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Causal Nexus between Growth and Savings in India: Using Nonlinear Causality Approach

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ABSTRACT

This paper analyses the nonlinear causal relationship between economic activities and savings over the period 1950-51 to 2011-12 for India. Empirical results from Gaussian second order Kernel density estimator highlights the nonlinear behaviour of growth and savings and suggest that there is no possibility of covariates to be linear as such. Further, to analyse the efficacy of the causal relationship between growth and savings, the study uses Himestra and Jones and Diks and Panchenko nonlinear causality approach. The results reveal a unidirectional causality that runs from savings to economic growth which suggests the need to accelerate domestic savings to promote higher income and growth.

Keywords: Economic Growth, Savings, Kernel Density, Nonlinear Causality, India

JEL Classification: E21, F4, O4

1. INTRODUCTION

Savings in an economy plays a pivotal role in achieving the growth targets. Economic growth attained with domestic savings is sustainable than the growth that is achieved through borrowed capital. In fact, it is the savings that determine the economic health of a country. Even an economic super power like U.S and the industrialized nations in the Europe are resorting to the measures of austerity and making serious attempts to save more then what they did till the cropping up of global financial crisis in 2007 and the European sovereign debt crisis in 2010 respectively. The reason for this structural shift in their saving behavior is that they spent more than what could afford to. Increasingly troublesome is the fact that the spending was driven by borrowed capital, instead of their domestic savings. The result of the savings indiscipline: U.S and Euro zone is paying a heavy price in terms of lost output, high unemployment and increasing economic inequalities.

If this is the case of industrialized nations, a typical emerging economy like India need to be much more careful on its savings front in order to achieve the growth targets and cater to the needs of a billion plus population. However, there is an alarming development in the Indian economy since 2008 that the savings as a percentage of GDP is falling steadily for a variety of reasons like rising inflation and fall in incomes.

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During the same period, growth also faltered from its peak level and Indian economy registered lowest growth rate i.e. 4.3 per cent of the decade during the first quarter of 2013-14. In this context an attempt is made to verify the causal nexus between savings and growth in Indian economy. To get a clear idea of the past trends, the post independent period is taken as the period of study.

There are theories aplenty that emphasizes the role of savings in achieving and maintaining high economic growth. Important among them is the Harrod-Domar growth theory that explains of how economic growth depends on the rate of saving or investment and the incremental capital-output ratio in the economy. The neo-classical growth theory due to Solow (1956) assigned a critical role to saving rate for facilitating a higher growth in per capita capital and per capita income in the transition to the steady state, and also implied that a high saving rate facilitates achieving a higher level of steady state per capita capital and income. On the other hand, there are fully endogenous growth models suggesting that, high savings rate and increased in the size of population contributes for the long-term growth rate. Consistent with theoretical underpinnings, empirical evidences also strongly support close inter-linkages between savings and economic growth in a cross-country perspective. It is observed that economies witnessing rapid economic growth such as China, India, Indonesia, Malaysia, Singapore, South Korea and Thailand, etc. also characterized by high saving rates during their developmental phase. Similarly, many countries in sub-Saharan Africa and Latin America typically save at a low rate and experience slow economic growth. Despite a large empirical evidence on the strong association between saving and growth, the direction of causality between saving and economic growth is highly debated both in the theoretical and empirical literature and the divergent views continue to persist.

Although a plethora of empirical literatures are available explaining the direction of causality between saving and growth, still the divergent views continue to persist. From the theoretical prospective, two school of thoughts i.e. Mill-Marshall-Solow view versus Marx-Schumpeter-Keynes view emerged in line of the causality between saving and growth (Gutirrez and Solimano, 2007). In the Mill-Marshall-Solow approach, all savings is automatically invested and translated into output growth under wage–price flexibility and full employment. Thus, the first view posits that saving leads economic growth. Similarly, Jappelli and Pagano also claimed that saving contribute to higher investment and higher GDP growth in the short-run. In contrast, the Marx-Schumpeter-Keynes view depicts that investment (Keynes and some extent Marx) and innovation (Schumpeter) are the two important drivers of output. In this context, savings adjusts passively to meet the level of investment required to hold macroeconomic equilibrium and deliver a certain growth rate of output. In this view growth leads savings. In the same fashion, the Carroll-Weil hypothesis (Carroll and Weil, 1994) also states that it is economic growth that contributes to saving, not saving to growth.

A strand of empirical results on the aforesaid issue for both the advanced and developing countries context do not reach at a settled conclusion. While a set of studies (Bachha (1990); Otani and Villanueva (1990); DeGregorio (1992); Morande (1998); Hebbel, Webb and Corsetti, G. (1992); Oladipo, (2010); Misztal (2011) supports unidirectional causality from saving to economic activity, another set (Cullison (1993); Mühleisen (1997); Alguacil, Cuadros and Orts (2004); Lorie (2007) supports the reverse causality. A third set of studies (Singh (2010)) supports bi-directional causality between saving and economic growth.

A handful of studies in Indian context also intensely debated the direction of causality between saving and economic activity since the economic crisis of late 80s and consequently financial reforms initiated in the early 90s. The empirical findings of such studies in connection to saving–growth causality in India are lopsided. To illustrate, Sinha (1996) looked at the causality between the growth rates of gross domestic saving and economic growth, and found that there was no causality running in either direction. While Agrawal (2000), Jangili (1996) found causality runs from saving to growth but rejected causality from growth to saving, Mühleisen (1997), Sahoo, Nataraj and Kamaiah (2001), Verma and Wilson (2005), Sinha and Sinha (2008); and Verma (2007) from their study reached at the conclusion that saving does not cause growth, but growth causes saving. However, Singh found bidirectional causality between saving and growth.

The earlier empirical literature has used linear/parametric way of estimating the causal relationship between economic growth and savings. Although this specification is simple and convenient to use, it is based on a very crucial assumption of predetermined linear distribution of data set. However, this *apriori* assumption on distribution and functional form may lead to specification bias which in turn leads to inconsistent estimates. Unlike the linear method of examining the causal relationship between economic growth and saving, a nonlinear approach allows one to draw a complete picture of the relationship. Hence, provides a full-information about the relationship without any underline assumptions on the distribution of data. The only requirement about the distribution of data is that the dataset should be smooth enough for meaningful analysis.

However, no study has been attempted so far in analysing the nonlinear causal nexus between real economic activity and savings in Indian context. This study aims at analysing the nonlinear causal relationship between economic activity and savings by using Kernel density estimates; Himestra & Jones and Diks & Panchenko nonlinear causality approaches.

This study contributes the existing literature by highlighting the specification issues carried by earlier literatures in defining the causal relationship between economic growth and savings. The nobility of the present approach allows us to fill hallow of misspecification and provide a holistic and comprehensive view about the nexus. The rest of the paper is sequenced in following way: The section 2 provides the description of the data. Section 3 gives the detailed information about the methodology. Section 4 presents the empirical results. Conclusion is outlined in the section 5.

2. DATA

The objective of the present study is being analysed and examined by using annual time series data for the period 1950-51 through 2011-12. Relevant data for the study has been obtained from Handbook of Statistics on the Indian Economy (RBI), 2011-12. The underline variables viz., Gross Domestic Product (GDP) and Gross Domestic Saving (GDS) have been taken in real terms (Constant Prices) and transferred into logarithm.

3. METHODOLOGY

This study will utilize Kernel density estimates to derive the distributional dynamics of the data used. With this reference we further use a nonlinear causal test to estimate the relationship between economic growth and saving.

3.1 Kernel Density Estimator

Kernel density estimates are one of the advanced methods to estimate the distributional dynamics of a particular dataset. Rosenblatt (1956) defined Kernel density function as:

$$\hat{f}(x)\frac{1}{nh}\sum_{i=1}^{m}k_h[\lambda_i] \tag{1}$$

where $\lambda_i = h^{-1}(x_i - \hat{x}_i)$, n is the number of observation and h is the bandwidth. In order to satisfy a Kernel density function will rely on following assumptions. (1) Kernel (K) should always be a symmetric function of the dataset. (2) K should always follow the lambda matrix with *K(λ)* is always greater than zero. Finally, the derivative function of Kernel with respect to lambda matrix should strictly equal to zero for all individual cross-sections.

The performance of Kernel density estimator lies in by choosing an appropriate bandwidth with minimum mean integrated squared error (MISE) for true density function and the estimator. In order to overcome the bias variance trade off, we have utilized a second order Gaussian Kernel density function following Li and Racine (2004).

$$w\left(x^g, X^g, h\right) = \frac{1}{\sqrt{2\pi}}\exp\left[-\frac{1}{2}\left(\frac{X_i^g - x^g}{h}\right)^2\right] \tag{2}$$

where $w\left(x^g, X^g, h\right)$ are the weighted smooth variables with respect to a [particular bandwidth and the weights will integrate to 1.

3.1 Nonlinear Granger Causality Test

While the linear granger causality approach is alluring due to its uncomplicatedness, the test has some limitations. As a parametric tests, it requires some modeling assumptions, the most important being linearity of the regression structure. However, it is now widely recognized that most economic and financial series are characterized by nonlinearities rising at times from structural breaks. Further, the linear test is only sensitive to causality in the conditional mean and may not be sufficient to detect nonlinear effects on the conditional distribution (Baek and Brock, 1992). Higher order structure, such as conditional heretoskedasticity, is also often ignored (Diks and Panchenko, 2005, 2005). Traditional linear Granger causality test have low power detecting certain kinds of nonlinear relations (Hiemstra and Jones, 1994). In view of this, nonparametric approaches are appealing because they place direct emphasis on prediction without imposing a certain functional form. Various nonparametric tests have been proposed in the literature. The most prominent one perhaps is developed by Hiemstra and Jones, which is a modified version of Baek and Brock.

3.1.1 Hiemstra and Jones Nonlinear Causality Test

Hiemstra and Jones proposed a nonparametric statistical method for detecting nonlinear causal relationships based on the correlation integral. To define nonlinear Granger causality, assume that there are two strictly and weakly dependent time series

For detecting nonlinear causal relationship, Hiemstra and Jones suggested a nonparametric statistical method based on the correlation integral. To define nonlinear Granger causality, assume that there are two strictly and weakly dependent time series $\{X_t\}$ and $\{Y_t\}$, $t = 1,2,3,...,T$. Let m- length lead vector of X_t be designated as X :

$$P(\left\| X_t^m - X_s^m \right\| < e \left\| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \right\| < e, \left\| Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly} \right\| < e) = P(\left\| X_t^m - X_s^m \right\| < e \left\| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \right\| < e) \tag{3}$$

where $P(\bullet)$ denotes probability and $\|\bullet\|$ denotes the maximum norm. The above equation states that the conditional probability that the two arbitrary m-length lead vectors of $\{X_t\}$ are e-close, is the same as when one also conditions on the L_Y-length lag vectors $\{Y_t\}$ of being e-close. A test on the above equation can be implemented by expressing the conditional probabilities in terms of the corresponding ratios of joint probabilities:

$$\frac{C1(m+L_x, L_y, e)}{C2(L_x, L_y, e)} = \frac{C3(m+L_x, e)}{C4(L_x, e)} \tag{4}$$

where C1, C2, C3 and C4 are the correlation integral estimator of the joint probabilities which are discussed in detail by Hiemstra and Jones. With an additional index *n*, Hiemstra and Jones show that, under the assumption that $\{X_t\}$ and $\{Y_t\}$ are strictly stationary, weakly dependent, if $\{Y_t\}$ does not strictly Granger cause $\{X_t\}$, then,

$$\sqrt{n}\left(\frac{C1(m+Lx, Ly, e, n)}{C2(Lx, Ly, e, n)}\right) - \left(\frac{C3(m+Lx, e, n)}{C4(Lx, e, n)}\right)^a \sim N(0, \sigma^2(m, L_x, L_y, e)) \tag{5}$$

where $n = T + 1 - m - \max(L_x, L_y)$.

To test for nonlinear Granger causality between $\{X_t\}$ and $\{Y_t\}$, the test in Eq. (5) is applied to the estimated residual series from the bivariate VAR model. The null hypothesis is that Yt does not nonlinearly strictly Granger cause X_t, and Eq. (5) holds for all $m, L_x, L_y \geq 1$ and $e > 0$. By removing linear predictive power from a linear VAR model, any remaining incremental predictive power of one residual series for another can be considered as nonlinear predictive power (Baek and Brock).

3.1.2 Nonparametric Diks-Panchenko Causality Test

The Baek, E & Brock proposed the nonlinear Granger causality to test the causality when the variables are nonlinear in nature. Later, Hiemstra and Jones modified the aforementioned nonlinear Granger causality test. In 2006, Diks and Panchenko propossed a new nonparametric Granger causality test to overcome problem of over rejection of the null hypothesis of noncausality in the Hiemstra and Jones nonlinear Granger causality.

The Diks and Panchenko nonparametric test is based on the standard Granger causality proposed by Granger (1969). According to this linear Granger causality, if two variables $\{X_t, Y_t, t \geq 1\}$ are scalar-valued strictly stationary time series, $\{Y_t\}$ Granger causes $\{X_t\}$ if past and current values of X contain additional information on future values of Y that is not contained only in the past and current values of Y_t values. Let, $F_{X,t}$ and $F_{Y,t}$ denote the information sets consisting of past observations of X_t and Y_t up to and including time t, and let '~' denote equivalence in distribution. Then $\{X_t\}$ is a Granger cause of $\{Y_t\}$ if, for $k \geq 1$:

$$(Y_{t+1},...,Y_{t+k})\,|\,(F_{X,t},F_{Y,t}) \sim (Y_{t+1},...,Y_{t+k})\,|\,(F_{X,t},F_{X,t}) \quad (6)$$

In practice one often assumes k = 1. In this case, Granger non-causality can be tested by comparing the one-step-ahead conditional distribution of $\{Y_t\}$ with and without past and current observed values of $\{X_t\}$. A conventional approach of testing for Granger causality among stationary time series is to assume a parametric, linear, time series model for the conditional mean $E(T_{t+1}\,|\,(F_{X,t},F_{Y,t}))$. We compare the residuals of a fitted autoregressive model of Y_t with those obtained by the regressing Y_t on past values of $\{X_t\}$ and $\{Y_t\}$. Suppose that $X_t^{lX} = X_{t-\ell+1}...X_t$ and $Y_t^{lY} = Y_{t-\ell+1}...Y_t\ Y_t^{l_Y}$ are the delay vectors – where $\ell_X,\ell_Y \ge 1$. In practice the null hypothesis that past observations of X_t^{lX} contain any additional information about Y_{t+1} (beyond that in $Y_t^{l_Y}$):

$$H_0 = Y_{t+1}\Big|(X_t^{l_x};Y_t^{l_Y}) \sim Y_{t+1}\ \Big|Y_t^{l_Y} \quad (7)$$

For a strictly stationary bivariate time series Eq. (7) come down to a statement about the invariant distribution of the $\ell_X+\ell_Y+1$ -dimensional vector $W_t = (X_t^{\ell X}, Y_t^{\ell Y}, Z_t)$, where $Z_t = Y_{t+1}$. If we ignore the time index and we assume that $\ell_X = \ell_Y = 1$, the distribution of *Z* - given that $(X,Y)=(x,y)$ - is the same as that of *Z* - given Y = y. In that case, equation (7) is restructured to take into account the ratios of joint distributions. In that sense, the joint probability density function $f_{x,y,z}(x,y,z)$ $f_{X,Y,Z}$(x,y,z) and its marginals must satisfy the following relationship:

$$\frac{f_{x,y,z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \bullet \frac{f_{X,Y}(y,z)}{f_Y(y)} \quad (8)$$

This explicitly states that X and Z are independent conditionally on $Y = y$ for each fixed value of y. Diks and Panchenko show that the restated null hypothesis implies:

$$q \equiv E[\,f_{X,Y,Z}(X,Y,Z)\,f_Y(Y) - f_{X,Y}(X,Y)\,f_{Y,Z}(Y,Z)] = 0 \quad (9)$$

Let $\hat{f}_w(W_i)$ is a local density estimator of a d_W-variate random vector W at W_i, defined by $\hat{f}_w(W_i) = (2\varepsilon_n)^{-d}\ w(n-1)^{-1}\Sigma_{j,j\ne i} I_{ij}{}^{w}$ where $I_{ij}{}^{W} = I\left(\left\|w_i - W_j\right\| < e_n\right), I(\bullet)$ the indicator function and ε_n the bandwidth, which depends on the sample size n. Then, the test statistic is a scaled sample version of q in equation (9):

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)}.\sum_i(\hat{f}_{X,Z,Y}(X_i,Z_i,Y_i)\,\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i,Y_i)\,\hat{f}_{Y,Z}(Y_i,Z_i)) \quad (10)$$

For $\ell_X = \ell_Y = 1$ and if $\varepsilon_n = Cn^{-\beta} (C > 0, \frac{1}{4} < \beta < \frac{1}{3})$, Diks and Panchenko prove under strong mixing that the test statistic in equation (10) satisfies:

$$\sqrt{n}\frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{D} N(0,1) \tag{11}$$

where $\xrightarrow{D}$ denotes convergence in distribution and S_n is an estimator of the asymptotic variance of $T_n(\cdot)$ (Diks and Panchenko, [9]). In this study, the Diks and Panchenko's suggestion, to implement a one-tailed version of the test, has been employed. The null hypothesis 'non-causality' can be rejected if the left-hand-side of equation (11) is too large.

4. FINDINGS

A simple graphical representation of growth and saving relationship provides us continuous pattern between the two with positive slope indicating that as savings go up growth follows the suite confirming the entire leading theoretical base. Figure 4.1 depicts the distribution of growth and saving over last sixty years. Clearly analyzing the graph we can see that both are following each other. This provides us some signs of causal relationship between the two, however, we cannot confirm the direction of the same. Although this representation is simple and convenient but may lead to biased and inconsistent estimates if data set is relaxed from the assumption of linear distribution (Pagan and Ullah, 1999).

In order to overcome the problem of distributional aspect, the present study uses nonparametric second order Gaussian Kernel Density estimator as explained in section 3.1. Before going to detailed explanation of Kernel Density estimators, we will present the model selection between parametric and non-parametric. The results are reported in Table 4.1. The parametric model has been tested against the non-parametric one. If the null of parametric specification is to be rejected, we can approach to estimate the model through alternative measures such as non-parametric model specification in our case. The selection criterion of the model specification has been chosen by using Hsiao *et al.*, (2007). The test rejects the null of parametric specification between growth and savings.

4.1 Growth vs. Saving under Kernel Density Estimates

Adopting Gaussian second order Kernel estimator to estimate the distributional dynamics of growth and saving over last six decades provides us a clear picture about the relationship with more accuracy. The distributional dynamic character of the relationship is being depicted in figures 2 and 3. This estimator helps to examine the concentration of the relationship across each time element and highlights the spurious nature of using a linear specification for determining the relationship between the growth and saving in India. Clearly examining the figure we can conclude that there is a strict non-linear character of relationship between growth and saving. This has been confirmed by both unconditional and conditional probability density functions.

Fig. 4.1: Growth vs Saving for 1950-51 to 2011-12

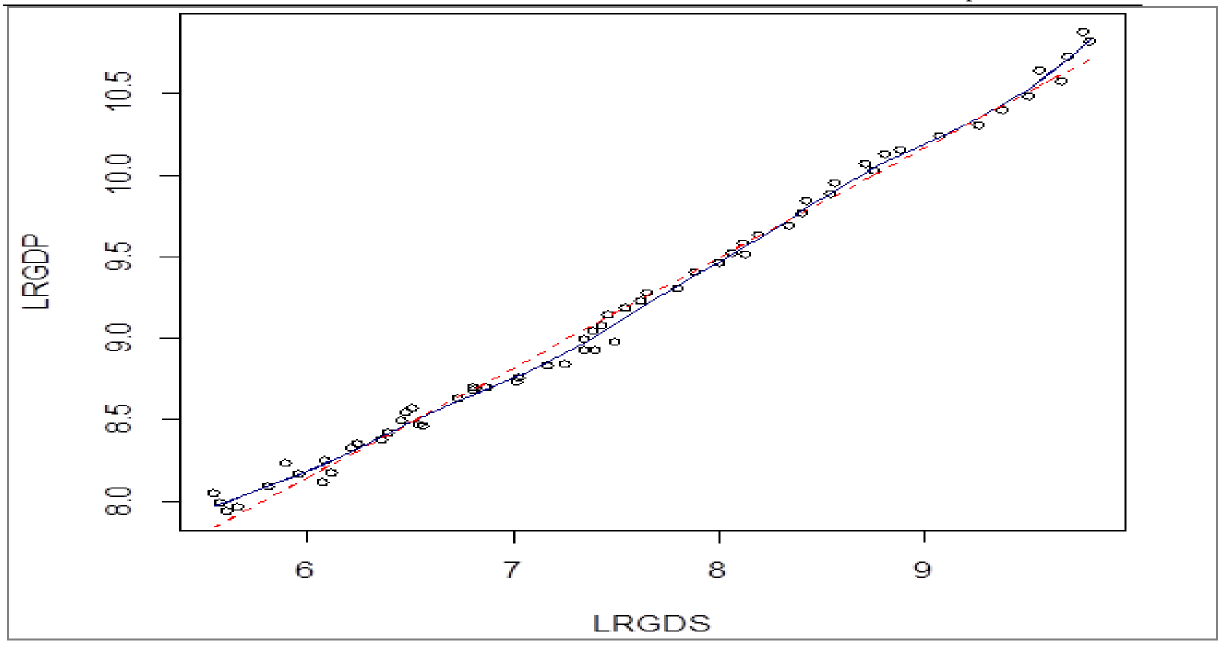


Table 4.1: Nonparametric model for Growth and Saving Relationship in India

Model	Criteria		Model Accepted
Parametric vs Nonparametric	Bandwidth: J-Statistics:	0.246* (0.000) 4.872* (0.000)	Nonparametric

Note: (*) represents significance level at 1%.

Fig. 4.2: Nonparametric Growth vs Saving (1950-51 to 2011-12)

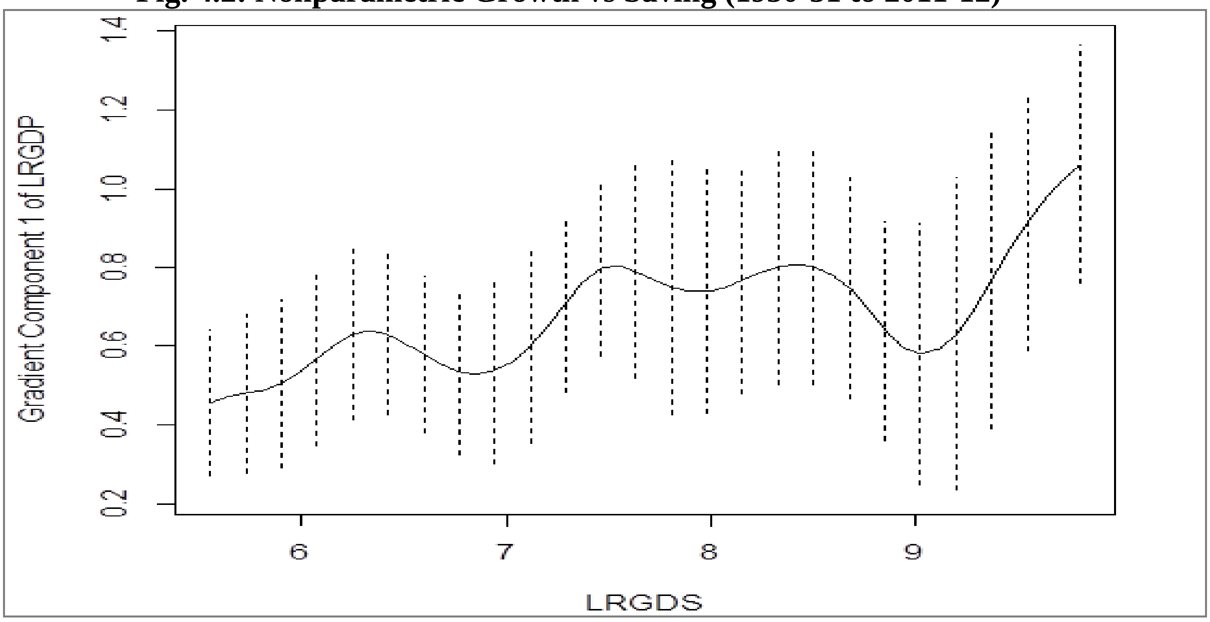
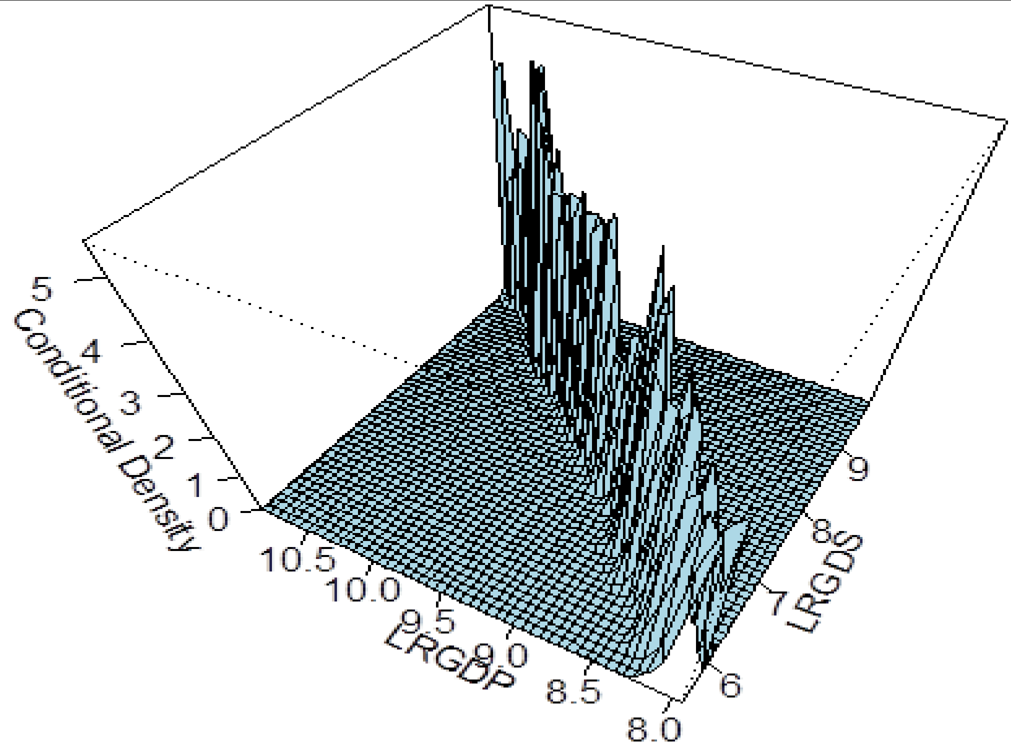


Fig. 4.3: Conditional Density: Growth vs Saving



4.2 Nonlinear Granger Causality Test

Given the potential existence of a nonlinear relationship between economic growth and domestic savings in Indian context, the nonlinear Granger causality tests was performed on the associated residual series obtained from the bivariate VAR to examine the relationship between economic growth and savings. Following Hiemstra and Jones, we set the value for the head length of $1 = m$, the common lag lengths (L_x, L_y) of 1 to 7 and a common scale parameter of e = 1.5 σ where $\sigma = 1$ denotes the standard deviation of the standardized time series test statistic.

The result presented in Table 1 depicts that the null hypothesis of RGDP does not Granger cause RGDS cannot be rejected at any lag at reasonable significance level. However, the null hypothesis of RGDS does not Granger cause RGDP is rejected at 1 percent significance level only at 3 and 5 lags and at 5 percent and 10 percent level at lag 6 and 7 respectively. Hence, the empirical results of the study confirm the unidirectional causality running from saving to growth.

Table 1. Results for nonlinear Granger causality test (Hiemstra and Jones test)

Lag length	**LRGDS → LRGDP**		**LRGDP → LRGDS**	
$L_u = L_w$	**CS**	**TS**	**CS**	**TS**
1	-0.71	-5.19	-0.82	-5.99
2	-0.44	-3.19	-1.00	-8.65
3	0.16	1.20*	-1.00	-10.75
4	-0.53	-3.83	-1.00	-7.93
5	0.29	2.14*	-0.14	-1.03
6	0.04	0.33***	-0.46	-3.38
7	0.08	0.60**	-1.00	-7.28

Notes: (*), (**) and (***) denote significance at the 1%, 5% and 10% levels respectively. Critical values for a small sample of 50 observations are obtained from the Monte Carlo experiment of Li and Shukur [18]. Critical values for the significant level at the 1%, 5% and 10% are 0.6437, 0.4347, and 0.3324.

Diks and Panchenko(205) identified that the Hiemestra and Jones test suffers from the limitations that it over-rejects the null hypothesis of non-causality in the case of increasing sample size and developed a new test in the year 2006 which overcomes the rejection problem of Hiemestra and Jones test. Therefore, the study also undertakes the nonlinear Granger causality test of Diks and Panchenko (2006).

Table 2 reports the nonlinear Granger causality proposed by Diks and Panchenko [9] with different dimensions. The bandwidth is set to $\varepsilon = 1$, because bandwidth 1 is within the common range (0.5, 1.5) used in practice (*see* Diks and Panchenko, 2006). The above results indicate that there is a unidirectional causality running from GDS to GDP at 1% significance level in dimension 2 and 5% significance level in all other dimensions.

Table 2. Results for nonlinear Granger causality test (Diks and Panchenko test)

	GDP $\nRightarrow$ GDS		**GDS $\nRightarrow$ GDP**	
Dimension				
2	1.22	(0.11)	2.36*	(0.00)
3	1.06	(0.14)	1.95**	(0.02)
4	1.10	(0.13)	1.69**	(0.04)
5	1.12	(0.13)	1.69**	(0.04)
6	1.13	(0.13)	1.68**	(0.04)

Note: (*) and (**) denote 1% and 5% significance level. Values in parenthesis are P-values. Dimensions indicate the lag orders.

Overall, both the Hiemestra and Jones test and Diks and Panchenko test of nonlinear Granger causality support the views of both the neoclassical exogenous and the post-neoclassical endogenous growth models and suggest the unidirectional causality running from saving to growth. Thus, the school of thought developed by Mill-Marshall-Solow (saving causes growth) validates in Indian context for the period 1951 through 2012 and goes against the other school of thought proposed by Marx-Schumpeter-Keynes view (economic growth causes saving).

5. CONCLUSION

Both the nonlinear causality tests (Hiemestra and Jones; Diks and Panchenko) support the prediction of both the neoclassical exogenous and the post-neoclassical endogenous growth models and suggest the unidirectional causality that runs from savings to economic growth. The stylized empirical evidence for the steady state effects of saving on economic growth suggests the need to accelerate domestic saving to finance domestic investment and promote higher income and growth. Therefore, a two pronged approach with the incentive-based measures to induce the motivation to save and the productivity-based measures to increase income and strengthen the capacity to save, would be useful to generate higher saving and reinforce the acceleration of income and growth.

The issue of nonlinear effect on the inter-linkages between savings and economic growth has been intensely debated in the present research. In previous empirical literature on saving-growth causality nexus, the possibility of nonlinearity in the relationship has been generally ignored. A plethora of studies based on the linear model were available, but no study to the best of our knowledge has been focused on nonlinearity in examining the causality nexus between savings and economic growth. The linear model may possibly overlook a significant nonlinear relationship. Hence, this paper analyses the nonlinear causal relationship between economic activities and savings in Indian context by using Gaussian second order Kernel density estimator to highlight the nonlinear behavior of growth and savings for India. Further, to analyze the efficacy of the relationship between growth and savings, the study uses Himestra and Jones and Diks and Panchenko nonlinear causality approaches over the period 1950-51 to 2011-12. The empirical evidence of the present study provide evidence the prediction of both the neoclassical exogenous and the post-neoclassical endogenous growth models and suggest of unidirectional causality that runs from savings to economic growth. The stylized empirical evidence for the steady state effects of saving on economic growth suggests the need to accelerate domestic saving to finance domestic investment and promote higher income and growth. Therefore, a two pronged approach with the incentive-based measures to induce the motivation to save and the productivity-based measures to increase income and strengthen the capacity to save, would be useful to generate higher saving and reinforce the acceleration of income and growth.

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