Integration between Economic Growth and Financial Development in India: An Analysis

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April 2019

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Abstract

About 50 years back, Raymond Goldsmith sought to document the relationship between financial and economic development. Since then, the enquiry has witnessed promising progress with a growing literature highlighting a strong positive link between the financial system and economic growth. The present study is a modest attempt at an empirical substantiation of the relationship between economic growth and financial development in the context of India. Evidently, the analysis is based on time series data on economic growth and indicators of financial development pertaining to India. Hence the first section of this study discusses the time series econometric methods that are utilized in the analysis of this study. The second section seeks to analyze the objective of this study, viz., assessing whether there exists a long-run equilibrium between economic growth and financial development in India. Using the conventional Johansen-Juselius cointegration test and the modern ARDL-based bounds test as well as the conventional Granger-causality tests, we show that there does exist a long-run relationship between the economic and financial variables in the face of the external sector indicators.

Part 1:
Analytical Methods

1 Introduction

About 50 years back, Raymond Goldsmith (1969) sought to document the relationship between financial and economic development. Since then, the enquiry has witnessed promising progress with a growing literature highlighting a strong positive link between the financial system and economic growth. It is argued that "we will not have a sufficient understanding of long-run economic growth until we understand the evolution and functioning of financial systems" (Levine, 1997: 720-721). The present study is a modest attempt at an empirical substantiation of the relationship between economic growth and financial development in the context of India. Evidently, the analysis is based on time series data on economic growth and indicators of financial development pertaining to India. Hence this section discusses the time series econometric methods that are utilized in the analysis of this study.

What follows is divided into five sections. The next section presents an introduction to the statistical concepts of time series and time series analysis, carried out in the two domains of frequency domain and time domain. Section 3 explains the central concept in time series, namely, stationarity, and introduces white noise, random walk and trend stationary process with their distinguishing marks. Section 4 gives a brief account of unit root tests in general, in the context of the statistical requirement of distinguishing between stationary and non-stationary time series. The next section goes into the concept of cointegration, introduced to solve the problem of the consequences of spurious regression with non-stationary time series. The two conventional cointegration tests and the modern bounds test for cointegration are discussed here. The final section concludes the section.

2 Time Series

> "The term "time series" appears in W. M. Persons's "The Correlation of Economic Statistics," Publications of the American Statistical Association, **12,** (1910), 287-322. The phrase "time series analysis" entered circulation at the end of 1920s, e.g. in S. Kuznets's "On the Analysis of Time Series," Journal of the American Statistical Association, **23,** (1928), 398-410, but it only became really popular much later."
>
> (http://jeff560.tripod.com/t.html, accessed on 19 March 2019)

Time series, the simplest form of temporal data, refers to a sequence of real values collected regularly in time, from a variety of domains of the economy. In statistical sense, a time series is a realization (sample) of a discrete time stochastic process, which is a sequence of random variables, y_t, equi-spaced in time. The traditional analysis of time series recognizes four components of a time series, as proposed in 1919 by W. M. Persons:

1. a tendency: a secular trend or long-term movement (T);
2. a seasonal fluctuation with known periodicity (S);
3. a deterministic cycle of a non-seasonal variety with unknown periodicity (C); and
4. a residual, irregular or random error (R).

These components make up a time series either additively or multiplicatively:

$$Y = T + C + S + R, \text{ or } \; Y = TCSR.$$

In general, an additive model is accepted when the seasonal fluctuations are almost constant and their effect on the trend does not depend on its level. On the other hand, the multiplicative model is chosen, when the seasonal variations have an amplitude almost proportional to that of the secular trends.

When trend is our primary concern, we may model it directly as a regression:

$$Y_t = f(\theta, t) + \varepsilon_t,$$

where f (θ.t) is the deterministic component of the series (with t representing time trend and θ, the corresponding parameter), and ε_t is the nondeterministic, error, component. Once the linear trend is thus estimated, we can remove the trend from the series (detrending). Nonlinear trends, such as the Gompertz curve (Benjamin Gompertz, 1825) or the logistic curve (of Pierre François Verhulst, 1844) also are applied. Another approach to detrending uses moving averages. Originally, the moving average method was used to estimate seasonal components and thence deseasonalized series, first studied by M.T. Copeland in 1915 and W.M. Persons in 1919. Such decompositions marked the traditional time series analysis. We always deseasonalize the data first and then detrend it before decomposing the cyclical variations.

2.1 Time Series Analysis

Time series analysis functions in two domains of methods: frequency domain and time domain.

> “The use of the designations TIME DOMAIN and FREQUENCY DOMAIN to distinguish the correlation and the spectral approaches to filtering theory, and to time series analysis generally, seems to have originated in communication engineering.”
>
> “"Frequency domain" appears in L. A. Zadeh's "Theory of Filtering" (Journal of the Society for Industrial and Applied Mathematics, **1,** (1953), 35-51).”
>
> “"Time domain" and "frequency domain" appear together in W. F. Trench's "A General Class of Discrete Time-Invariant Filters," Journal of the Society for Industrial and Applied Mathematics, **9,** (1961), 405-421.”

> “The terms soon became established in statistical time series analysis, see e.g. M. Rosenblatt & J. W. Van Ness's "Estimation of the Bispectrum," Annals of Mathematical Statistics, **36,** (1965), 1120-1136.”
>
> (http://jeff560.tripod.com/t.html, accessed on 19 March 2019)

Time series analysis started first in the frequency domain, where a time series is represented, as per the early ideas of Fourier analysis, by a set of independent cosine and sine waves that vary in amplitude and angular frequency. The main aim of the methods in this domain is to assess the variance of the series in terms of the oscillations of different frequencies by means of a plot of the squared amplitude against angular frequency, known as spectral density, that yields the power (or variance explained) at that frequency.

The more popular time domain methods are based on the direct modeling of the random variable y_t in terms of autoregressive process, that is, lagged relationship between a time series and its past, as suggested by George Udny Yule (Scottish statistician: 1871-1951) in 1927. This led to the development of correlogram (autocorrelation function), a plot of the lagged correlations (or autocorrelations) of a time series against its lag size, used as an initial step in the identification of a time series. Yule’s approach was extended by Sir Gilbert Thomas Walker (British physicist and statistician: 1868-1958) and he defined in 1931 the general autoregressive scheme.

Evgeny Evgenievich (or Eugen) Slutsky (Russian Statistician, Economist: 1880-1948) in 1927 (in Russian; English translation in 1937) described a ‘moving summation’ of random series, which was rechristened by Herman Ole Andreas Wold (1908- 1992: Swedish Statistician) as moving average process; Wold also demonstrated (1938) the theoretical foundation of combined autoregressive-moving average (ARMA) processes and paved the way for modern time domain analysis.

George Edward Pelham Box and Gwilym Meirion Jenkins (1970) codified the applied univariate time series autoregressive-integrated-moving average (ARIMA) modeling, also known as Box-Jenkins modeling.

3 Stationarity

> "'Stationary Stochastic Process' appears in the title of A Khintchine's "Korrelationstheorie der Stationären Stochastischen Prozesse, Mathematische Annalen, 109, (1934), p. 604. Berlin."
>
> "H. Wold translated it as "stationary random process" (A Study in the Analysis of Stationary Time Series (1938)). "
>
> "The phrase "stationary stochastic process" appears in J. L. Doob's "What is a Stochastic Process?" American Mathematical Monthly, **49,** (1942), 648-653."
>
> "An older term was "fonction éventuelle homogène," which appears in E. Slutsky's "Sur les Fonctions Éventuelles Continues, Intégrables et Dérivables dans la Sens Stochastique". Comptes Rendues, **187,** (1928), 878."
>
> (http://jeff560.tripod.com/t.html, accessed on 19 March 2019)

Stationarity is the central concept in time series analysis, signifying that the probability structure of a time series is time-invariant; that is, the process is in a particular state of 'statistical equilibrium', such that its properties are unaffected over time. Thus, in particular, a stationary time series has a constant mean and variance along with a covariance (more properly, auto-covariance) that depends only on the difference between two time points (that is, time lag), but independent of time. The simplest form of a stationary time series is a white noise, a purely random process, with zero mean, constant variance and zero auto-covariance (and hence zero auto-correlation); thus a white noise process is a sequence of random variables, which are uncorrelated over time. Note that a white noise is a stationary process, but a stationary process need not be white noise.

We can represent time series relationships in terms of a regression model of fixed coefficients only if the concerned time series are stationary (with time-invariant mean, variance and covariance). If these properties are time-varying (as for a non-stationary time series), then we cannot model the relationship in terms of fixed regression coefficients. On the contrary, any such attempt at modelling regression with non-stationary variables will perforce result in spurious regression only, as illustrated by the famous Granger-Newbold experiment in 1974.

Following Yule, we know that any time series may be represented as an autoregressive process (a regression of a variable on its own past) of a definite order. Consider, for example, a first order autoregressive, AR(1), model:

$$y_t = \alpha + \beta y_{t-1} + u_t, \qquad (1)$$

where u_t is a white noise and β is the root of (1).

Note that the AR(1) model is a stochastic non-homogeneous first order difference equation. Now consider a homogeneous first order difference equation (that is, without intercept), given by $y_t = \beta y_{t-1}$. Its time path or solution is given by $y_0\beta^t$, where y_0 is the initial value of y_t ($t = 0$). This time path will converge, persist in oscillation or diverge if the root $|\beta|$ is less than, equal to or greater than unity. If we add a white noise to this first order difference equation, we get a stochastic homogeneous first order difference equation ($y_t = \beta y_{t-1} + u_t$), which is nothing but an AR(1) process without intercept. This process will have the same time path as its non-stochastic counterpart, the homogeneous first order difference equation. Thus with a less-than-unit-root, that is, $| \beta | < 1$, this AR(1) process is dynamically stable (i.e., stationary); otherwise it is non-stationary. Thus if the process has a unit root, i.e., if $|\beta| = 1$, it becomes $y_t = y_{t-1} + u_t$, which is called a random walk without drift (no intercept), in recognition of the analogy of the evolution of y_t with the random stagger of a drunkard. We can represent such a random walk, through a process of successive backward substitution and assuming that the initial value $y_0 = 0$, in terms of the accumulation of all the past random shocks: $y_t = u_t + u_{t-1} + .. = \Sigma u_t$; thus it is a stochastic trend, the accumulation of past random shocks, that solely determines the behaviour of a random walk y_t. This means that the shock persists and the process is non-stationary. Such a random walk has a zero mean (that is, its trend, $y_t = \Sigma u_t$, is stochastic, that cannot be predicted perfectly), but its variance and autocovariances, being functions of time, increase infinitely with time.

If we add an intercept to this random walk (without drift), we get a random walk with drift, $y_t = \alpha + y_{t-1} + u_t$, which can be represented, through a process of successive backward substitution and assuming that the initial value $y_0 = 0$, as $y_t = \alpha t + \Sigma u_t$. The process now has both a deterministic trend (αt) and a stochastic trend (Σu_t), so that the mean, variance and autocovariances of the process are all functions of time, increasing infinitely with time.

On the other hand, if the process in (1) above is a stationary (less-than-unit root) process, all the statistical characteristics are constant so that we can have valid econometric estimation of relationships with constant coefficients. However, if the variable under consideration is non-stationary with its characteristics increasing infinitely over time, we cannot think of constant-coefficient estimators. For example, consider the OLS slope estimator from a regression of y_t on x_t, given as the ratio of the covariance between y_t and x_t to the variance of x_t. If y_t is a stationary (less-than-unit-root) variable and x_t is non-stationary (root $|\beta| = 1$), the OLS estimator from the regression of y_t on x_t cannot have an asymptotic distribution, as it collapses asymptotically. This is because the variance of the non-stationary x_t, the denominator of the OLS estimator, increases infinitely with time and dominates the covariance between y_t and x_t, the numerator. Thus, regression with non-stationary variable(s) cannot be determinate. However, if the non-stationary x_t variable in the above case is transformed into a stationary variable, then we can have a valid regression of y_t on x_t. Suppose x_t is a random walk without drift: $x_t = x_{t-1} + v_t$, where v_t is a white noise. Then the change in x_t, i.e., the first difference $\Delta x_t = x_t - x_{t-1}$, is simply a (stationary) white noise (v_t). Thus in this case x_t can be made stationary through first-differencing. A series that can be made stationary through differencing is said to be difference stationary process (DSP). It is also called an integrated process, and in general is denoted as I(d), that is, integrated of order d, where d refers to the number of unit roots in the process, or the number of times of differencing to make the series stationary. For example, the above non-stationary x_t has one unit root and requires one-time differencing to make it stationary; therefore, it may be denoted as $x_t \sim I(1)$. A stationary series is then denoted as I(0), as there is no unit root; the first difference $\Delta x_t \sim I(0)$.

In short, only with stationary variables can we have valid, determinate, regression. If any variable is non-stationary, we have to difference it appropriately to make it stationary before going for regression. The significance of this step was illustrated by Granger and Newbold (1974). They generated two independent random walk processes and ran a regression between them; contrary to the expectation of no significant relationship (between the independent series), they found the regression coefficient statistically significant, with very high R^2, but very low Durbin-Watson (DW) statistic (indicating high autocorrelation in the residuals that violates model adequacy assumption). On the other hand, when they ran the regression in first differences of the random walk series, they got the expected result, with the R^2 close to zero and the DW statistic close to 2, that indicates that there was actually no relationship between the series and the significant results of a relationship obtained earlier was spurious. Hence they suggested that whenever a regression has $R^2 > DW$, it meant 'spurious regression' and the series should therefore be first-differenced for modelling a relationship.

Remember that any time series may have stochastic trend or deterministic trend or both. Differencing is the method used to eliminate stochastic trend from non-stationary variables to induce stationarity in them, as we have seen above, and is a significant stage in ARIMA modelling of Box and Jenkins (1970). Similarly, eliminating deterministic trend from trending variables (detrending) has been a major practice in regression analysis for a long time to identify cyclical components in business cycle theory (Nelson and Plosser, 1982). Detrending has got its highest regard in regression analysis thanks to the classic result of Ragnar Frisch and F. V. Waugh (1933) that including a time trend in a regression is equivalent to detrending the variables through individual time regression. The contexts of these two practices, detrending and differencing, have in turn led to the differentiation between DSP and trend stationary process (TSP). DSP as we have already seen is a time series that can be made stationary through differencing. A TSP is then defined as a process that is stationary about a linear deterministic trend such that it can be detrended.

A TSP may be represented as $y_t = a + bt + \varepsilon_t$, where ε_t is a white noise process. Its mean is given by the deterministic trend $E(y_t) = a + bt$, which is a function of time; however, its variance is $Var(y_t) = Var(\varepsilon_t) = \sigma_\varepsilon^2$, a constant; and its auto-covariance is $Cov(y_t , y_{t-k}) = Cov(\varepsilon_t , \varepsilon_{t-k}) = 0$, unlike the integrated series (DSP), in which case, these characteristics are all functions of time. Note that the detrended y_t (that is $[y_t – E(y_t)]$) is stationary, equal to the white noise. Instead of detrending, if we difference a TSP, we will have a problem. We know the first difference is $\Delta y_t = y_t - y_{t-1}$. Lagging the above TSP by one period we get $y_{t-1} = a + b(t-1) + \varepsilon_{t-1}$; now, taking the first difference $\Delta y_t = y_t - y_{t-1} = b + \varepsilon_t - \varepsilon_{t-1}$, a unit root MA process! This shows that differencing a TSP does detrend, but also generates a moving average process that can show a cycle when there is none in the original series: a 'spurious cycle', called Slutzky effect (Slutzky 1937).

The upshot of all this is that it is essential to assess the nature of a time series, whether it is trend stationary or difference stationary. We know that a series is stationary, if it has a less-than-unit root in its AR structure. That is, given $y_t = \alpha + \beta y_{t-1} + u_t$, if $| \beta | < 1$, then y_t is stationary. This in turn takes us to testing for a unit root in a series.

4 Unit Root Tests

Let us consider an AR(1) model with a deterministic trend:

$$y_t = a + bt + \beta y_{t-1} + u_t , \qquad (2)$$

where u_t is a white noise and β is the root of the series. We know that when $b \neq 0$, and $| \beta | < 1$, y_t is stationary with a linear trend and hence is a TSP. On the other hand, when $b = 0$, and $| \beta | < 1$, we have $y_t = a + \beta y_{t-1} + u_t$, with two possibilities:

(i) if $| \beta | < 1$, then y_t is a stationary process and

(ii) if $| \beta | = 1$, then y_t is a DSP (random walk) with drift.

When $a = b = 0$, we have $y_t = \beta y_{t-1} + u_t$, again with two possibilities:

(i) if | β | < 1, then y_t is a stationary process and

(ii) if | β | = 1, then y_t is a DSP (random walk) without drift.

Thus we have three possible formulations of the above model (2):

(i) the original model (2) with a linear trend (and a constant),

(ii) with a constant only: $y_t = a + \beta y_{t-1} + u_t$ (3)

and finally,

(iii) with neither constant nor trend: $y_t = \beta y_{t-1} + u_t$ (4)

We can find out whether a series y_t is stationary or not by first running a regression on any of the equations above [(2) – (4)] and then statistically testing for a unit root in the series with the null hypothesis of H_0: $\beta = 1$, against the one-sided alternative | β | < 1. However, it is possible to modify these equations such that we can write the null in the usual way as H_0: parameter = 0. If we subtract y_{t-1} from both the sides of (2), we get

$$\Delta y_t = a + bt + \rho y_{t-1} + u_t, \qquad (2a)$$

where $\rho = (\beta - 1)$. Now, we can test the null hypothesis H_0: $\rho = 0$, which is equivalent to testing H_0: $\beta = 1$. Similarly, we can write (3) and (4) as

$$\Delta y_t = a + \rho y_{t-1} + u_t \qquad (3a)$$

and

$$\Delta y_t = \rho y_{t-1} + u_t \qquad (4a)$$

We can now run a regression on any of these modified equations and test the null hypothesis H_0: $\rho = 0$, which is the same as testing H_0: $\beta = 1$. Usually, as we know, we test for the significance of the individual regression estimates on the basis of t-statistic, which is the ratio of the estimate to its standard error. However, Dickey and Fuller (1979) have shown that we cannot use this t-statistic to test for a unit root null, because this statistic does not follow Student's t-distribution when the null is for a unit root (random walk); it does not have even an asymptotic normal distribution (as the sample size increases infinitely). This test statistic under the unit root null follows a random walk distribution, known as Dickey-Fuller distribution and the statistic is called Dickey-Fuller τ (tau) statistic, in analogy with the conventional t-statistic. Its critical values, tabulated by Dickey and Fuller (1979, 1981) and MacKinnon (1990) are mostly negative, and hence the inference procedure is as follows: if the estimated τ–value is more negative (that is, less) than the critical value at the given significance level, we reject the null hypothesis of unit root and accept the alternative (research) hypothesis of stationarity. This is the Dickey-Fuller (DF) unit root test.

The Dickey and Fuller unit root test assumes that the errors u_t are iid(0, σ^2). If this assumption is violated, that is, when the errors are non-orthogonal (serially correlated), however, the test fails to be appropriate. Under such conditions, we have to correct for the autocorrelation in the errors by means of a 'whitening' procedure by including sufficient number of lagged terms of the dependent variable as explanatory variables. This modified DF test, formulated by Dickey and Fuller (1979) and Said and Dickey (1984) is known as augmented Dickey-Fuller test (ADF). The ADF formulation corresponding to equation (2) above is:

$$\Delta y_t = a + bt + \rho y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + u_t .$$

Note that following the introduction of the ADF test, a large number of unit root tests have come up, including a non-parametric unit root test, known as PP test, due to Phillips and Perron (1988) that is valid even if the errors are serially correlated and heteroscedastic. Perron (1989) has proposed a modified DF test for a unit root under exogenous (known) structural breaks in the series; criticisms on his assumption of a known, exogenous break has subsequently led to formulation of some unit root tests under endogenous breaks. Another popular test method is KPSS test, given by Kwiatkowski, Phillips, Schmidt and Shin (1992), which tests the null hypothesis that a time series is stationary around a deterministic trend (that is, trend-stationary) against the alternative of a unit root, the reverse of the ADF and PP tests.

5 Cointegration

We have already seen that in a regression between y_t and x_t, if one or both of them are non-stationary (integrated) series, then the regression is spurious, and a valid regression is possible only after making the integrated variable(s) stationary by appropriate differencing. This procedure was in vogue in the conventional Box-Jenkins time series analysis for a long time until questions were raised out of a new awakening that solving the non-stationarity problem by means of differencing was equivalent to "throwing the baby out with the bath water", as differencing leads to "valuable long-run information being lost". We know that most of the economic relationships refer to long-term relationships between variables in their levels, not to short-term relationships in their differences. This posed a new problem with two seemingly irreconcilable objectives of conserving long-run information in the level variables and avoiding spurious regression of integrated variables. A solution to this problem appeared in the form of cointegration, a concept introduced by Clive WJ Granger (1981) to describe the long-run equilibrium relationship of economic time series. According to the Granger Representation Theorem, if there is an equilibrium relationship between two economic variables, they may deviate from the equilibrium in the short run, but will adjust towards the equilibrium in the longer run.

Suppose we have two series y_t and x_t, both are integrated of first order, I(1); then in general, we can expect any linear combination of them also as I(1). However, the I(1) variables have an important property that there can be some linear combinations of them that are stationary, I(0); this property gives rise to cointegration. For instance, consider the series on income and consumption over a long period that are I(1); their difference (linear combination: saving) also may be I(1); in case saving is I(0), then income and consumption are said to be cointegrated, denoted by CI(1, 1). That is, both income and consumption move together through time in a stochastic equilibrium, each following its own random walk. In general, if both y_t and x_t are I(d), then they are cointegrated with CI(d, b), if their linear combination is integrated of order (d – b), with $b > 0$; that is, if their linear combination is I(d – b), with $b > 0$.

When two variables are cointegrated, the regression of these two variables is not spurious, as cointegration refers to a long-run equilibrium relationship between them; that is, we can have a valid regression in their levels, without going for any differencing.

5.1 Cointegration Tests

There are two conventional cointegration tests and a modern one. The traditional tests are:

(i) Two-step single equation residual-based test, formulated by Engle and Granger (1987), using the ADF τ-statistic, and known as augmented Engle-Granger (AEG) test; and

(ii) System (multiple equation) method of Johansen and Juselius (1990), called JJ test (Johansen 1988; Johansen and Juselius 1990).

The modern, recent, test is autoregressive-distributed-lag (ARDL) model-based bounds test for cointegration, proposed by Pesaran and Shin (1999) and Pesaran et al. (2001).

The AEG test (with, say, two variables, y_t and x_t) consists in three steps. In the first step, we test that both the variables under consideration are of the same order of integration, say, that they are I(1), using a unit root test. In the second step, we estimate the long-run relationship of our interest by OLS:

$$y_t = a + bx_t + u_t.$$

In the final step, we extract the residuals of the regression (estimates of u_t) and test for a unit-root in this series, using, say, ADF test statistic. If the residuals series is non-stationary with a unit root, then there is no cointegration between the two variables. Remember that the null hypothesis of ADF test here is that the residuals series (linear combination of the two variables) has a unit root. Thus the null hypothesis of the AEG test is that there is no cointegration between the variables.

The main problem with the AEG test is that it cannot test for the number of cointegrating relationships (vectors) when we have more than two variables. Therefore, the most preferred method is the system method of Johansen (or Johansen and Juselius, JJ) test, conducted in the framework of vector autoregression (VAR) that treats all the variables as endogenous. Like the AEG test, the JJ test also requires the condition that all the variables under question are of the same order of integration. There are two likelihood ratio (LR) tests: trace test and maximum eigenvalue test. The first (trace test) considers the null that there are at most r cointegrating relationships (vectors), and the second (maximum eigenvalue test) has the null hypothesis that there are r cointegrating relationships against the alternative that there are $r+1$ cointegrating vectors. According to the JJ method, if there are n variables of the same order of integration, say, I(1), then there exist r cointegrating I(0) linear combinations with $r < n$. If r happens to be equal to n, it simply means that all the n variables are in fact I(0), and the unit root tests that identified them initially as I(1) all went wrong somehow.

5.2 Granger-Causality Test

We have already seen that the JJ-test is conducted in the framework of vector autoregression (VAR), in which all the variables are endogenous. Suppose we have two variables, y_t and x_t. In a VAR model of these two variables, we have two equations, one with y_t as the dependent variable, which is explained by its own lagged values and the lagged values of x_t, and the other with x_t as the dependent variable, as a function of its own lagged values and the lagged values of y_t, as given below:

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + ... + \alpha_p y_{t-p} + \beta_1 x_{t-1} + \beta_2 x_{t-2} + ... + \beta_p x_{t-p} + e_{1t},$$
$$x_t = \gamma_1 y_{t-1} + \gamma_2 y_{t-2} + ... + \gamma_p y_{t-p} + \delta_1 x_{t-1} + \delta_2 x_{t-2} + ... + \delta_p x_{t-p} + e_{2t},$$

where e_{1t} and e_{2t} are independently distributed white noises.

If for the first equation, we hypothesise that H_0: $\beta 1 = \beta_2 = ... = \beta_p = 0$, it means that the past values of x_t do not help to predict y_t. Therefore we say that x_t does not 'Granger-cause' y_t. Similarly, for the second equation, if we hypothesise that H_0: $\gamma 1 = \gamma_2 = ... = \gamma_p = 0$, it means that the past values of y_t do not help to predict x_t. Therefore we say that y_t does not 'Granger-cause' x_t.

5.3 ARDL Model based Bounds Tests for Cointegration

Compared with the traditional methods of cointegration, the Autoregressive Distributed-Lag (ARDL) method of cointegration introduced by Pesaran and shin (1999) and Pesaran, Shin and Smith (2001) has a number of advantages:

(i) Unlike the traditional methods, ARDL method does not require the stringent precondition that all the variables under consideration must be integrated of the same order. The method can be applied irrespective of whether the underlying variables are integrated of order one, order zero or mutually integrated. This in fact obviates the necessity of the pre-tests on non-stationarity. However, unit root testing is advised to see that there are no I(2) variables among the variables of our interest.

(ii) Since all the variables are assumed endogenous, as in a vector autoregression (VAR) model, and the ARDL model is a least squares regression using lags of the dependent and independent variables as regressors, we need to estimate only single equations, making it simple to carry out and interpret. Moreover, it involves no problem of endogeneity.

(iii) Unlike in the VAR model, different variables can have different lag-lengths in this model.

(iv) From the ARDL model, it is easier to derive the Error Correction Model (ECM), which integrates the short run dynamic adjustments with the long run equilibrium.

Let us first explain the structure and nature of an ARDL model, before going into the ARDL method of cointegration. As the name suggests an ARDL model combines an autoregression (AR) with a distributed lag (DL) model. As we have already seen, an autoregression is a regression of a variable on its own lagged terms; for instance: $y_t = \alpha + \beta y_{t-1} + v_t$ is an AR(1) process. On the other hand, a distributed lag model includes current and lagged terms of exogenous (explanatory) variable(s), such that the effect of the explanatory variable on the dependent one is distributed over a number of its past values. With one exogenous variable and one lag, a DL(1) model is: $y_t = \delta + \gamma_0 x_t + \gamma_1 x_{t-1} + w_t$. Note that x_t has current and past effects on y_t. Now combining these two models, we get an ARDL(1, 1) model:

$$y_t = \alpha + \beta y_{t-1} + \gamma_0 x_t + \gamma_1 x_{t-1} + u_t.$$

The advantage of the model is that we can have both short run and long run multipliers of this relationship; note that the ARDL model is a dynamic model, with the adjustment coefficient given by β. Here we have two short run multipliers: the impact multiplier is given by γ_0, and the one-period multiplier (or transient response or impulse response) by γ_1. The long run multiplier is obtained from this model as $(\gamma_0 + \gamma_1)/(1 - \beta)$.

Let us now consider the ARDL method of cointegration. We start with the long-run cointegrating relationship:

$$y_t = \alpha_0 + \alpha_1 x_t + v_t.$$

The conventional ECM corresponding to this model is given by

$$\Delta y_t = \beta_0 + \Sigma\beta_i\Delta y_{t-i} + \Sigma\gamma_j\Delta x_{t-j} - \lambda u_{t-1} + \varepsilon_t,$$

where the range of summation for the first term ($\Sigma\beta_i\Delta y_{t-i}$) is 1 to p, and for the second term ($\Sigma\gamma_j\Delta x_{t-j}$) is from 0 to q.

From the long-run cointegrating relationship given above, we can have the lagged residuals series (estimates of the error term v_t) as $u_{t-1} = (y_{t-1} - a_0 - a_1 x_{t-1})$, where the a_0 and a_1 are the OLS estimates of α_0 and α_1. Utilizing this parenthesised term for u_{t-1} in the above ECM model we get our ARDL model as:

$$\Delta y_t = \beta_0 + \Sigma\beta_j\Delta y_{t-j} + \Sigma\gamma_k\Delta x_{t-k} + \theta_0 y_{t-1} + \theta_1 x_{t-1} + \varepsilon_t,$$

with the range of summation as given above. Pesaran et al. (2001: 290) call this model "a conditional unrestricted equilibrium correction model (ECM)", because, unlike the conventional ECM, they are not restricting the coefficients.

Given our ARDL model, we can carry out the bound test for cointegration with a Wald or F statistic on the hypothesis H_0: $\theta_0 = \theta_1 = 0$, against the alternative that the null is not true. Just like the conventional cointegration testing, here also our null hypothesis is 'no cointegration', that is, no long-run equilibrium relationship between the variables; this is represented in the above null in terms of the zero coefficients for y_{t-1}, and x_{t-1} of our ARDL model. If we reject the null hypothesis, we have long run equilibrium (cointegration). Pesaran et al. (2001: 290) show "that the asymptotic distributions of both statistics are non-standard under the null hypothesis that there exists no relationship in levels between the included variables, irrespective of whether the regressors are purely I(0), purely I(1) or mutually cointegrated."

They derive its asymptotic distribution under the null, which yields two sets of asymptotic critical values "for the two polar cases which assume that all the regressors are, on the one hand, purely I(1) and, on the other, purely I(0)" (ibid). Note that this testing procedure is called a bounds test, as "these two sets of critical values provide critical value bounds for all classifications of the regressors into purely I(1), purely I(0) or mutually cointegrated" (ibid). That is, the two sets of critical values (Pesaran et al. 2001: 303-304) represent lower and upper bounds on the critical values; with the lower bound based on the assumption that all the variables are I(0), and the upper bound on the assumption that all the variables are I(1).

Thus the testing procedure is: if the computed Wald or F-statistic exceeds the upper bound, we can conclude that there is cointegration; on the other hand, if the estimated Wald or F-statistic falls below the lower bound, we conclude that the variables are I(0), and there is no scope for cointegration, However, if the computed statistic falls inside the two bounds, the test remains inconclusive.

Pesaran et al. (2001) also propose a bounds t-test for the coefficient of y_{t-1} in our ARDL model, with H_0 : $\theta_0 = 0$, against H_1 : $\theta_0 < 0$. If the estimated t-statistic for this coefficient (of y_{t-1} in our

ARDL model) is greater than the upper I(1) bound, we have cointegration; but if the t-statistic is less than the lower I(0) bound, we are left with stationary variables.

6 Conclusion

The present Chapter has presented a detailed discussion of the popular time series econometric methods that are of analytical use for this study that attempts to empirically substantiate the relationship between economic growth and financial development in the context of India, using time series data on the relevant variables. The analysis based on these methods is undertaken in the next Chapter. We take the log-difference of the quarterly data on gross domestic product (GDP) of India at constant prices (base: 2011-12) to represent the quarterly growth rate of the economy (from 1996 quarter 2 to 2018 quarter 3), which is the dependent variable in our ARDL model. The financial variables considered are (i) market capitalisation rate of BSE, (ii) that of NSE, (iii) turnover rate of BSE, (iv) that of NSE, (v) net investment by FIIs in the Indian capital market; all the five variables as a percentage of GDP; and (vi) real exchange rate (using GDP deflator with base 20111-12). To find out whether there is long run equilibrium between economic growth and these financial indicators, we make use of the ARDL-based cointegration method. To this empirical exercise we are now turning.

Part 2:
Long-Run Equilibrium Relationship between Economic Growth and Financial Development in India: Analysis

1 Introduction

This section constitutes the core of our study; it seeks to analyze the objective of this study, viz., assessing whether there exists a long-run equilibrium between economic growth and financial development in India. Using the conventional and modern time series econometric tools, we show that there does exist a long-run relationship between the economic and financial variables in the face of the external sector indicators.

This part is divided into four sub-sections. The next part discusses the data source and the variables used. Part 3 deals with the data analysis, starting with a graphical analysis of the temporal behavior of the variables under study, along with their statistical summary measures; we then go on to the unit root tests on the variables, using the most powerful ADF-GLS unit root test, which in turn takes us to the cointegration tests, using both the conventional Johansen-Juselius cointegration test and the modern ARDL-based bounds test. In the conventional case, we carry out the Granger-causality tests also. The last section concludes the part.

2 Data Source and Variables

We carry out our objective of assessing the relationship between economic growth and financial development in two scenarios: one with real per capita GDP and the other with real GDP growth rate.

The secondary data for this study is sourced from the Reserve Bank of India (RBI)'s Data Base on Indian Economy (*Handbook of Statistics on the Indian Economy*, available at https://dbie.rbi.org.in/DBIE/dbie.rbi?site=publications accessed during March 2019).

Since quarterly data on GDP is available from 1996 onwards only, the first quarter of 1996 is the start point of our data analysis. Quarterly data on GDP are available at both current prices and constant prices, the latter at different bases (1999-2000, 2004-05 and 2011-12); using the splicing method, we have converted the quarterly GDP series at constant prices with bases 1999-2000 and 2004-05 into the constant price series with base 2011-12. We use this series to estimate the real per capita GDP and also the quarterly growth rate of GDP using the log-differencing method.

Note that the growth rate of a time series y_t is given by

$$(y_t - y_{t-1})/ y_{t-1} = (y_t / y_{t-1}) - 1 \approx \ln(y_t / y_{t-1}) = \ln(y_t) - \ln(y_{t-1}).$$

In addition to a symmetry property (a log-difference of 0.1 now and –0.1 later will leave the value unchanged, that is, the mean remains constant), log-differencing has also a bounding property that helps control heteroscedasticity. While the usual growth rate is a period-over-period rate, the log-differencing yields continuously compounded or exponential growth rate. Thus in effect we are using the quarterly exponential growth rate of the economy through log-differencing; however, for simplicity, we denote this as 'growth rate' hereafter.

To estimate the corresponding quarterly real per capita GDP, we make use of a Stata module, called "dataex" that helps expand an annual data series into a quarterly one. Note that population data are available in annual frequency only. Using the above Stata module, we convert the annual population data into a quarterly data series, which then we use to estimate the quarterly per capita GDP.

Among the financial indicators, we have market capitalization and turnover, representing respectively market size and financial liquidity, essential for economic growth. RBI Data Base provides monthly market capitalization (in Rupees billion) data for both BSE and NSE. Since market capitalization represents a price (remember, market capitalization = stock price *times* number of outstanding stocks), we take 3-month moving average and using the Excel's "vlookup" functions, we convert the monthly moving average series into quarterly series. Then, dividing this by the quarterly GDP (at current prices), we get the market capitalization rate (%) for BSE and NSE. Similarly, the monthly turnover (in Rupees billion) data for BSE and NSE are converted into quarterly data by summing the corresponding three-month values (using the Excel's "sum(offset)" function), since turnover represents sales revenue (remember, the ratio of market capitalization to turnover is called price to sales ratio); dividing this by the quarterly GDP (at current prices), we get the turnover rate (%) for BSE and NSE.

Two variables are considered in this study to represent the external sector, namely, net foreign investment and real exchange rate. We employ the same procedure (as used in the case of monthly turnover) for converting the monthly net investment by the foreign institutional investors (FIIs) in the Indian capital market into quarterly data; that is, by summing the corresponding three-month values (using the Excel's "sum(offset)" function) and dividing this by the quarterly GDP (at current prices), we get the net foreign investment rate (%). In the case of the variable exchange rate, we proceed as we did for market capitalization; from the monthly averages of the exchange rate (Indian Rupees per US Dollar), first we get 3-month moving average and then using the Excel's "vlookup" functions, we convert the monthly moving average series into quarterly series. Dividing this by the quarterly GDP deflator, we get the real exchange rate variable.

3 Data Analysis

We start our data analysis with a look into the pattern (time series plot) and statistical properties (summary statistics) of the variables under study. Then we check for their degree of integration by unit root test, and finally turn to the cointegration test.

3.1 Pattern and Summary Statistics

Fig. 1 presents a visual account of the behavior of the eight variables under study. The quarterly real per capita GDP (base 2011-12) shows some seasonal fluctuations over time, which however almost subsides during the 2010s. The same pattern is observable in the case of the real growth rate of the economy (real GDP) that highly fluctuates around the mean 1.69% (reported in Table 1 below). Also note the usual exponential trajectory of the per capita GDP. We do not go for deseasonalizing the real per capita GDP series for fear of the consequences of data mining.

The stock market capitalization rates (as a percentage of GDP) series of BSE and NSE have almost the same behavior over time, with an increasing trend since the early 2000s. The statistical characteristics also do not differ much (Table 1), which is confirmed by statistical tests also, as Table 2 shows: the F-test does not reject the null hypothesis of equal variances of the two series, as the p-value is greater than 5% significance level; similarly, the t-test (assuming equal variances) also does not reject the null of equal means.

The stock market capitalization rate (as a percentage of GDP) may be used to determine whether a market is undervalued or overvalued; if the rate falls within the range of 90% and 115%, the market is said to be modestly overvalued. Note that both the NSE and BSE are highly over-valued markets.

Fig. 1: Patterns of the Variables under Study

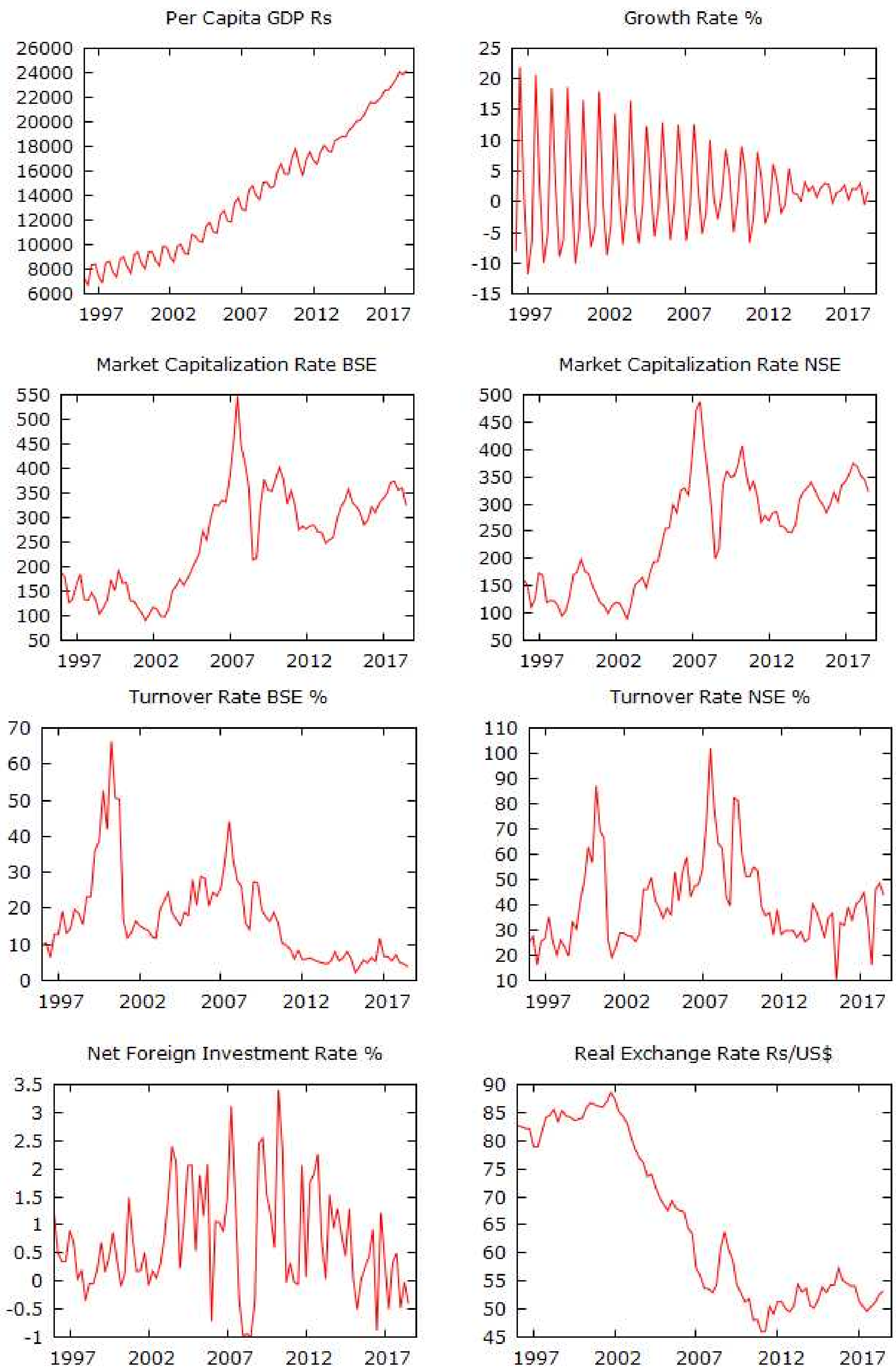

Table 1: Summary Statistics of the Variables

Variables	Mean	Median	Minimum	Maximum	Std. Dev.	C.V.	Skewness	Ex. kurtosis
Per Capita GDP (Rs)	14058	13678	6723.8	24188	5067.9	0.36	0.36	-1.09
GDP Growth Rate (%)	1.69	1.33	-11.81	21.91	7.31	4.32	0.81	-1.42
Market Capitalization Rate BSE (%)	254.17	271.1	90.72	546.78	103.12	0.41	0.13	-0.82
Market Capitalization Rate NSE (%)	248.04	263.22	89.68	487.06	99.66	0.40	0.05	-1.05
Turnover Rate BSE (%)	17.10	14.54	2.27	66.22	12.48	0.73	1.50	2.52
Turnover Rate NSE (%)	40.76	37.26	10.46	101.98	17	0.42	1.14	1.41
Net FII Investment Rate (%)	0.70	0.49	-0.99	3.40	0.94	1.35	0.59	-0.03
Real Exchange Rate (Rs/US$)	65.72	60.90	45.94	88.53	7.31	4.32	0.81	0.49

Table 2: Statistical Tests on Market Capitalization Rates

F-test
Null hypothesis: The population variances are equal
Sample 1: Market Capitalization Rate (%) BSE
n = 91, variance = 10634.5
Sample 2: Market Capitalization Rate (%) NSE
n = 91, variance = 9932.29
Test statistic: F(90, 90) = 1.0707
Two-tailed p-value = 0.7466
(one-tailed = 0.3733)
t-test
Null hypothesis: Difference of means = 0
Sample 1: Market Capitalization Rate (%) BSE
n = 91, mean = 254.167, s.d. = 103.124
standard error of mean = 10.8103
95% confidence interval for mean: 232.691 to 275.644
Sample 2: Market Capitalization Rate (%) NSE
n = 91, mean = 248.037, s.d. = 99.6609
standard error of mean = 10.4473
95% confidence interval for mean: 227.281 to 268.792
Test statistic: t(180) = (254.167 - 248.037)/15.0336 = 0.407804
Two-tailed p-value = 0.6839
(one-tailed = 0.342)

On the other hand, the turnover rates (as a percentage of GDP) series of the two stock exchanges, even though with almost similar behavioural pattern over time (Fig. 1), significantly differ in their magnitudes, as the summary statistics (Table 1) and the statistical tests (Table 3) show. The F-test rejects the null hypothesis of equal variances of the two series, as the p-value is much less than 5% significance level; similarly, the t-test (assuming unequal variances) also rejects the null of equal means (with almost zero p-value). Thus in terms of market size, both the stock exchanges of India are almost similar, while the NSE is much larger than BSE in terms of financial liquidity. Note that the mean-based volatility (measured by coefficient of variation) of liquidity is much higher for BSE.

Table 3: Statistical Tests on Turnover Rates

F-test
Null hypothesis: The population variances are equal
Sample 1: Turnover Rate (%) BSE
n = 91, variance = 155.675
Sample 2: Turnover Rate (%) NSE
n = 91, variance = 289.016
Test statistic: F(90, 90) = 1.85654
Two-tailed p-value = 0.003686
(one-tailed = 0.001843)
t-test
Null hypothesis: Difference of means = 0
Sample 1: Turnover Rate (%) BSE
n = 91, mean = 17.0968, s.d. = 12.477
standard error of mean = 1.30794
95% confidence interval for mean: 14.4984 to 19.6953
Sample 2: Turnover Rate (%) NSE
n = 91, mean = 40.7553, s.d. = 17.0005
standard error of mean = 1.78213
95% confidence interval for mean: 37.2148 to 44.2958
Test statistic: t(165) = (17.0968 - 40.7553)/2.21059 = -10.7023
Two-tailed p-value = 1.24e-020
(one-tailed = 6.2e-021)

The net foreign investment rate (as a percentage of GDP) also is highly volatile, with a rising trend initially and then a falling one since 2010 quarter 2. However, it is the real exchange rate (along with the GDP growth rate) that is of the highest volatility among all these variables (both the variables have the same coefficient of variation). Note that the real exchange rate, after a modest rise in the early 2000s, started drastically falling till 2010, under the heavy weight of inflation despite a rising trend in the nominal rates; and it registered a modest rise again thereafter.

3.2 Unit Root Tests

Now we turn to the unit root test results of the study variables.

Most of the studies use ADF and/or PP test to check for a unit root in a series; however, these tests suffer from a very low power. In 1996, Elliott, Rothenberg and Stock devised an efficient, more powerful, test, modifying the ADF test statistic using a generalized least squares (GLS) method, called ADF-GLS test. According to them, this test "has substantially improved power when an unknown mean or trend is present." (Elliott, Rothenberg and Stock, 1996: 813).

Moreover, the ADF test is very much sensitive to the lag length selected for the 'augmenting' term (lagged dependent variable term, used to 'whiten' the residual, that is, to remove the possible autocorrelation in the residual). The ADF-GLS test has an inherent mechanism to find out the optimum lag for unit root test. In this study we use this test procedure, available in Gretl with corresponding p-values in the specification with a constant, which is the default. In identifying the optimum lag order, we use the 'modified' BIC criterion, as described in Ng and Perron (2001), with the amendment proposed by Perron and Qu (2007) to improve the finite sample properties of the unit root test. We use Gretl because the Perron and Qu (2007) modification as well as p-value for the ADF-GLS unit root test is not available in other packages, where the test-statistic is reported along with the critical values.

Table 4: ADF-GLS Unit Root Tests Results

	Level Variable			First Difference		
Variable (in log)	Optimum Lag	tau-statistic	p-value	Optimum Lag	tau-statistic	p-value
Per Capita GDP	4	0.766476	0.8792	0	-6.52092	2.68E-10
MCR BSE	0	-1.25751	0.1924	0	-7.75743	2.04E-13
MCR NSE	2	-1.20762	0.2087	0	-6.50651	2.91E-10
TOR BSE	0	-1.82073	0.06538	0	-11.1473	1.47E-22
TOR NSE	1	-2.74346	0.005905			
Real Exchange Rate	0	-0.00405	0.6814	1	-5.13442	3.90E-07
Variable (no log)						
GDP Growth Rate	0	-6.55883	2.68E-10			
Net FII Investment	7	-1.85365	0.06083	0	-10.1974	5.57E-20

The ADF-GLS unit root tests results are reported in Table 4. Real per capita GDP, market capitalization rate of BSE and NSE, turnover rate of BSE and NSE, and real exchange rate are taken in natural log values, and the other two variables (real GDP growth rate and net FII investment) without log transformation, in view of negative values. The null hypothesis of unit root is rejected in the case of real GDP growth rate (as expected, since it is the log-difference of real GDP) and log of turnover rate of NSE, both at level; thus these two variables at level have no unit root and hence are I(0). For all other variables, the unit root null fails to reject at level, and rejects at first-difference (Table 4); thus these variables all have unit root at level and hence are I(1).

Next we turn to the cointegration tests.

3.3 Cointegration Tests

In order to find out whether there exists a long run equilibrium relationship between economic growth and financial development, we carry out cointegration tests in two scenarios: one with real per capita GDP and the other with real GDP growth rate. Since real per capita GDP is I(1), we go for the system method of Johansen-Juselius (JJ) cointegration test in one scenario with other I(1) variables; and in the next scenario, we do the ARDL bound test of cointegration as the relevant variable, real GDP growth rate, is I(0).

3.3.1 JJ Cointegration Test

For JJ test, we include only the I(1) variables, viz., the log values of real per capita GDP, market capitalization rate of BSE and NSE, turnover rate of BSE and real exchange rate, and net foreign

Table 5: JJ Cointegration Test Results

```
. vecrank lpcgdp lmcb lmcn ltrb lrer fii, trend(constant) max

                        Johansen tests for cointegration
Trend: constant                                        Number of obs =      89
Sample:  1996q4 - 2018q4                                        Lags =       2
```

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	42	562.66555	.	126.7508	94.15
1	53	594.14508	0.50708	63.7918*	68.52
2	62	607.17822	0.25389	37.7255	47.21
3	69	619.16516	0.23614	13.7516	29.68
4	74	624.05629	0.10409	3.9693	15.41
5	77	625.51725	0.03230	1.0474	3.76
6	78	626.04096	0.01170		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	42	562.66555	.	62.9591	39.37
1	53	594.14508	0.50708	26.0663	33.46
2	62	607.17822	0.25389	23.9739	27.07
3	69	619.16516	0.23614	9.7822	20.97
4	74	624.05629	0.10409	2.9219	14.07
5	77	625.51725	0.03230	1.0474	3.76
6	78	626.04096	0.01170		

investment (without log). Table 5.5 reports the test results, obtained with an optimum lag of 2 from Stata. Note that in the results, maximum rank = 0 refers to the null hypothesis of no cointegration. Both the estimated trace and maximum eigenvalue statistics for testing this null are greater than the corresponding critical values at 5% significance level, and therefore we reject the null hypothesis of no cointegration, Since we reject the first row, we go to the second row that tests the null of maximum one cointegration vector (maximum rank = 1). Here both the estimated statistics are less than the 5% critical value such that we fail to reject the null. So we stop here and conclude that there is one cointegration vector, that is, there exists cointegration among the given variables. This proves that there exists a long run equilibrium relationship between economic growth (proxied by real per capita GDP) and financial development, represented by market capitalization rate of BSE and NSE, and turnover rate of BSE in the presence of real exchange rate and net foreign investment.

3.3.2 Granger Causality

Though vector autoregression (VAR) model as such is not much useful, it is in general highly used to estimate what is called 'Granger-causality' (Granger 1969). A time series x_t is said to Granger-cause another time series y_t, if in the presence of the past values of y_t, the past values of x_t can predict the current value of y_t. For this we first regress y_t on its own past (lagged) values and the past values of x_t and then test the null hypothesis that all the estimated coefficients of the past values of x_t are jointly zero. If the test rejects the null hypothesis, then x_t is said to Granger-cause y_t; otherwise (if not rejected), we say x_t does not Granger-cause y_t.

Stata reports Wald tests of Granger-causality for all the variables under study, each variable with another one (pair-wise) and each variable with all other variables together (reported as 'ALL' in the results). Now we turn to the Granger-causality tests results, given in Table 6. The first part of the Table considers the equation for real per capita GDP ('lpcgdp' as dependent variable); 'Excluded' (in the Stata result) refers to the variable(s) that is considered for Granger-causality with the dependent variable (say, 'lpcgdp'). The optimum lag for all the variables is 2 (given as degrees of freedom, df). The first line shows that the p-value is less than 5% significance level, and hence we reject the null hypothesis that market capitalization rate of BSE ('lmcb') does not Granger-cause real per capita GDP ('lpcgdp'); and conclude that the market capitalization rate of BSE Granger-causes real per capita GDP. However, we find that the market capitalization rate of NSE and the two financial liquidity indicators of both BSE and NSE do not Granger-cause real per capita income. On the other hand, both real exchange rate and net foreign investment do

Granger-cause real per capita income. Even though only the market size of BSE has individual Granger-causality with real per capita income, all the variables jointly as a group does Granger-cause real per capita income.

Table 6: Granger Causality Tests Results

```
. vargranger

  Granger causality Wald tests
```

Equation	Excluded	chi2	df	Prob > chi2
lpcgdp	lmcb	7.2555	2	0.027
lpcgdp	lmcn	4.3582	2	0.113
lpcgdp	ltrb	.20753	2	0.901
lpcgdp	ltrn	.17797	2	0.915
lpcgdp	lrer	10.409	2	0.005
lpcgdp	fii	13.438	2	0.001
lpcgdp	ALL	24.04	12	0.020
lmcb	lpcgdp	18.988	2	0.000
lmcb	lmcn	54.716	2	0.000
lmcb	ltrb	.89102	2	0.640
lmcb	ltrn	.48922	2	0.783
lmcb	lrer	1.169	2	0.557
lmcb	fii	1.6172	2	0.445
lmcb	ALL	86.636	12	0.000
lmcn	lpcgdp	22.913	2	0.000
lmcn	lmcb	10.074	2	0.006
lmcn	ltrb	1.6769	2	0.432
lmcn	ltrn	.52581	2	0.769
lmcn	lrer	.71924	2	0.698
lmcn	fii	3.8512	2	0.146
lmcn	ALL	44.535	12	0.000
ltrb	lpcgdp	6.4594	2	0.040
ltrb	lmcb	8.4007	2	0.015
ltrb	lmcn	25.219	2	0.000
ltrb	ltrn	3.9112	2	0.141
ltrb	lrer	.09512	2	0.954
ltrb	fii	3.9977	2	0.135
ltrb	ALL	46.657	12	0.000

ltrn	lpcgdp	8.6223	2	0.013
ltrn	lmcb	17.804	2	0.000
ltrn	lmcn	27.566	2	0.000
ltrn	ltrb	39.642	2	0.000
ltrn	lrer	.02024	2	0.990
ltrn	fii	3.4382	2	0.179
ltrn	ALL	82.559	12	0.000
lrer	lpcgdp	6.6214	2	0.036
lrer	lmcb	2.8655	2	0.239
lrer	lmcn	8.224	2	0.016
lrer	ltrb	.78136	2	0.677
lrer	ltrn	.20506	2	0.903
lrer	fii	9.8719	2	0.007
lrer	ALL	38.277	12	0.000
fii	lpcgdp	2.7494	2	0.253
fii	lmcb	4.1912	2	0.123
fii	lmcn	13.336	2	0.001
fii	ltrb	1.0485	2	0.592
fii	ltrn	1.6851	2	0.431
fii	lrer	3.6898	2	0.158
fii	ALL	21.237	12	0.047

We summarize the entire information in Table 7. Among the financial indicators, only the market capitalization rate (MCR) of BSE influences real per capita GDP, which, in turn, influences all the financial indicators (market size of both BSE and NSE and their financial liquidity) as well as the real exchange rate (RER). There is a two-way feedback (Granger-causality) between real per capita GDP and MCR of BSE; both the variables influence each other. Similarly, a two-way feedback exists between per capita GDP and RER; as well as between MCR of BSE and that of NSE. It is worth noting that in each variable's case, all other variables together ('ALL') have a say.

Table 7: Granger-Causality: Summary

Real Per capita GDP (PCGDP)	Granger-causes	MCR-BSE, MCR-NSE, TOR-BSE, TOR-NSE, RER
MCR-BSE	Granger-causes	PCGDP, MCR-NSE, TOR-BSE, TOR-NSE
MCR-NSE	Granger-causes	MCR-BSE, TOR-BSE, TOR-NSE, RER, NFI
TOR-BSE	Granger-causes	TOR-NSE
TOR-NSE	Granger-causes	no variable
Real Exchange Rate (RER)	Granger-causes	PCGDP
Net Foreign Investment (NFI)	Granger-causes	PCGDP, RER
'ALL'	Granger-causes	PCGDP, MCR-BSE, MCR-NSE, TOR-BSE, TOR-NSE, RER, NFI

Note: MCR = Market capitalization rate; TOR = Turnover rate; BSE = Bombay stock exchange; NSE = National stock exchange.

3.3.3 ARDL-Based Bounds test for Cointegration

Now we turn to the modern Bounds test for cointegration, based on ARDL model. Since growth rate is an I(0) variable, we use this variable now in relation to the financial indicators and the external sector indicators. The result is given in Tables 8. Note that we have already seen ftom the JJ-test that there exists a long run equilibrium relationship among the variables under study, with significant Granger-causality. Here also, we have the same result, which is reported in Table 8, on the ARDL-based bounds test of Pesaran, Shin and Smith (2001).

The Bounds test result (Table 8) shows that the estimated F-value is highly significant, greater than even the 1% level critical value for I(1), the upper bound, with close to zero p-value (0.004); this in turn means that we reject the null hypothesis that all the coefficients of the ARDL-based error correction model (ECM) are jointly zero; and thus we conclude that there is cointegration. in addition to this joint significance, we also have individual significance of the coefficients, as the corresponding t-statistic is more negative than even the 1% level critical value for I(1), the upper bound, with close to zero p-value (0.008); this in turn means that we reject the null hypothesis that all the coefficients of the ECM are individually zero; and thus we conclude that there is cointegration.

Thus the ARDL-based Bounds tests also confirm cointegration among the variables under study.

Table 8: ARDL-Based Bounds Test Result

```
. estat ectest

Pesaran, Shin, and Smith (2001) bounds test

H0: no level relationship                                    F =     5.477
Case 3                                                       t =    -5.219

Finite sample (6 variables, 86 observations, 4 short-run coefficients)

Kripfganz and Schneider (2018) critical values and approximate p-values
```

	10%		5%		1%		p-value	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F	2.200	3.383	2.574	3.862	3.408	4.909	0.000	0.004
t	-2.532	-4.030	-2.854	-4.403	-3.489	-5.123	0.000	0.008

```
do not reject H0 if
    both F and t are closer to zero than critical values for I(0) variables
      (if p-values > desired level for I(0) variables)
reject H0 if
    both F and t are more extreme than critical values for I(1) variables
      (if p-values < desired level for I(1) variables)
```

4 Conclusion

The core of this study has provided the empirical exercise of the objective of this study, namely, finding out whether there exists a long-run equilibrium between economic growth and financial development in India. We have started with a graphical analysis of the temporal pattern of the variables under study, along with their summary statistics; we have then moved on to the unit root tests on the variables, using the most powerful ADF-GLS unit root test, which in turn took us to the cointegration tests. We have carried out two cointegration tests, namely, the conventional Johansen-Juselius test and the modern ARDL-based bounds test. Both these time series econometric tools have shown that there does exist a long-run relationship between the economic and financial variables in the face of the external sector indicators. Further, in the conventional case, we have also carried out the Granger-causality tests. These tests have also clearly shown that there are certain short-run dependences among the variables concerned.

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