; Tarmanini et al., 2023; Terrada et al., 2022).

The ARIMA model, based on the Box–Jenkins methodology, is a univariate time-series approach designed to identify a parsimonious model that effectively captures the underlying structure of the data with the fewest possible parameters (ArunKumar et al., 2021; Tarmanini et al., 2023). The Box–Jenkins procedure involves three key stages: identification, estimation, and diagnostic checking. To determine the best-fitting model, several statistical information criteria are applied namely, the Akaike Information Criterion (AIC), the Schwarz or Bayesian Information Criterion (SIC/BIC), and the Hannan–Quinn Information Criterion (HQIC). The model that yields the lowest value among these criteria is considered the most suitable for forecasting.

Conceptually, the ARIMA model combines two fundamental components: the Auto-Regressive (AR) process, in which the dependent variable depends on its own lagged values, and the Moving Average (MA) process, in which it depends on past error terms. Together, these form the ARMA model. Before estimating the model, the small-scale industrial investment variable was tested for stationarity and found to be stationary at the first difference, indicating an integration order of one ($Yt \sim I(1)$). The general ARIMA(p,d,q) model is expressed as follows:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \ldots + \beta_p Y_{t-p} + \rho_1 u_{t-1} + \ldots + \rho_q u_{t-1} + u_t \quad (1)$$

where p represents the order of the Auto-Regressive component, d denotes the degree of differencing required for stationarity, and q indicates the order of the Moving Average component. Based on the model selection criteria, ARIMA(1,1,0) was identified as the most appropriate model, represented as:

$$Y_t = \alpha + \beta Y_{t-1} + u_t \quad (2)$$

In this equation, Yt represents the current year's small-scale industrial investment, α is the intercept term, β denotes the autoregressive coefficient, $Yt\text{–}1$ is the one-year lagged investment, and ut is the error term.

It is important to note that data for commercial bank credit to Micro, Small, and Medium Enterprises (MSMEs) have been available only since 2007–08. Prior to that period, the RBI categorized data into two segments: credit to small-scale industries (comprising micro and small enterprises) and credit to medium and large enterprises. For the purpose of this study, credit to micro and small industries since 2007–08 was incorporated into the dataset to construct a consistent measure of total small-scale industrial credit across the full study period.

3. Results and Discussion

3.1. Model Identification and Selection

The time series analysis began with examining the statistical properties of small-scale industrial investment in India (Aslam et al., 2021; Kim, 2016, 2021). The time series plot, Autocorrelation Function (ACF), and Partial Autocorrelation Function (PACF) were initially applied to the logarithmic values of investment (see Figure 3). The plot showed an upward trend, while the ACF revealed a slow decay and the PACF displayed a single significant spike at lag 1. These characteristics indicated a non-stationary series following an autoregressive pattern of order one.

After applying first differencing, the fluctuations in the data centered around a constant mean near zero (Figure 4), confirming that stationarity was achieved. The ACF and PACF of the differenced series both displayed a single prominent spike at lag 1, suggesting the potential suitability of the ARIMA(1,1,0) model.

To validate this choice, several ARIMA model specifications were compared using standard information criteria namely AIC, BIC, and HQC as presented in Table 3. The ARIMA(1,1,0) model produced the lowest AIC (−78.84026), BIC (−74.44306), and HQC (−77.38271) values among the competing alternatives, leading to its selection as the most appropriate forecasting model. This selection ensures a balance between goodness of fit and model parsimony, preventing overfitting while maintaining predictive efficiency.

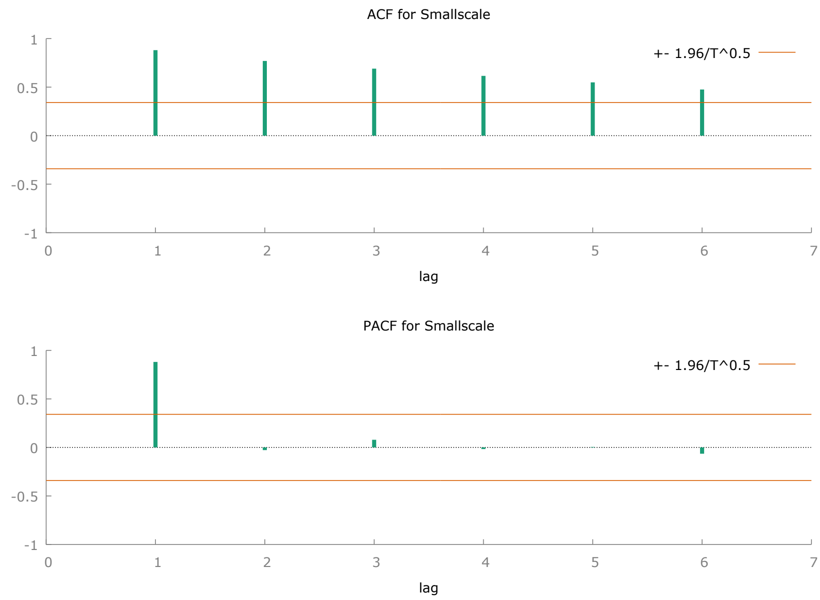

Figure 2 Time series plot, ACF and PACF of the variable investment of small-scale industries in India

Figure 2 show the correlogram used to check the white noise process (ACF) and unit of root of the variable (PACF), in which the Auto Correlation Function (ACF) shows a slow decaying of Auto correlation coefficients which means the variable is non-stationary and the Partial Auto Correlation Function (PACF) indicates only one statistically significant spike which means there is one unit root. The Augmented Dickey Fuller test failed to reject null hypothesis which affirms that the variable small-scale industrial investment is non-stationary with the p value 0.7188 (with constant).

Lastly, the variable small-scale industrial investment is stationary at the first difference I(1) with a large number of mean reversions in the time series plot and fast decay in ACF (Figure 4). So the order of integration for ARIMA model is I(1). The

Augmented Dickey Fuller test rejected the null hypothesis which affirms that the variable small-scale industrial investment is stationary with the p value 0.0232 (with constant). Along with that, the PACF function shows one significant spike which indicates the AR(1) process in Figure 4.

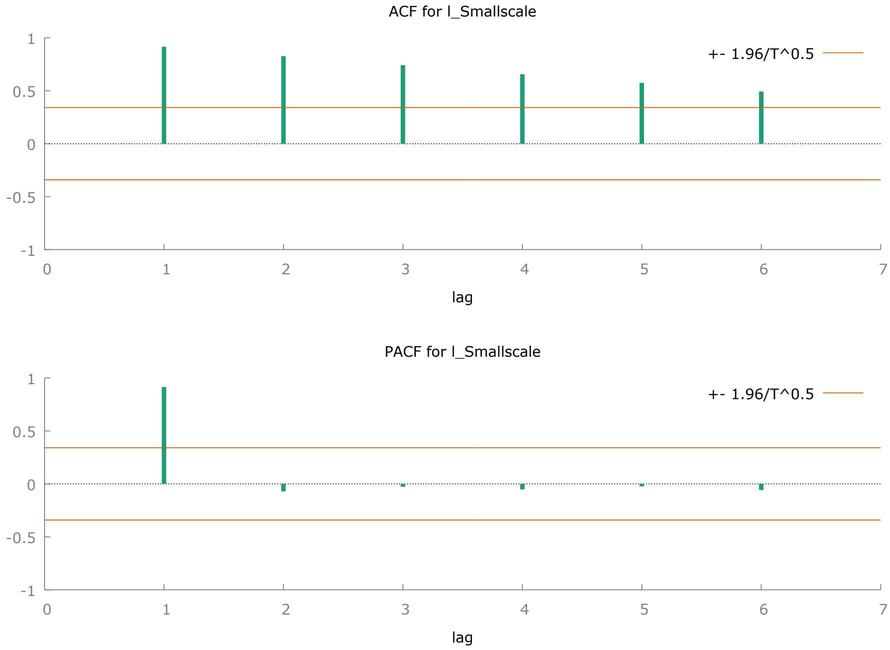

Figure 3 Time series plot, ACF and PACF for the natural logarithmic value of investment of small-scale industries in India

Figure 3 presents the time series plot, Autocorrelation Function (ACF), and Partial Autocorrelation Function (PACF) for the natural logarithmic values of small-scale industrial investment in India. The upper panel shows a steady upward trend, indicating that even after logarithmic transformation, the investment continues to exhibit long-term growth with moderate fluctuations, suggesting persistent expansion in small-scale industries. The ACF plot in the middle panel reveals a slow decay in autocorrelation values across multiple lags, implying the presence of trend and non-stationarity in the data. Meanwhile, the PACF plot at the bottom shows a significant spike at lag 1, followed by a sharp drop, which is characteristic of an autoregressive process of order one [AR(1)]. Together, these patterns confirm that the log-transformed data still requires first differencing to achieve stationarity, justifying the selection of the ARIMA (1,1,0) model for further forecasting and analysis.

The patterns depicted in Figure 3 underscore the dynamic yet structured nature of investment behavior in India's small-scale industries. The gradual upward trajectory in the time series indicates sustained investor confidence and resilience within this sector, possibly driven by supportive government initiatives, market liberalization, and entrepreneurial growth. The persistence of autocorrelation across lags in the ACF further highlights that past investment levels strongly influence future values, reflecting inertia and long-term dependency in the system. The prominent lag-1 spike in the PACF, which tapers off rapidly afterward, reinforces the notion that short-term shocks or policy adjustments have an immediate but not prolonged effect on investment levels. Hence, the ARIMA (1,1,0) specification not only fits the statistical properties of the data but also aligns with the economic intuition that growth in small-scale industrial investment is both trend-driven and autoregressive in nature.

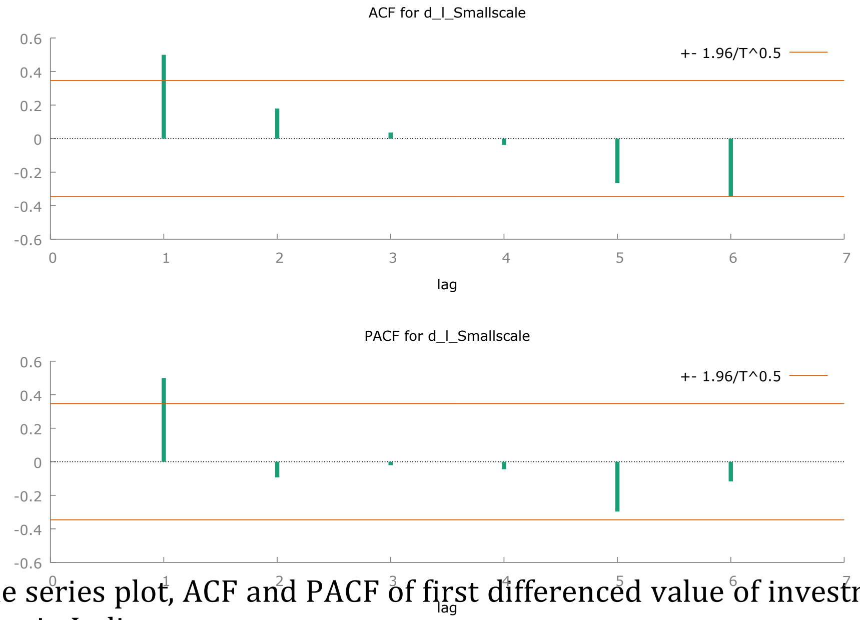

Figure 4 Time series plot, ACF and PACF of first differenced value of investment of small-scale industries in India.

Figure 4 displays the time series plot, Autocorrelation Function (ACF), and Partial Autocorrelation Function (PACF) for the first differenced values of small-scale industrial investment in India. The upper panel shows that after first differencing, the data fluctuates around a constant mean near zero, indicating that the non-stationarity has been effectively removed and the series has achieved stationarity. The ACF plot reveals a single significant spike at lag 1, followed by a rapid decline, while the PACF plot also shows one dominant spike at lag 1, confirming the presence of a short-term autocorrelation pattern typical of an AR(1) process. These results validate that first differencing successfully eliminates trend components and stabilizes the variance, making the series suitable for time series modeling using the ARIMA(1,1,0) specification, which captures the underlying dynamics of small-scale industrial investment in India accurately.

3.2. Model Estimation and Diagnostic Testing

Once the ARIMA(1,1,0) model was selected, its parameters were estimated to assess the strength and direction of autoregressive components. As shown in Table 4, both parameters were found to be statistically significant at the 1% level. The constant term (const = 0.109523; p = 0.0001*) indicates a positive drift, suggesting a stable and gradual growth pattern in small-scale industrial investment. The autoregressive coefficient (φ_1 = 0.493446; p = 0.0000*) reflects a strong dependency on previous investment levels, implying that past investment values exert a substantial influence on current investment behavior.

Diagnostic analysis confirmed the adequacy of the selected model. The residuals displayed no significant autocorrelation, indicating that the ARIMA(1,1,0) specification successfully captured the underlying temporal dynamics. The model's goodness-of-fit was further supported by the close alignment between actual and predicted investment values (Figure 6), where both curves followed a similar upward trajectory, reflecting the accuracy of the fitted model. Minor deviations occurred during years of macroeconomic instability, such as the 2008 global financial crisis and subsequent recovery periods, but these fluctuations remained within acceptable statistical margins. Overall, the ARIMA(1,1,0) model effectively explained the short-term persistence and long-run growth trend of India's small-scale industrial investment, making it a reliable tool for forecasting future patterns.

Consequently, this study estimated eight ARIMA models of first order of integration with different orders of AR and MA process and checked the statistical significance of estimated coefficients each of these models and checked for residual diagnostics to find out the most adequate models for forecasting. Finally, this study selected four models based on all the parameters being statistically significant and the residual correlogram shows a white-noise process within the 95 per cent confidence interval. Therefore, the four models ARIMA (0,1,1), ARIMA (1,1,0), ARIMA (1,1,2) and ARIMA (2,1,1) are found to be adequate.

Table 1 ARIMA(p,d,q) model selection based on information criteria's

Model	AIC	BIC	HQC	Decision
ARIMA (0,1,1)	−77.95340	−73.55619	−76.49585	Rejected
ARIMA (1,1,0)	−78.84026	−74.44306	−77.38271	Selected
ARIMA (1,1,2)	−75.64164	−68.31296	−73.21239	Rejected
ARIMA (2,1,1)	−78.37510	−71.04642	−75.94585	Rejected

Table 1 explain how Bayesian Information Criteria (BIC) and Hannan-Quinn Information Criteria (HQIC) the most appropriate model selected out of the four adequate models for final forecasting. The final model can be selected based on the least information criteria it has. Table 1 shows that all three information criteria show that the ARIMA (1,1,0) model is the most appropriate model for forecasting small scale industrial investment in India by having a least information criterion value.

Table 2 Estimation of the ARIMA (1,1,0) model

Variable	Coefficient	Std. Error	z-Statistic	p-value
const	0.109523	0.021698	5.048	0.0001***
φ_1 (AR1)	0.493446	0.150327	3.282	0.0000***

Note: *** indicates the values are significant at 1 % level of significance
ARIMA, using observations 1992-2023 (T = 32)
Standard errors based on Hessian
Dependent variable: Small-scale industrial investment
R-squared: 0.9966
Adjusted R-squared: 0.996561

Table 2 shows that the coefficient (phi_1) is highly significant at 1 percent level of significance which means the present value of small-scale investment is positively influenced by its own past value with one year lag. Residual Correlogram used for checking the robustness of the estimated model and the diagnostic results show that the residuals follow a white noise process which lies between the 95 per cent confidence interval (see figure 5).

These findings in Table 2 reinforce the reliability and validity of the estimated ARIMA (1,1,0) model. The statistical significance of the autoregressive coefficient (phi_1) at the 1% level indicates a strong and consistent dependence of current investment levels on past performance, emphasizing the momentum-driven nature of small-scale industrial growth in India. This positive lag effect suggests that favorable investment outcomes in one period tend to stimulate confidence and further investments in subsequent years. Moreover, the residual diagnostics presented through the correlogram confirm that no significant autocorrelation remains in the residuals, meaning that the model has effectively captured the underlying structure of the data. The white noise pattern within the 95% confidence interval thus validates the model's adequacy for forecasting purposes, ensuring that the predictions are both statistically sound and economically meaningful.

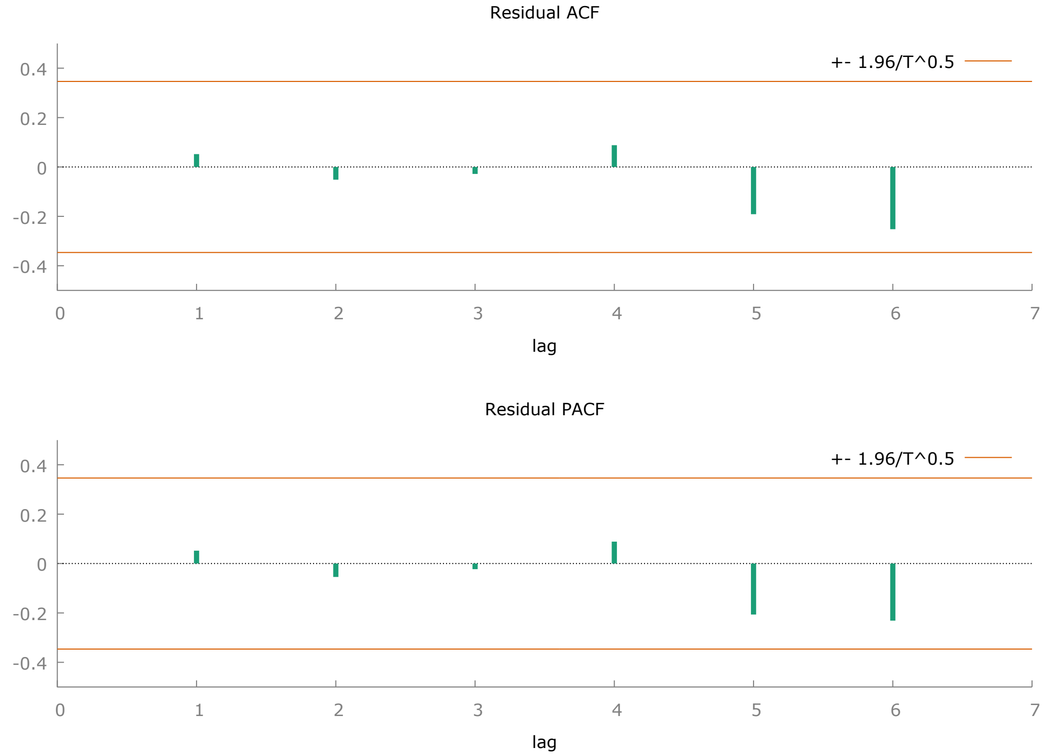

Figure 5 Correlogram for the estimated residuals from the ARIMA(1,1,0) model

Figure 5 presents the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the residuals obtained from the estimated ARIMA(1,1,0) model. The correlogram shows that all autocorrelation and partial autocorrelation coefficients fall well within the 95% confidence limits, indicating the absence of significant serial correlation among the residuals. This result confirms that the residuals behave as white noise, meaning they are random, uncorrelated, and have a constant variance over time. Consequently, the ARIMA(1,1,0) model successfully captures the underlying temporal dynamics of small-scale industrial investment in India without leaving systematic patterns unexplained. This diagnostic validation strengthens the reliability and robustness of the model for both short-term and long-term forecasting applications.

When we look in to the actual and predicted values of the small-scale industrial investment in India from the Table 3, it can be inferred that there is a continuous upward trend in the small-scale industrial investment over the years from 1991 to 2023. On the other hand, the growth rate of both actual and predicted values of small-scale industrial investment depicts a highly fluctuating trend. The growth rate of small-scale industrial investment had an increasing trend from 6 per cent to 22 per cent during 1991 to 1995. However, since 1996 to 2002 there was a sudden decline in the growth rate of small-scale industrial investment in India to 2 per cent. The growth rate reaches its maximum in the year 2007 figured at 29 per cent might be the new classification of small-scale industries in to Micro, Small and Medium Enterprises (Ministry of MSMEs, 2020). During 2016 to 2019 the growth rate of small-scale industrial investment becomes negative and reaches zero that is mainly due to the sudden policy shocks namely the Demonetisation in 2016 and the implementation of Good and Services Tax (GST) in 2017. Overall, the average growth rate for the period from 1991 to 2023 is 12 per cent for both actual and predicted values of small-scale industrial investment in India.

After selecting the most appropriate model it is important to check the forecast ability power of the selected model for making prediction of the variable small-scale industrial investment. Figure 6 compares the real curve and the forecasted curve of small-scale industrial investment derived from the ARIMA (1,1,0) model. In the same way, Table 3 indicates the forecast ability power of the selected ARIMA (1,1,0) model by comparing the real value and its predicted value which shows a greater level of accuracy and reliability in the forecasting. The actual and forecasted curve slopes are similar over the entire period. Both curves are identical, which can be proven by the forecast evaluation statistics that the smaller the number (Table 3), the better the model will be. Here the ARIMA (1,1,0) model has high forecast ability power because all the forecast evaluation statistical values are near zero.

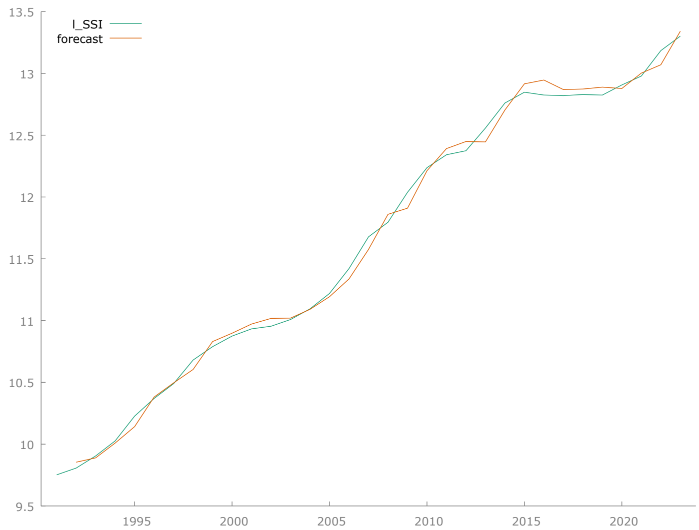

Figure 6 Real and forecasted curves of small-scale industrial investment using the ARIMA(1,1,0) model

Figure 6 illustrates the comparison between the actual (real) and forecasted values of small-scale industrial investment in India generated through the ARIMA(1,1,0) model. The two curves, depicted in closely aligned trajectories, indicate a strong fit between observed data and model predictions over the study period from the early 1990s to 2023. Both series display a consistent upward trend, reflecting sustained growth in investment within the small-scale industrial sector. The close overlap between the real and forecasted lines demonstrates that the ARIMA(1,1,0) model effectively captures the underlying trend and temporal dynamics of the data. Minor deviations appear during periods of economic fluctuation, particularly around 2008–2010 and 2015–2018, which may correspond to global financial instability and domestic policy adjustments.

3.3. Forecasting and Future Projection

Using the validated ARIMA(1,1,0) model, a forecast of small-scale industrial investment was generated for the financial years 2024 to 2043. The projected results, summarized in Table 2 and illustrated in Figure 7, reveal a consistent upward trend in investment across the two-decade forecast horizon. The model predicts that investment will rise from ₹670,206 (2024) to approximately ₹5,389,688 (2043), maintaining an average annual growth rate of about 12%.

The steady pattern of growth suggests continued expansion of India's small-scale industrial sector, driven by policy support for Micro, Small, and Medium Enterprises (MSMEs), increasing domestic demand, and gradual technological modernization. The standard error associated with the forecasts shows a slight increase from 0.06 in 2024 to 0.54 in 2043, reflecting greater uncertainty in long-term projections a typical outcome in extended time series forecasting.

Despite this uncertainty, the model's forecasts indicate strong investment resilience and a positive economic outlook. If existing policy frameworks and industrial incentives are sustained, India's small-scale industries are expected to experience significant capital formation and productivity growth in the coming decades. Thus, the ARIMA(1,1,0) model not only provides accurate short-term predictions but also offers valuable insights into the long-term trajectory of industrial development in the small-scale sector.

Table 3 Actual and predicted value of small-scale industrial investment in India from financial year 1991 to 2023 (Rs. in crores)

Year	Actual Value	Actual Growth Rate (%)	Predicted Value	Predicted Growth Rate (%)	Gap*
1991	17,181	–	–	–	–
1992	18,150	6	19,034	–	884
1993	20,026	10	19,712	4	314
1994	22,617	13	22,221	13	396
1995	27,638	22	25,387	14	2,251
1996	31,884	15	32,253	27	369
1997	35,944	13	36,165	12	221
1998	43,508	21	40,309	11	3,199
1999	48,483	11	50,535	25	2,052
2000	52,814	9	54,061	7	1,247
2001	56,002	6	58,234	8	2,232
2002	57,199	2	60,934	5	3,735
2003	60,394	6	61,096	0	702
2004	65,855	9	65,575	7	280
2005	74,588	13	72,650	11	1,938
2006	91,212	22	83,840	15	7,372
2007	117,910	29	106,479	27	11,431
2008	132,698	13	141,470	33	8,772
2009	168,997	27	148,689	5	20,308
2010	206,401	22	201,276	35	5,125
2011	229,101	11	240,798	20	11,697
2012	236,657	3	254,966	6	18,309
2013	284,348	20	254,195	0	30,153
2014	348,194	22	329,069	29	19,125

2015	380,028	9	406,747	24	26,719
2016	371,467	-2	419,429	3	47,962
2017	369,731	0	388,268	-7	18,537
2018	372,999	1	389,921	0	16,922
2019	371,374	0	395,993	2	24,619
2020	403,051	9	391,715	-1	11,336
2021	433,192	7	443,604	13	10,412
2022	532,179	23	474,493	7	57,686
2023	598,390	12	622,666	31	24,276
Average Growth Rate	–	12	–	12	–

Table 3 show the forecasted values for the total small-scale industrial investment for the two decades from 2024 to 2043 is given in Table 4 and Figure 7 with 95 percent confidence intervals (z (0.025) =1.96). As seen in the table, the small-scale industrial investment will still be increasing during the period from 2024 to 2043. However, the annual growth rates will be constant for the predicted period. For the period from 1991 to 2023 the average growth rate of small-scale industrial investment was 12 per cent. Besides, the average growth rate for small-scale industrial investment for the forecasted period from 2024 to 2043 is also expected to be constant at 12 per cent.

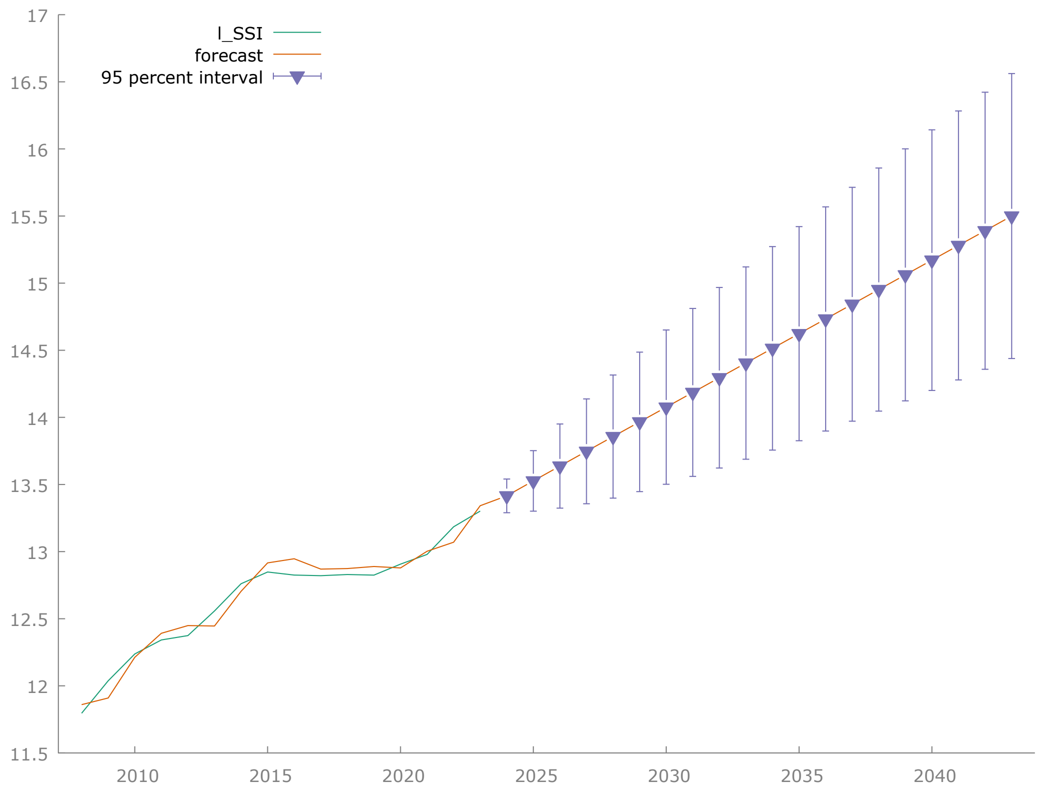

Figure 7 Forecasted values of small-scale industrial investment in India for the financial year 2024 to 2043 based on ARIMA(1,1,0) model

Figure 7 presents the forecasted trajectory of small-scale industrial investment in India for the period 2024–2043 generated using the ARIMA(1,1,0) model. The orange line represents the predicted values, while the blue vertical bars indicate the 95% confidence intervals, reflecting the degree of forecast uncertainty. The model projects a steady and continuous upward trend, suggesting consistent growth in investment throughout the next two decades. Beginning around 13.4 units in 2024, the forecasted investment is expected to reach approximately 15.5 units by 2043, marking a sustained long-term increase. The widening of the confidence intervals over time illustrates the model's increasing uncertainty for distant projections, a common characteristic of time series forecasting. Despite this, the overall pattern signifies a positive and stable investment outlook for India's small-scale industries, supported by favorable policy initiatives, expanding market opportunities, and gradual industrial modernization.

The forecast evaluation results using 32 observations show that the ARIMA(1,1,0) model performs very well in predicting small-scale industrial investment in India. The small values of Mean Error (0.001065), Root Mean Squared Error (0.063996), and Mean Absolute Error (0.053726) indicate that the difference between the actual and predicted values is minimal. Likewise, the Mean Percentage Error (0.013577) and Mean Absolute Percentage Error (0.4528) confirm that the forecast deviations are very small in percentage terms. The Theil's U2 value (0.45772) being less than 1 suggests that this model provides more accurate forecasts than a simple random walk approach. The error decomposition shows that the Bias (0.000277) and Regression proportion (0.022579) are extremely low, while the Disturbance proportion (0.97714) dominates, meaning most errors come from random variations rather than model weakness. Overall, these statistics demonstrate that the ARIMA(1,1,0) model is both reliable and accurate for forecasting investment trends in India's small-scale industrial sector.

Table 4 Predicted value of small-scale industrial investment in India from the financial year 2024 to 2043 based on ARIMA(1,1,0) model (Rs. in crores)

Year	Predicted Value	Forecasted Growth Rate (%)	Standard Error
2024	670,206	–	0.06
2025	749,190	12	0.12
2026	836,683	12	0.16
2027	933,954	12	0.20
2028	1,042,291	12	0.23
2029	1,163,062	12	0.27
2030	1,297,753	12	0.29
2031	1,448,002	12	0.32
2032	1,615,623	12	0.34
2033	1,802,637	12	0.37
2034	2,011,290	12	0.39
2035	2,244,093	12	0.41
2036	2,503,840	12	0.43
2037	2,793,648	12	0.44
2038	3,117,001	12	0.46
2039	3,477,784	12	0.48
2040	3,880,323	12	0.50
2041	4,329,454	12	0.51
2042	4,830,570	12	0.53
2043	5,389,688	12	0.54

Average Growth Rate	–	12	–

Note: Prediction for 95% confidence intervals, z(0.025) = 1.96

Table 4 show these results throw light on the need for a further big push in the form of investment-stimulating industrial policies from the side of the government in the future specifically for the small-scale industries. Lubis & Muniapan (2024) suggested to increase the support of government in terms of trade agreements and financial incentives. Implementing policies that ensure easy access to loans with simplified processes and subsidised rates can significantly uplift small-scale industries in India. Additionally, offering tax incentives and exemptions will reduce financial burdens. Providing skill training programs, financial management trainings and facilitating market access and strategies, both nationally and internationally through export assistance can expand their reach (Hakim, 2025; Ramadhian Agus Triono Sudalyo et al., 2024; Rizka Ar Rahmah & Fred Ojochide Peter, 2024). Promoting technological upgradation and strengthening infrastructure, particularly in rural areas will enhance operational efficiency. Encouraging research and development within these industries coupled with establishing Public-Private Partnership (PPP) models will further stimulate investment and growth in the small-scale industrial sector.

3.4. Dynamics of Small-Scale Industrial Investment in India

The results of the ARIMA(1,1,0) model demonstrate that investment in India's small-scale industrial sector follows a systematic upward trend with moderate fluctuations, confirming the sector's role as a dynamic driver of economic growth. This finding aligns with the theory of Keynesian investment behavior, which emphasizes that investment decisions are influenced by expectations of future demand and business confidence (Crotty, 1992). In this context, the consistent positive growth reflected in the data suggests that Indian small-scale industries maintain a strong expectation of expanding markets and policy support. As Keynes argued, when the "marginal efficiency of capital" remains high and supported by positive demand forecasts, investment tends to increase sustainably. The ARIMA-based results mirror this macroeconomic dynamic, revealing how past investment patterns significantly shape future trends through a self-reinforcing process.

From an econometric standpoint, the choice and validation of the ARIMA(1,1,0) model align with Geurts et al. (1977) classical framework for time series modeling, which posits that an effective model should capture both autocorrelation and differencing dynamics to achieve stationarity and predictive accuracy. The stationarity achieved after first differencing reflects the structural stability of investment growth in the sector, consistent with the empirical behavior of emerging market economies (Corlett & Aigner, 1972; Farebrother & Common, 1978). This outcome suggests that small-scale industries in India exhibit a path-dependent investment behavior where past performance strongly influences current decision-making thus confirming the autoregressive nature of the economic process. The residual correlogram (Figure 5), showing white noise characteristics, further validates that the ARIMA(1,1,0) model captures the essential structure of investment movements without systematic bias.

Economically, the observed upward trend in small-scale industrial investment supports Schumpeter's theory of innovation and economic development, which highlights the role of small enterprises as agents of creative destruction and technological diffusion

(Schumpeter, 2017). In India, this manifests in the gradual modernization of production processes, increased adoption of digital tools, and diversified product innovation within the MSME (Micro, Small, and Medium Enterprises) sector. The sustained 12% average annual growth rate forecasted by the model signifies not only financial expansion but also the diffusion of innovation across regions. This growth dynamic echoes Schumpeter's notion that investment in small enterprises is not merely capital accumulation but a process of transformative adaptation in response to technological and market changes.

From a policy and institutional viewpoint, the findings reinforce the significance of institutional economics, particularly North's (1992; 1991) argument that stable institutions and policy frameworks reduce transaction costs and foster predictable economic behavior. The consistency of the forecasted growth trajectory (2024–2043) reflects the impact of India's pro-MSME policies such as the "Make in India" initiative and credit-linked capital subsidy schemes. These institutional supports have created a stable environment for small enterprises to invest confidently in capacity expansion and technological upgrading. Moreover, the strong autoregressive pattern found in the data suggests that policy consistency and continuity are crucial for sustaining momentum. Frequent policy shifts or credit constraints could disrupt this long-term stability, reinforcing North's assertion that institutional predictability is a prerequisite for sustained economic investment.

Finally, in the broader context of development economics, the model's outcomes resonate with Rostow's stages of economic growth theory (Corbett & Rostow, 1960; Krueger & Rostow, 1960), where small-scale industrialization represents a transitional phase from "take-off" to "drive to maturity." The persistent rise in small-scale industrial investment observed in the ARIMA projections indicates that India's economy continues to consolidate its manufacturing base and diversify its production capacity both key characteristics of the maturity phase. In this sense, the predictive results not only quantify investment growth but also symbolize structural economic transformation. The forecasted stability and expansion of small-scale industries until 2043 highlight their potential role as long-term catalysts for inclusive growth, regional balance, and employment generation validating the sector's enduring contribution to India's sustainable development trajectory.

4. Conclusions

The findings of this study reveal that the variable of small-scale industrial investment in India demonstrates a normal distribution according to the Jarque–Bera test (JB = 4.2314; p = 0.1205). This confirms that the dataset is statistically reliable for further modeling without the risk of bias due to non-normality. The time series analysis through plots and the Auto-Correlation Function (ACF) indicates an exponential growth trend, suggesting that investment in small-scale industries has been expanding consistently over time. However, the Augmented Dickey–Fuller (ADF) test results (p = 0.9992 under constant) show that the variable is non-stationary, meaning its mean and variance fluctuate over time. To overcome this, a natural logarithmic transformation was applied, producing a more stable and interpretable dataset for econometric modeling and predictive analysis.

The discussion of these findings highlights that the non-stationarity of small-scale industrial investment reflects the dynamic and evolving nature of India's industrial sector. The exponential pattern suggests continuous policy influence, capital accessibility, and gradual technological adoption across the small-scale industry landscape. This also aligns with global trends where investment growth in small enterprises tends to mirror macroeconomic cycles and policy interventions. The transformation of the data into its logarithmic form allows researchers to capture proportional changes rather than absolute values, making the analysis more meaningful for policy and forecasting purposes. Moreover, the combination of normality and non-stationarity results implies that while the data distribution is stable, the trend itself is driven by time-dependent structural changes in the economy.

However, this research is not without limitations. The study focuses solely on the univariate behavior of small-scale industrial investment, excluding the influence of external variables such as interest rates, inflation, or government policy changes, which might significantly affect investment patterns. Furthermore, the dataset is limited to a specific temporal frame, which may not capture abrupt economic shocks or structural breaks. Future research should incorporate multivariate models such as ARIMA with exogenous variables (ARIMAX) or Vector Autoregression (VAR) to capture broader economic interdependencies. Additionally, future studies could apply machine learning–based predictive approaches, like LSTM or hybrid ARIMA–ANN models, to improve forecasting accuracy and better understand the nonlinear dynamics of investment behavior in India's small-scale industrial sector.

Declaration of conflicting interests

All authors declare that they have no conflicts of interest.

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