An Econometric Study on Effect of Industrial Growth on Technological Innovation in India

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Abstract

This paper examines the causal relationship between industrial growth and technological innovation of India. The study focused on whether or not industrial growth leads technological innovation in India. The methodology applied in the paper is the standard Granger causality tests and Toda- Yamamoto test for causality to time series annual data covering the period 1968 to 2016. The empirical findings reveal the absence of a long-run equilibrium relationship between the variables but there exists uni-directional short-run Granger causality running from industrial growth to technological innovation without any feedback effect. The results are confirmed by cross-checking with the Toda-Yamamoto causality approach.The findings of this study support the "demand-led" or "market-pull" approach to innovation. Therefore, the study suggests an integrated innovative-industrial policy thereby increasing the industrial growth of a developing country like India.

Keywords: *Innovation, Patents, Industrial growth, Causality, Co-integration, India*

Introduction

The Indian industrial sector holds a key position in the Indian economy since it is considered to be crucial for employment generation and development of the economy. To address the problem of unemployment and poverty, industrial development is vital for any country.Industrial growth plays a significant role in the overall development of any economy as it raises the productive capacity of people by creating employment opportunities, raising their standard of living, by promoting international trade, boosting national income and by pushing the overall growth of any economy into a higher trajectory. The Government of India has undertaken various economic and institutional reforms including launching ambitious programmes such as Make in India, Start-up India, reforms for improving ease of doing business which has led to significant up-gradation of India's ranking in the Ease of Doing Business by the World Bank 2018 and pushing industrial growth. The promotionof inclusive employment-intensive industry and building resilient infrastructure are vital factors for economic growth and development. The Government is taking several sector-specific measures in this direction to promote sustainable growth of the industry. Industrial growth depends on a variety of factors like adequate infrastructure, availability of skilled labour, adequate expenditure on R&D and Innovation.

Innovation is a crucial factor for the sustained growth of a country and can also help reduce poverty. The Oslo Manual, a worldwide reference for innovation, defines it as "Implementation of new or significantly improved products (goods and services), processes, marketing and organizational methods"[1]. It is a wide known fact that innovation is integral to the long-term growth of a nation.Technology is the key to expanding the manufacturing base in the country and increasing India's presence in the global market. Also, India is a heterogeneous market with diverse needs. This heterogeneity in Indian market calls for manufacturing players to innovate. Hence, the Indian industrial sector recognizes the importance of constant innovation in order for survival in a globalised world as a long-term need[2]. According to the World Bank report, India is increasingly becoming a top global innovation player in biotechnology, pharmaceuticals, automotive parts and assembly, IT software and IT-enabled services[3]. In today's knowledge world, we believe that no firm can survive without innovation.

Technological innovation is not only a way to bring the world closer and closer but it also helps to resolve problems in today's integrated world economy. In addition to trade integration and trade openness in the era of globalization, we are witnessing a technological revolution. There are a growing and large body of literature illustrating the positive impact of technological innovation on the industrial growth of a country. Artz et al.(2010)analyzed the impact of patents acquired and product innovation on firm performance in different industries of the US and Canada during the period 1986-2004 using multiple regression models. They found that product innovation had a significant impact on firm performance. Cozza et al. (2012) studied the impact of product innovation on the economic performance of firms (in terms of profitability and growth) using a large sample of Italian firms operating in Medium and High-Tech (M&HT) industries. They used Propensity Score (PS) matching methods and found out a positive and statistically significant relationship between innovation and economic performance of the firms. Atalay et al. (2013) examined the relationship between different types of innovation and performance of firms operating in the automotive supplier industry in Turkey. The data obtained from the questionnaire was analyzed through factor analysis and regression analysis. The results demonstrated that technological innovation (product and process innovation) had a significant and positive impact on firm performance, but no evidence was found for a significant and positive relationship between non-technological innovations (organizational and marketing [1]innovation) and firm performance.

Although there exist behemoth literature on the impact of technological change or innovation on industrial growth, the causal relations among these variables remain somewhat vacuous. To fill this literature gap, this paper focuses exclusively on the causal relations between technological innovation (proxied by a number of patent applications by both residents and non-residents) and the industrial growth (measured by Industrial value added at constant 2010 US$) in the case of India. The major contributions of this study in the present literature are: Firstly, different from previous various studies that studied the relation or impact among the variables, this study exclusively tests for the direction of causality among these two variables. Secondly, apart from this, the paper uses the most updated and longest time series data (1968-2016) from world-renowned source 'World Development Indicators' of the World Bank. Thirdly, divergent views exist in the literature regarding the effect of innovation on industrial growth but most of them are confined to developed countries. Very few researchers have attempted to describe the issue in case of a developing country like India. Fourthly, the empirical findings of this study will strengthen the understanding of causal relations between industrial growth and technological innovation which would further help the policymakers to identify sectors to be focused first thereby formulating a coherent and integrated innovative-industrial policy to foster economic growth of India. Against this background, the paper is motivated to explore the causal relationship between technological innovation and industrial growth in the case of India.

The remainder of the paper is organized as follows: Second section explains the review of the past literature; In the third section, the econometric methodology is presented;the fourth section explains the main findings, analysis and discussions; thelast section concludes the paper and suggests some imperative policy implications for India which could be applicable to other developing countries as well.

Literature Review

The available empirical evidence in assessing the effect of innovation on industrial growth is limited since it is difficult to quantify the amount of innovation in any economy. When trying to identifying proxy variables for innovation, researchers have used many proxies to quantify the technological change such as expenditure on research and development activities (R&D), patent citations, imports of capital goods, royalties and license fees, accumulation of ICT capital, change in Total Factor Productivity (Vashisht, 2017).

The patent counts were taken as a proxy variable for measuring industrial innovative capabilities following Scherer, (1965), Schmookler (1966), Griliches (1984) and Crosby (2000). Patents are used to protect the firm's invention. They have the ability to reflect inventive activity and innovation. Therefore, patents can be used to examine technological change since (i) Compared to R&D expenditure, patent data is more associated with innovative output (ii) Patents data is available for a relatively longer period of time (suitable for time series analysis) (iii) Patent data is easy to measure, access and quantify (iv) Also, it is easily comparable with other countries. The major limitation of using patent data as a proxy variable is its inability to capture the whole range of innovations as not all inventions get patented nor do all patents gives rise to successful innovations. Inspite of these shortcomings, as Comanor & Scherer (1969) interpreted in detail, patent data still provide valuable and significant information on innovation.A number of studies have emerged in order to study the effect of innovation on industrial growth at both the firm and industry level.

Fan et al.(2018)estimated the long run as well as short-run cointegration relationship between technological innovation, infrastructure and industrial growth in Bangladesh over the period 1974-2016 using the ARDL Bounds Test methodology and Granger Causality test in an augmented VECM framework. The results showed a positive and significant impact of infrastructure and technological innovation on industrial growth in the short run but technological innovation showed a negative impact on industrial growth in the long run. The VECM Granger causality test suggested a unidirectional causality running from industrial growth to technological innovation. The study recommended an integrated macro-variable policy instead of any single or individual policy action to ensure the sustainable growth of a developing country like Bangladesh as well as other developing countries.

Crosby(2000) explored the importance of innovation in promoting Australian economic growth by using the VAR modelling and found that with the increase in patenting activity (proxy variable for innovation), both labour productivity and economic growth increased, though this increase could take up to 15 years. Pantano et al. (2017) provided a detailed overview of the level of innovation using text mining (i.e. the text describing the patent) and bibliometric analysis (i.e. the number of patents in a certain period of time) and showed a positive effect of innovation on retailing. They concluded their paper by suggesting the need to push more towards innovation-oriented strategies to propose innovative consumers solutions.

San & Huang(2010)analysed the causal relationship among technological innovation, capital investment, and market performance for four major industries with different technological levels, namely, the electronics, chemical, machinery and textile industries using Taiwan's annual data for the period 1988-2005 by using the Granger causality test. They found out that only in the high-tech electronics industry, a complete triumvirate causal relationship among patents, capital investment, and production value exist while there were some missing linkages in terms of technological innovation in the mid-tech and low-tech industries, thereby, suggesting taking sectoral specifications into account while considering innovation policies. Çetin (2013) examined the causal relationship between R&D expenditures and economic growth based on the standard Granger and Toda-Yamamoto tests for causality to time series data covering the period 1981-2008 for nine European countries. Their findings supported the innovation-based growth hypothesis for some European countries and recommended that the government should increase R&D intensity and apply co-ordinated, coherent and effective R&D policies for a sustainable growth.

Guloglu & Tekin (2012)investigated the causal relationship between R&D expenditure, innovation (proxied by the number of triadic patents) and economic growth in 13 high-income OECD countries for the period 1991-2007 by estimating a trivariate panel VAR model through the GMM and panel fixed effects method. The pairwise Granger Causality test suggested that R&D intensity triggers innovation which further enables economic growth, while multivariate causality revealed a multiple of causal relations among their variables implying support for both the "demand-pull" and "technology-push" models of innovation.

Econometric Methodology

The study has employed the standard Granger(1969) and Toda & Yamamoto(1995) tests to determine the causality relationship between innovation and industrial growth. This study takes Patents counts as a proxy variable to measure technological innovation in India.

Data Construction: In order to explore the impact of technological innovation (TI) on Industrial Growth (ING) of India, data have been taken from the 'World Development Indicators' of the World Bank published in 2017. The study has covered the longest time period from 1968 to 2016 (that is, duration of 49 years) which is suitable for time series analysis. We have used Industrial value added (constant 2010 US$) as a proxy variable for measuring Industrial Growth (ING) in India. The sum of the number of patents applied by residents and non-residents is taken as a proxy variable for measuring technological innovation. We have converted all-time series data to their natural logarithm form for standardization of data.

Model Framework: The empirical analysis takes into account the following linear regression models to investigate the causal link between technological innovation and industrial growth.

$ING_t = \beta_0 + \beta_1 TI_t + u_t$ - (1)

$TI_t = \alpha_0 + \alpha_1 ING_t + v_t$ - (2)

Where ING indicates the Industrial value added which has been used as a proxy variable for Industrial Growth and TI denotes the technological innovation; $\beta_0$and α_0 are the intercept term and $\beta_1$and α_1 is the coefficient of the technological innovation and industrial growth respectively;u_t and v_t are the residual terms. The subscript t denotes the time period of each variable being taken in the study. By taking the natural logarithm on both sides of the equation, our final equation becomes:

$Log(ING_t) = \beta_0 + \beta_1 log(TI_t) + u_t$ - (3)

$Log\ (TI_t) = \alpha_0 + \alpha_1 \log\ (ING_t) + v_t$ - (4)

Granger Causality Procedures: A standard procedure with three steps is employed to examine the causality linkage between the two variables:

Unit Root Testing: First, in order to determine the time series properties, the unit root properties of the series are tested. In our study, we have applied two kinds of unit root tests: a. Traditional unit root test and b. Unit root with structural break. The reason being if structural breaks are there, the usual approach of unit root testing may get invalidated. The unit root test will show whether the series (LTI, LIVA) are stationary or not. The Augmented Dickey-Fuller (ADF) and the Phillips and Perron unit root testing methods were used to determine the traditional unit root of the variables and modified ADF for structural break unit root tests. The ADF test takes care of the possible serial correlation in the errors term by adding the lagged difference terms of the regressand. Phillips and Perron use the nonparametric statistical methods to take care of the serial correlation in the error term without adding lagged difference terms.

The traditional view of the unit root hypothesis assumed that the current shocks would have only temporary effects and the long-run movement in the series would be unaffected by such shocks. But, the unit root hypothesis propagated by Nelson & Plosser (1982) revealed that random shock does have a permanent effect on the long run level of macroeconomics and hence fluctuations are not transitory. Additionally, Perron (1989) showed that failure to allow for an existing break which may be due to some unique economic events leads to a bias that reduces the ability to reject a false unit root null hypothesis. To overcome this, Perron proposed allowing for a known or exogenous structural break in the Augmented Dickey-Fuller (ADF) tests. Taking these things into consideration, we checked structural breakpoints using Bai & Perron(2003) multiple breakpoint tests and conducting structural break unit tests in the modified ADF test.

Cointegration Test: Cointegration implies that despite being individually non-stationary, a linear combination of two or more time series can be stationary. If there is a long-run or equilibrium relationship between the two given series, then they are said to be cointegrated. The error correction term which is used to tie the short run behaviour to the long run value can only arise if there is cointegration. Therefore, the first step has to be testing for cointegration. If evidence for cointegration is positive, then error correction term will be present in the equation. The simplest test for cointegration is the one suggested by Engle and Granger which is applicable only for two time series as required in our study. The Engle & Granger(1987)cointegration technique is employed to examine whether there exists the long run relationship between any two variables.

Procedure:

1. Determine whether y_t and x_t are I(d).
2. Provided they are both I(d), estimate the parameters of the cointegration relation.
3. Test to see whether the least squares residual appears to be I(0) or stationary, then the series are cointegrated and the regression equation would not be spurious.

If two or more time series are cointegrated, then there must be Granger causality between them which can either be one way or bidirectional.

Granger-Causality Test: According to Granger (1969), a variable (in this case technological innovation) is said to Granger-cause another variable (industrial growth) if past and present values of technological innovation help to predict industrial growth. The Vector Auto Regression (VAR) framework allows testing for Granger causality and explicitly includes the possibility of feedback causality.

According to Sekantsi & Thamae(2016) there are two approaches to Granger causality which are as follows:

1. If the series X and Y are individually I(1) and cointegrated, then Granger causality tests may use I(1) data because of the super-consistency properties of estimation

$$X_t = \alpha + \sum_{i=1}^{m} \beta_i X_{t-i} + \sum_{j=1}^{n} \gamma_j Y_{t-j} + u_t \text{ - (5)}$$

$$Y_t = a + \sum_{i=1}^{q} b_i Y_{t-I} + \sum_{j=1}^{r} c_j X_{t-j} + v_t \text{ – (6)}$$

Where u_t and v_t have zero mean, serially uncorrelated, random disturbances

For equations (5) and (6), Y Granger Causes (GC) X

if $H_0 : \gamma_1 = \gamma_2 = \ldots = \gamma_n = 0$ is rejected

against H_A : = at least one $\gamma_j \neq 0$, j = 1…n

and X GC Y if, $H_0 : c_1 = c_2 = \ldots = c_n = 0$ is rejected

against H_A : = at least one $c_j \neq 0$, j = 1…r

2. If the series isI(1) but are not cointegrated, valid Granger type tests require transformation to make them I(0). So, in this case, the equations become

$$X_t = \alpha + \sum_{i=1}^{m} \beta_i \text{Ä}X_{t-i} + \sum_{j=1}^{n} \gamma_j \text{Ä}Y_{t-j} + u_t \text{ - (7)}$$

$$Y_t = a + \sum_{i=1}^{q} b_I \text{Ä}Y_{t-i} + \sum_{j=1}^{r} c_j \text{Ä}X_{t-j} + v_t \text{ – (8)}$$

For equations (7) and (8), ÄY GC ÄX if,

$H_0 : \gamma_1 = \gamma_2 = \ldots \gamma_n = 0$ is rejected

against H_A : = at least one $\gamma_j \neq 0$, j = 1…n

and X GC Y if, $H_0 : c_1 = c_2 = \ldots = c_n = 0$ is rejected

against H_A : = at least one $c_j \neq 0$, j = 1…r

The optimal lag length m,n,q and r are determined on the basis of different information criterion such as Akaike's (AIC) and/or Schwarz Bayesian (SBC) and/or log-likelihood ratio test (LR) Criterion since the results of Granger's test of causality are too sensitive to the selection of the length of lag.

The Toda-Yamamoto Causality Approach: To investigate the causality between industrial growth and technological innovation in India, this study also employed the Toda-Yamamoto (TY) causality approach. This approach is a modified version of the ordinary Granger causality. The reasons for employing TY in this paper are as follows:

1. The TY approach is applicable for any arbitrary levels of integration for the variables. Furthermore, the TY minimize the risks associated with the possibility of wrongly identifying the order of integration of variables. See Dembure and Ziramba(2013)
2. In case of ordinary Granger Causality, the standard VAR is estimated with the variables at their first difference, on the other hand, the TY approach is suitable for the VAR whereby the variables can be estimated at their levels and therefore researcher does not need to transform the standard VAR model.

The TY causality approach involves three stages as follows:

Determining the maximum order of integration: The first step involves the testing of the time series using unit root tests to determine the maximum order of integration (d_{max}) of the variables in the system.

Determining the optimal lag length (k): The optimal lag length can be obtained from estimating VAR with variables at the level. The k can be determined using different lag length criterion such as the Akaike's Information Criterion (AIC), Schwarz Information Criterion (SC), Hannan Quinn (HQ) Information Criterion etc.

Testing for Causality: This is done by using the Modified Wald (MWALD) procedure to test for the VAR (p) where p = ($k+d_{max}$). The modified Wald Test (MWald) follows a Chi-square ($\div^2$) distribution asymptotically and the degrees of freedom is equal to the number of time lags ($k+d_{max}$). The rejection of the null hypothesis entails the rejection of Granger causality.

Toda-Yamamoto causality test involving two variables, technological innovation and industrial growth is written as:

$$Y_t = \alpha_0 + \beta_{1i}\sum_{i=1}^{k} Y_{t-i} + \beta_{2j}\sum_{j=k+1}^{d(max)} Y_{t-j} + \gamma_{1i}\sum_{i=1}^{k} X_{t-i} + \gamma_{2j}\sum_{j=k+1}^{d(max)} X_{t-j} + e_{1t} \quad – (9)$$

$$X_t = \alpha_1 + \lambda_{1it-i} + \lambda_{2jt-j} + \ddot{a}_{1it-i} + \ddot{a}_{2jt-j} + e_{2t} \quad – (10)$$

Where the error terms e_{1t} and e_{2t} are assumed to be white noise with zero mean, constant variance and no autocorrelation. The series X_t Granger causes Y_t if the $\tilde{a}_{1i}$ are jointly significant, while Y_t Granger causes X_t if the $\ddot{a}_{1i}$ are jointly significant, if both the $\tilde{a}_{1i}$ and the $\ddot{a}_{1i}$ are jointly significant, there is evidence for bi-directional causality between X_t and Y_t.

Result Analysis and Discussion

The study started analysis with simple statistical tools as descriptive statistics and correlation presented in the below Table 1:

Table 1. Descriptive Statistics and Correlation of Variable

Variables	IVA	TI
Mean	221000	13477.29
Median	140000	4826.000
Std. Dev.	189000	15057.75
Jarque-Bera (Probability)	3.374285 (0.185048)	6.696049(0.035154)
IVA	1	
TI	0.967744 (0.0000)	1

Note: IVA: Industrial Value-Added; TI: Technological Innovation

Table 1 above illustrates the mean, median and standard deviation of the series. The Jarque-Bera test is a test of normality wherein the null hypothesis indicates the error term to be normally distributed. Based on the p-value, the test shows that the residual of the variable industrial value added is normally distributed but it is not normal in case of technological innovation. We know that this is not a problem for our analysis since the multivariate framework does not require the normality assumption. The correlation matrix indicates a strong and significant positive relationship between technological innovation and industrial value added.

Unit Root Testing: A test of stationarity (or non-stationarity) that has become widely popular over the past several years is the unit root test. In literature, there are numerous unit root tests available like ADF, PP, KPSS, Ng-Perron and also other special unit root tests as Zivot-Andrews unit root test. According to the discussion in the methodology section, Table 2 reports the unit root tests results for the series in their level and difference forms considering ADF and PP tests. The test options considered (a) Intercept and (b) Intercept and Trend.

Table 2: Unit Root without Structural Break

Variable	ADF (Level)		ADF (First Difference)		PP (Level)		PP (First Difference)	
	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend
Log(IVA)	2.6084	-1.7055	-4.9851***	-5.7898***	3.2758	-1.6492	-5.0214***	-5.8070***
	(1.0000)	(0.7335)	(0.0002)	(0.0001)	(1.0000)	(0.7580)	(0.0001)	(0.0001)
Log(TI)	0.6855	-2.2398	-5.5724***	-5.9852***	0.6855	-2.2625	-5.5773***	-5.9286***
	(0.9906)	(0.4575)	(0.0000)	(0.0000)	(0.9906)	(0.4454)	(0.0000)	(0.0001)

Note: *, ** and *** indicate statistical significant at the 10%, 5% and 1% level respectively.

Table 2 describes the findings of ADF and PP test. The ADF test uses the existence of a unit root as the null hypothesis. To doublecheck, the robustness of results, Phillips and Perron test of stationarityhave also been applied. The findings of both ADF and PP test indicates that both the variables are non-stationary at level but becomes stationary at first difference and are significant at all the levels of significance. Thus, implying that both the variables are integrated to the same order i.e. I (1).

It has been witnessed that macroeconomic variables like industrial growth, GDP etc mostly in the developing country like India faces structural changes. Also, as Perron (1989) argues that in the presence of a structural break, the standard ADF tests are biased towards the non-rejection of the null hypothesis. The idea is to confirm that the unit root observed for a particular series is not due to structural breaks. This procedure gives an added advantage of identifying when the structural break occurred and if this break is associated with a particular government policy, economic crises, war or other factors. Taking these insights, we checked structural breakpoints using (Bai and Perron, 2003) multiple breakpoint tests and again conducting structural break unit root tests. The results are shown in below table 3:

Table 3. Bai-perron Multiple Breakpoints date

Log (IVA)		Log (TI)	
No of Breaks	Break Dates	No of Breaks	Break Dates
4	1995, 2006, 1983, 1976	3	1995, 2003, 2010

The calculated F-statistic of break tests is significant at 5% level as provided by Bai-Perron (Econometric Journal, 2003) critical values.

The results of the table indicate that there are 4 and 3 structural breaks of the variables industrial growth and technological innovation in the years 1995, 2006, 1983, 1976 and 1995, 2003, 2010 respectively. After identifying the structural breaks in the given series, we conducted the structural break unit root tests. Table 4 reports the results of unit root with a structural break in levels and first differences.

Table 4: Unit Root with Structural Break

Variable	SC (Level)		SC (First Difference)		AC (Level)		AC (First Difference)	
	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend
Log (IVA)	0.3164 (0.99)	-3.4017 (0.7483)	-5.6279*** (0.01)	-6.0321*** (0.01)	0.3164 (0.99)	-3.8916 (0.4411)	-5.6279*** (0.01)	-5.9404*** (0.01)
Log (TI)	-3.2805 (0.5155)	-4.8858** (0.0464)	-8.0451*** (0.01)	-8.0294*** (0.01)	-3.2805 (0.5155)	-4.8858** (0.0464)	-8.0451*** (0.01)	-8.0294*** (0.01)

Note: *, ** and *** indicate statistical significant at the 10%, 5% and 1% level respectively.

SC: Schwarz criterion; AC: Akaike criterion

The unit root test results represented in the above table show that the series have different orders of integration [both I(0) and I(1)].

Test for Cointegration: The Engle-Granger Test

Considering the unit roots test without a structural break, we infer that both the series are non-stationary at level but becomes stationary at first difference, that is,both are integrated to the same order I (1). Also, there are only two-time series. Both these conditions fulfil the criteria to apply the Engle and Granger's Approach. In this method, we first estimated the equation and checked if the residuals obtained are free from unit roots. The result obtained is illustrated in the below Table 5:

Table 5: The Engle-Granger Test for Cointegration

Null Hypothesis: U has a unit root				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-2.81196	0.0641
Test critical values:	1% level		-3.57445	
	5% level		-2.92378	
	10% level		-2.59993	
*MacKinnon (1996) one-sided p-values.				

Note: Engle-Granger critical value at a 10% level of significance is 3.04

With regard to the interpretation of the above table, we used the Enger-Granger critical values at 10% level of significance. It is apparent from the results that the test statistics is less than the critical value, thereby accepting the null hypothesis of residual having a unit root. The results, therefore, implies that the series are not cointegrated and thus do not converge to a long-run equilibrium. Next, we apply the VAR Granger Causality test to check the direction of the relationship between the variables.

Considering the results of unit root with a structural break, we found out that the series was, in fact, a mixture of I (0) and I (1). Since none of the series was insignificant at I (2) we could not apply ARDL Bound Testing as this could have to lead us to spurious results. Hence, the Toda-Yamamoto Model for causality was considered since this methodology could be applied to series with different orders of integration [say I(0) and I(1)].

Diagnostic Test of the Model

Here, the classical VAR model was preferred to check the Granger causality relationship. Before employing the VAR model, appropriate lag length was chosen using different information criterion. The results of which are shown in Table 6 below:

Table 6: VAR Lag Order Selection Criterion

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-58.5468	NA	0.057291	2.816132	2.898048	2.846340
1	112.7755	318.7392*	2.39e-05*	-4.966301*	-4.720552*	-4.875677*
2	115.3199	4.497092	2.56e-05	-4.8986	-4.48902	-4.74756
3	118.7108	5.677801	2.65e-05	-4.87027	-4.29686	-4.65881
4	120.9892	3.603038	2.89e-05	-4.7902	-4.05295	-4.51832
5	125.6085	6.875294	2.83e-05	-4.819	-3.91792	-4.48671
6	126.0596	0.629420	3.39e-05	-4.65394	-3.58902	-4.26123

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

The difference information criterion is used to select the appropriate lag length of the model such as AIC, SC, HQ etc. By looking at Table 6, lag 1 is coming out to be most appropriate as confirmed by all the information criterion. In order to check the stability and fitness of our model, the issues of autocorrelation, constant variance and normal distribution were checked for the optimal lag.

VAR Residual Serial Correlation LM Test and Heteroskedasticity Tests

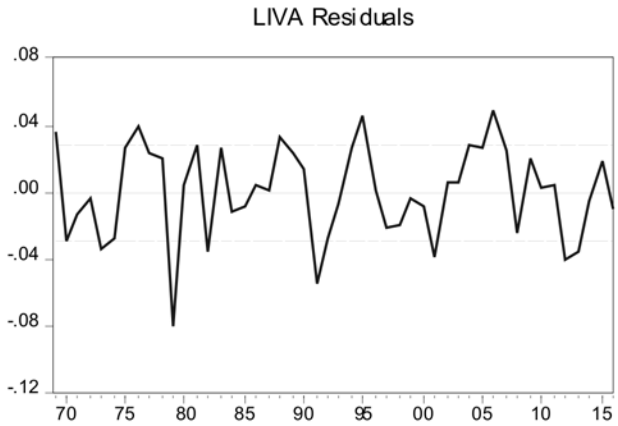
	Table 7: Diagnostic Test	
Test	**Value of test statistic**	**Probability**
Serial Correlation Test (LM-Stat)	4.713393	0.3180
Heteroskedasticity Test (Chi-sq)	13.82243	0.3122

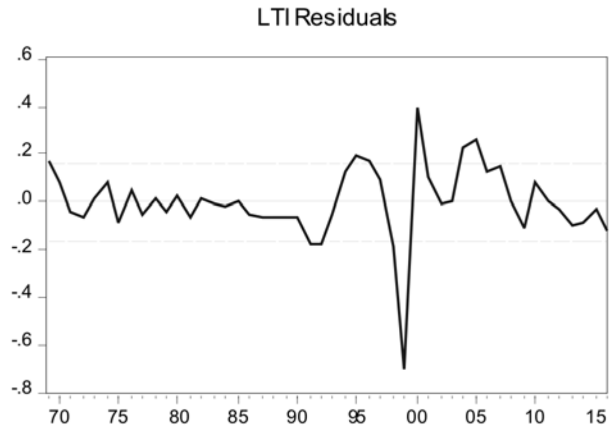
The results of the above Table 7 reports that the probability of the test statistic is greater than 5% level of significance, thereby accepting the null hypothesis of no serial correlation and no heteroskedasticity. In this situation, we can conclude that this model is of a good fit.

Normality Test of Residuals

In order to check the normality condition of the residuals, graphs of residuals of the series were obtained as shown in the below Graph 1:

Graph 1: VAR Residuals





By looking at the graphs above, one can say that the residuals of LIVA (log of industrial value added) and LTI (log of technological innovation) are showing normalbehaviour apart from a few spikes. We see while plotting the graph of technological innovation a major plummet in the year 1999-2000. The reason behind this is that during the year 1999-2000, industrial growth was low, agricultural productivity was low and even export growth was low. All these lead to a decline in technological innovation as well.

Stability Test of the VAR Model

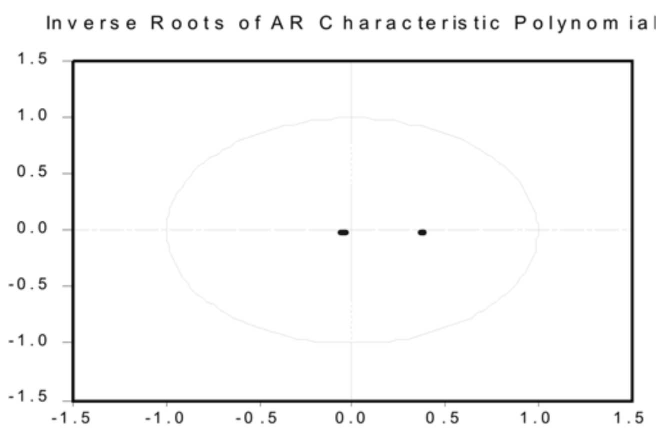
For a VAR Model, the stability condition requires that the roots of the characteristic polynomial should be less than one. The results are shown below in Table 8:

Table 8: Roots of the Characteristic Polynomial

Root	Modulus
0.374879	0.374879
-0.054041	0.054041

The table above reports the modulus of both the roots is less than 1. Also, since no root lies outside the unit circle as shown in below Graph 2, a conclusion can be made that the VAR Model satisfies the stability condition.

Graph 2: Inverse Roots of AR Characteristic Polynomial



Given that our model passes all the diagnostic tests, we conclude that our model is a good fit and can be used for further analysis.

Causality Tests

Granger Causality Test: Based on study findings, wherein the unit root test without structural break estimated series to be I(1), the Granger Causality test to the bivariate VAR has been examined and results are reported in the below Table 9. If the series is I(1) but not cointegrated, causality test may give misleading results unless the data are transformed to induce stationarity(Sekantsi & Thamae, 2016).

Table 9: Granger's Causality Tests

Null hypothesis	Chi-Sq (γ^2)	Dof[a]	p – value[b]
Non causality LIVA => LTI	6.315990	1	0.0120
Non causality LTI => LIVA	0.425654	1	0.5141

Note: [a] Degrees of freedom; [b] Acceptance Probability

As per the table, the LR ratio statistic for the test of non-causality from technological innovation to industrial growth which is asymptotically distributed as a chi-square variate with one degree of freedom is clearly not statistically significant. While testing the non causality from industrial growth to technological innovation, the observed LR statistic (follows a chi-square distribution with 1 d.o.f) 6.315990 is found to be statistically significant. This indicates the existence of short-run causality running from industrial growth to technological innovation with the absence of any feedback effect.

Toda-Yamamoto Causality Test: Based study findings, wherein the unit root test with structural break estimated series to be a mix of I(0) and I(1), the Toda-Yamamoto Granger Causality approach is utilized to determine the direction of causality between industrial growth and technological innovation since this approach is valid regardless of whether a series is I(0), I(1) or I(2), non-cointegrated or cointegrated of any arbitrary order Wolde-Rufael(2005). The results of unit root with astructural break in Table 4 indicated that the maximum order of integration is 1. After determining the maximum order of integration, the next step is to determine the optimal lag length as explained in the methodology section. The optimal lag length as shown by different information criterion in Table 6 above came out to be 1. Finally, the results of Granger Causality based on the Toda-Yamamoto estimated by the MWALD test with a lag length of 2, that is, ($k + d_{max}$) equal to 2, are reported in below Table 10:

Table 10: Toda-Yamamoto Causality (modified WALD) Test Results

Null hypothesis	Lag (k)	Lag ($k+d_{max}$)	Chi-Sq	p -value	Direction of Causality
LTI does not Granger Cause LIVA	1	1+1	1.002468	0.6058	LTI # LIVA
LIVA does not Granger Cause LTI	1	1+1	15.13060	0.0005	LIVA '! LTI

Note: LTI is the log of Technological Innovation; LIVA is the log of Industrial Growth

: ($k+d_{max}$) denotes VAR order

: '! denotes one-way causality

: # denotes no causality

: Eviews 9.0 was used for all computations

The Toda-Yamamoto Granger Causality also indicates that we can reject the null hypothesis of no causalityfrom LIVA to LTI and conclude that there is a one-way causality running from industrial growth to technological innovation without any feedback effect.

Conclusion and Policy Implication

A strong industrial sector coupled with growth-oriented industries, conducive tax policies encouraging business and investment growth, promoting inclusive employment intensive industry and building resilient infrastructure are crucial factors for the overall economic growth and development. In order to push industrial productivity and growth, it is necessary to enhance the competitiveness of industry by reducing the cost of infrastructure such as power, strengthening ease of doing business environment, easing regulatory/ compliance burden, reducing the cost of capital, improving labour productivity, skill development, among others in the coming times.

Technological innovation is regarded as a major force driving the economic growth and development of a country. In order to maintain a competitive edge in today's world, technological change is imperative and requires constant monitoring to keep up with the pace of a fast-moving economy.Indian industry has been progressing towards adopting new andadvanced technologies. However, the faster mechanism should beadopted as inefficient technologies led to low productivity and highercosts adding to the disadvantage of Indian products in internationalmarkets. Advances in technology result in the emergence of newactivities and bring changes to the existing system. One of thesignificant developments these days is of the industry 4.0, which isexpected to impact all the industries. However, appropriate use ofnew technologies needs to be adopted to ensure greater productivityand competitiveness.

The study investigated the causal relationships among the technological innovation and industrial growth for India over the period of 1968-2016 by applying the standard Granger-causality test and the Toda-Yamamoto approach of causality. The Engle-Granger's cointegration method results indicated the absence of a long-run relationship between innovation and industrial growth. Granger causality test reveals the unidirectional short-runcausality running from industrial growth to technological innovation. The finding of the Granger causality tests supports the results obtained in the Toda-Yamamoto approach in our study. The findings obtained from this empirical analysis have an imperative policy implication for a developing country like India as well as other developing countries.

The empirical findings of this paper challenge the generallyaccepted notion that it is the technological innovation (patents count) which triggers the industrial growth of any country. The reason being that patents play an important role in providing incentives to the industry in order to create new technology, commercialize their inventions and thereby increasing investments leading to industrial growth. Also, as the number of patents granted increases, it leads to greater FDI inflows and trade Mukherjee & Chawla(2018). But in the case of India, we see the absence of this causality. The several reasons for technological innovation not resulting in industrial growth could be (i) less investment in Research and Development fund: Idea generated is not converted into an application that will lead to more growth (ii) lack of persistence of idea: Generally innovation takes some time to show the result. There is a gestation period of every idea and perfect innovation out of several ideas needs continuous persistence. It is seen in general that Indian Industries lacks this persistence (iii) Lack of Vision: Most industries are looking for that kind of innovation that will give them profit immediately. But they have myopic vision. They are not thinking about long-term profitability which hinders long-term sustainable growth.

The finding of this paper instead suggests a reverse causality running from industrial growth to technological innovation in India **supporting the "demand-led" or "market-pull" approach to innovation** rather than the "technology-push" approach to innovation. There are two rival views in the literature regarding the source of technological innovation: (a).The first and older view is associated with the **Schumpeterian idea**(Schumpeter, 1975) that it is the progress in basic sciences or the supply of technology which determines the rate and direction of innovation. There is thus a transmission of knowledge from basic sciences to applied research that results in the design, development, and commercialization of new products Nemet (2009). Hence, in the "technology-push" approach to innovation, the causality runs from R&D intensity/ Patents to technological change. (b). The second view is the "market/demand-pull" approach to innovation influenced by the study of **Schmookler (1966)**. This view says that it is the demand or needs of the customers that drive the emergence of new products. This approach suggests that both inventive activity and innovation are pro-cyclical.Hence, with a rise in industrial growth, the demand in market increases which further triggers the demand for innovative products with low cost of production implying the causality running from industrial growth to technological innovation. Therefore**, the findings of our study support the "demand-led" or "market-pull" approach to innovation.**

In conclusion, there is a need to boost manufacturing and startups, strengthen startups, investments and availability of capital for industrial growth plus to bring effective financial reforms for the speedy growth of industry and the overall economy. Also, there is a need to bring incentivize and boost indigenous manufacturing with the availability of low costs of operation which would further promote productionand employment generation and boost industrial growth in the near future.One of the major factor required to become globally competitive isthrough major investment in technological upgradation and researchand development. Research and Development and innovation shouldbe promoted across the board helping Indian businesses/firmsincrease their R&D spends and startup ecosystem need to beencouraged and facilitated in the longer run for buddingentrepreneurs. There is an urgent need to strengthen the linkage betweenacademia, research institutions and industry, in order to fulfil theindustry demands for producing innovative outputs. The thrivinginnovation ecosystem that provides appropriate support at the rightstage of innovation, strengthen and diversifying information technology industry focusing on commercialisation of innovation –incubation and acceleration, among others should be focused in thecoming times. From the policy point of view,since it is expensive for a developing country like India to import new technology, the need of the hour is to have an updated and improved integrated innovative-industrial policy which would help to reduce the production cost thereby increasing the Industrial growth of a country.

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Endnotes

1. Refer (OECD and Eurostat, 2005)
2. A Report by (India Brand Equity Foundation)
3. See (Dutz et al., 2007)