Selecting appropriate methodological framework for time series data analysis[☆]

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Abstract

Economists face method selection problem while working with time series data. As time series data may possess specific properties such as trend and structural break, common methods used to analyze other types of data may not be appropriate for the analysis of time series data. This paper discusses the properties of time series data, compares common data analysis methods and presents a methodological framework for time series data analysis. The framework greatly helps in choosing appropriate test methods. To present an example, Nepal's money–price relationship is examined. Test results obtained following this methodological framework are found to be more robust and reliable.
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Keywords: Time series analysis; Unit root test; Methodological framework; Money–price relationship in Nepal

1. Introduction

Time series data is a sequence of observations of the defined variable at a uniform interval over a period of time in successive order. Most common series are in annual, quarterly, monthly, weekly and daily frequencies. Economic time series data often possess unique features such as clear trend, high degree of persistence on shocks, higher volatility over time and meandering and sharing co-movements with other series.[1] Researchers need to understand such features of time series data properly and address them.

In time series analysis, it is important to understand the behavior of variables, their interactions and integrations over time. If major characteristics of time series data are understood and addressed properly, a simple regression analysis using such data can also tell us about the pattern of relationships among variables of interest. This paper attempts to highlight the basic econometric issues related to the time series data and provides a basic methodological framework for time series analysis. In addition, the paper analyses the relationship between money and price in Nepal using the methodological framework presented in this paper to provide practical example.
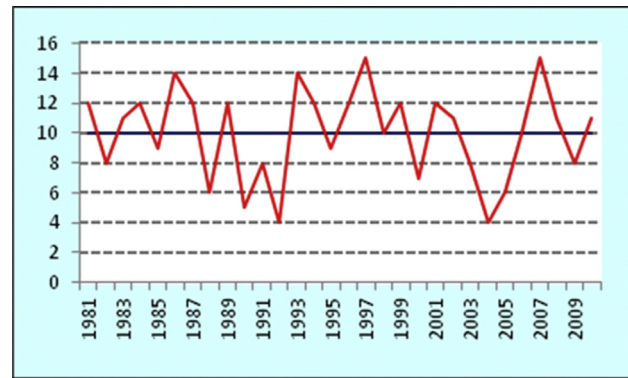
Fig. 1. Stationary time series.

2. Properties of time series data

2.1. Autoregressive character of time series

Time series data may have some kind of relationship with its previous values. The autoregressive (AR) character of time series model indicates that present value of any variable is determined by its past value and some adjustment factors. Such adjustment factors are estimated from the relation of current value with past values. If the current value is based solely on the immediate preceding value, it is termed as first order autoregressive, AR (1), and if it is based on two preceding values, second order autoregressive, AR (2), and so on.

A univariate linear regression model[c] can be estimated as:

$$Y_t = \mu + \rho Y_{t-1} + \varepsilon_t \tag{1}$$

where, Y_t is a dependent variable, Y, at period t. μ is a constant parameter. ε_t is the unexplained part (gap) of actual data and fitted line by regression equation, termed as error. Y_{t-1} is the first lagged value of Y, ρ is the coefficient of Y_{t-1}.

Eq. (1) says that the value of Y_t equals the constant μ plus ρ times its previous value and an unknown component ε_t

The model to be estimated in Eq. (1) is an AR (1) process.

Similarly,

$$Y_t = \mu + \rho_1 Y_{t-1} + \rho_2 Y_{t-2} + \varepsilon_t \tag{2}$$

The model to be estimated in Eq. (2) is an AR (2) process.

Besides the AR process, moving average (MA) model also estimates the present value of a variable based on the current and previous years' error terms.[d] As in AR process, there can be more than one order of integration in MA as well.

2.2. Stationary and non-stationary series

A time series data is called stationary if its value tends to revert to its long-run average value and properties of data series are not affected by the change in time only (Fig. 1).[e] On the contrary, the non-stationary time series does not tend to return to its long-run average value, hence, its mean, variance and co-variance also change over time (Fig. 2).

Most of the macroeconomic variables such as volume of gross domestic product (GDP), consumption, consumer price index, etc. exhibit a strong upward or downward movement over time with no tendency to revert to a fixed mean.

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[c] For details, see Stigler (1981).[2]

[d] Error terms are the unobserved factors of regression that may affect the dependent variable. These are residuals of actual and fitted values of a regression. It is represented by ε or u. Wooldridge (2002) mentions that "dealing with this error term is the most important component of any econometric analysis".

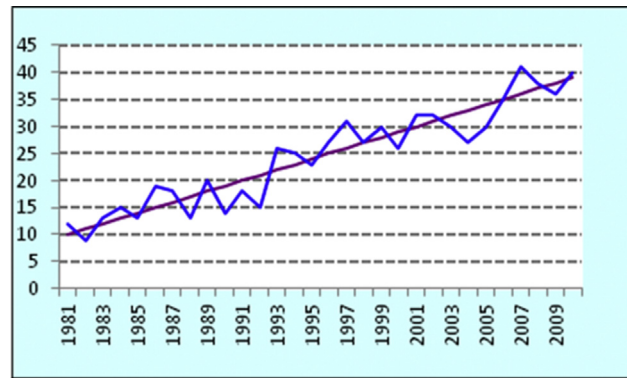[e] For details, see Verbeek (2017)[3], Chapter 8.

Fig. 2. Non-stationary time series.

Hence, they are non-stationary series. If the time series is non-stationary, it is said to have a unit root. Therefore, in econometrics, the stationarity of a time series is examined by conducting unit root test.

Mathematically, the series Y_t is stationary if:

$$E(Y_t) = E(Y_{t-s}) = \mu, \; for\; some\; s > 0 \tag{3}$$

$$Var(Y_t) = Var(Y_{t-s}) = \sigma y^2 \; and \tag{4}$$

$$Cov(Y_t, Y_{t-s}) = \gamma_s \tag{5}$$

where,

$E(Y_t)$ = Expected value of Y at period t
Var = Variance, the variation or spread of Y_t from $E(Y_t)$
Cov = Covariance, the joint variation of Y_t and Y_{t-s}
Y_{t-s} = Lag of Y up to period $t-s$

2.3. Trend, cycle and seasonality in time series data

Trend is a sustained upward or downward movement in time series data over the long run (Fig. 3). Cycle is a short-run fluctuation which occurs in a given interval such as monthly, quarterly or annual (Fig. 4). Trends are always non-stationary whereas cycles may be either stationary or non-stationary.

Seasonality is a kind of pattern in a high frequency data such as quarterly, monthly, weekly or daily. For instance, we may observe a high volume of sales in festive season, more currency coming into circulation during *Dashain* festival and increased government spending at the last quarter of the fiscal year in Nepal.[f]

3. Determining stationary of time series

Most of the modeling techniques applied in time series analysis are primarily concerned with stationarity of the data. The starting point is to examine the properties of series graphically and confirming it statistically. Graphs are the most preliminary tool to get the rough idea about the stationarity of the series. However, statistical tests are required for final decision. Unit root tests provide statistical evidence on the stationarity of a given series.

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[f] The easiest way of identifying seasonality is seasonal graphs that can be drawn using EViews. It gives a graphical plot of the series for each season. If the series is found to be higher or lower than the average at any particular season, say a month, we can declare that there is seasonality. If the seasonality is detected in the series, it should be addressed while modeling. The possible solution for the seasonality is generation of seasonally adjusted series by using available methods. In EViews, Census X13, Census X12, X11 (Historical), Tramo/Seats and Moving Average Methods are available. These methods generate seasonally adjusted additional variable of the original seasonal unadjusted series.
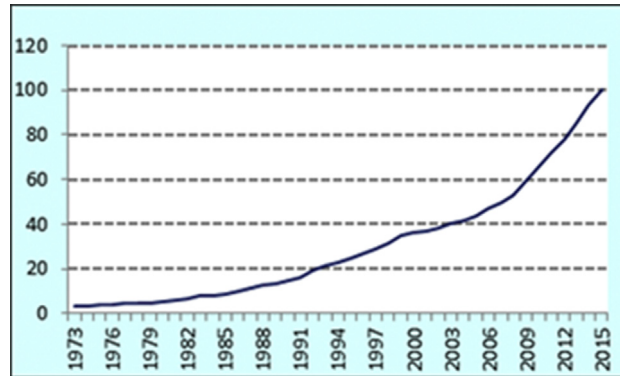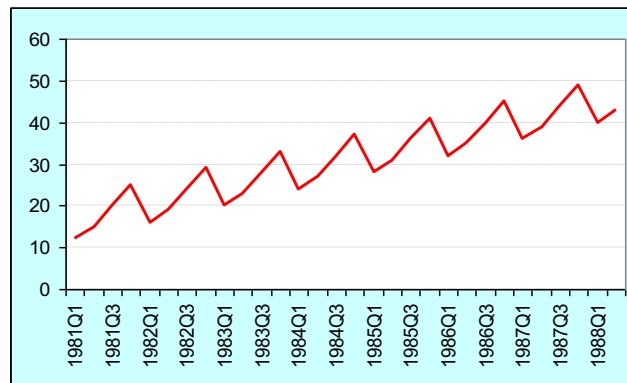
Fig. 3. Trend.

Fig. 4. Cycle.

3.1. Unit root test methods

The statistical procedure employed to determine the stationarity of a series is called 'unit root test'. The following section discusses the widely used stationarity test methods, namely Augmented Dickey−Fuller, Phillips−Perron and KPSS tests.

3.1.1. Augmented Dickey Fuller (ADF) test

The Augmented Dickey−Fuller (ADF) test is the most common method for testing unit root. Suppose, we have a series y_t for testing unit root. Then, ADF model tests unit root as follows.

$$\Delta y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + e_t \tag{6}$$

where,

$\delta = \alpha - 1$

$\alpha =$ coefficient of y_{t-1}

$\Delta y_t =$ first difference of y_t, i.e. $y_t - y_{t-1}$

The null hypothesis of ADF is $\delta = 0$ against the alternative hypothesis of $\delta < 0$. If we do not reject null, the series is non-stationary whereas rejection means the series is stationary.

3.1.2. Phillips−Perron (PP) test

Phillips−Perron (PP) test is an alternative model to test the presence of unit root in a time series. This model tests in the following form:

$$\Delta y_t = \pi y_{t-1} + \beta_i D_{t-i} + e_t \tag{7}$$

where,

e_t is a I(0) with zero mean and D_{t-i} is a deterministic trend component.

The hypothesis is tested for $\pi = 0$. The basic difference between the ADF and PP tests is that PP is a non-parametric test, meaning that it does not need to specify the form of the serial correlation of Δy_t under the null hypothesis. Thus, the calculation procedure of t-ratio to get the value of π becomes different. Furthermore, PP corrects the statistics to consider the autocorrelation and heteroskedasticity issues. The hypothesis testing procedure is similar as of ADF test.

Although the ADF test has been reported to be more reliable than the PP test, the problem of size distortion and low power of test make both these tests less useful.[4] For the larger volume of financial data, PP test is also suggested.

3.1.3. Kwiatkowsky, Phillips, Schmidt and Shin (KPSS) test

The classical testing framework is found sometimes to be biased towards accepting null hypothesis (H_0). Hence, Kwiatkowsky, Phillips, Schmidt and Shin (KPSS) have developed another method to test the stationarity. In KPSS test, null hypothesis is stationary and alternative hypothesis is non-stationary. KPSS test model is as follows:

$$Y_t = X_t + \varepsilon_t \ and \ hence, X_t = X_{t-1} + u_t \tag{8}$$

In the above model, hypothesis is tested for u_t. The reported critical values of the KPSS test is derived from the Lagrange Multiplier (LM) test statistics.

3.2. Structural break in time series

Structural break is a sudden jump or fall in an economic time series which occurs due to the change in regime, policy direction, and external shocks, among others. Structural break may occur in intercept, trend or both (Fig. 5). Structural breaks can create difficulties in unit root test. As shown by Perron (1989),[5] in the presence of structural break, conventional unit root test methods may show a time series to be non-stationary, which in fact is a stationary series. In other words, a stationary series which has a structural break may be regarded as a non-stationary series by the above mentioned unit root test methods because these methods do not make adjustment for structural break.

To address the structural break issue Perron (1989),[5] has developed a unit root test method, which accommodates a known structural break in the time series. More recently, some new methods have been proposed for unit root test allowing unknown single and multiple structural breaks.[6−9g]

4. Methods for time series analysis

### 4.1. Method selection framework

Applying appropriate methodology for the time series data is most crucial part of the time series analysis as wrong specification of the model or using wrong method provides biased and unreliable estimates. Primarily, the method selection for time series analysis is based on the unit root test results which determine the stationarity of the variable. Methods commonly used to analyze the stationary time series cannot be used to analyze non-stationary series. If all the variables of interest are stationary, the methodology becomes simple. In such a case, ordinary least square (OLS) or vector autoregressive (VAR) models can provide unbiased estimates. If all the variables of interest are non-stationary, OLS or VAR models may not be appropriate to analyze the relationship. Similarly, additional problem arises when variables used in the analysis are of mixed type, i.e., some are stationary and others are non-stationary.

Following is a general methodological framework for time series analysis.

The method selection criteria of Fig. 6 should be treated as the most basic approach. This is because there are other several considerations in time series models.

The non-stationary variables can be made stationary by taking first difference. Similarly, the non-stationary data with a persistent long-run trend can be made stationary with either i) putting time variable in the regression or ii) extracting trends and cycles from the single series by using popular filtering techniques such as Hodrick Prescott (HP) filter. Nevertheless, it should be noted that the long-run relationship/information of the variables may be lost when we modify them to make stationary such as by differencing, de-trending or filtering.

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g See Shrestha and Chowdhury (2005)[10] for detailed discussion on unit root test with the structural break.
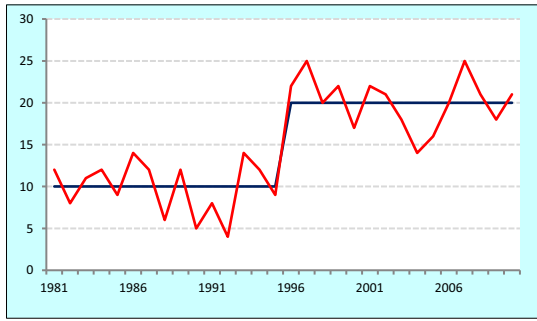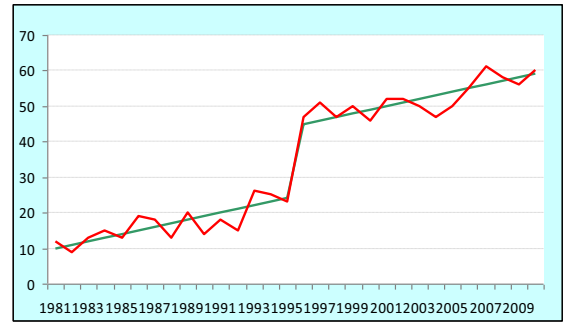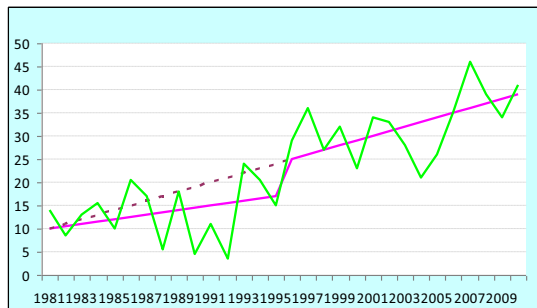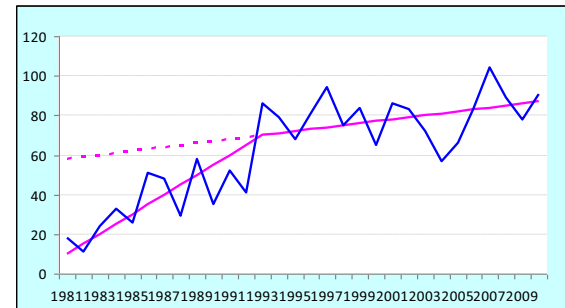
Fig. 5. Structural break in time series data, a. Structural break in intercept, b. Structural break in intercept, c. Structural break in trend, d. Structural break in intercept and trend.
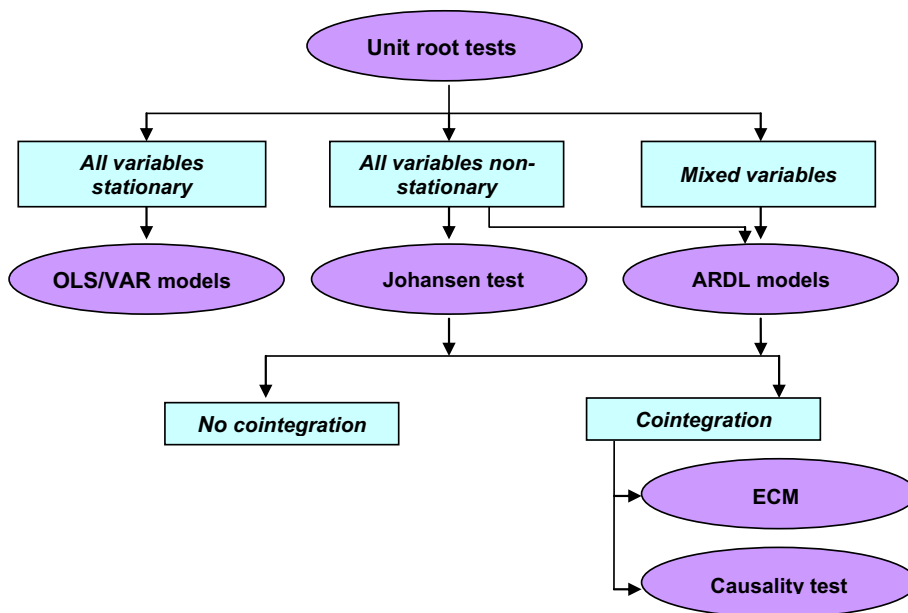
Fig. 6. Method selection for time series data. OLS: Ordinary least squares; VAR: Vector autoregressive; ARDL: Autoregressive distributed lags; ECM: Error correction models.

4.2. Ordinary least square (OLS) method

The first step to start the time series analysis is to conduct unit root test. If unit root test results show that all variables being analyzed are stationary, then OLS method can be used to determine the relationship between the given variables. A bivariate linear regression model, termed as ordinary least squares (OLS), can be estimated as:

$$Y_i = b_1 + b_2 X_i + e_i \tag{9}$$

which can be written as:

$$e_i = Y_i - \widehat{Y}_i \tag{10}$$

$$= Y_i - b_1 - b_2 X_i \tag{11}$$

Above model shows that the residuals (e_i) are simply the difference between the actual (Y_i) and estimated ($\widehat{Y}_i$) values. OLS minimizes the residual sum of squares while choosing b_1 and b_2.[h]

As mentioned above, a non-stationary time series can be converted into a stationary series by differencing. If a time series becomes stationary after differencing one time, then the series is said to be integrated of order one and denoted by I(1). Similarly, if a time series has to be differenced two times to make it stationary, then it is called integrated of order 2 and written as I(2). As the stationary time series need not to be differenced, it is denoted by I(0).

Taking difference of non-stationary time series and using OLS method after making all the variables stationary may seem to be an easy way to analyze the relationship. However, the difference represents only the short-run change in the time series but totally misses out the long-run information. Hence, this method is not suggested for the analysis of non-stationary variables.

4.3. Vector autoregressive (VAR) model

Vector Autoregressive (VAR) model allows the feedback or reverse causality among the dependent and independent regressors using their own past values. In the general VAR model, no exogenous variables require as it assumes all the regressors endogenous.

The simpler VAR dimension[i] for two variables X and Y with only one lag is given below:

$$Y_t = \delta_1 + \theta_{11} Y_{t-1} + \theta_{12} X_{t-1} + \varepsilon_{1t} \tag{12}$$

$$X_t = \delta_2 + \theta_{21} Y_{t-1} + \theta_{22} X_{t-1} + \varepsilon_{2t} \tag{13}$$

where ε_{1t} and ε_{2t} are uncorrelated white noise disturbances or error terms.

Choosing appropriate lag length is important in VAR modeling. Optimal number of lags can be selected by using available lag length selection criteria. Most popular criteria are Akaike Information Criterion (AIC), Schwartz Bayesian Criterion (SBC), and Hannan Quinn criterion (HQC).

4.4. Cointegration test

Using ordinary least square or other similar methods for non-stationary time series may produce spurious results. In other words, the test results of regression may show that a significant relationship exists between two given variables, which in fact are un-correlated. This type of regression is termed as 'spurious regression' which mainly occurs due to the non-stationarity of the time series used in the regression model. On the other hand, two or more variables may form long term equilibrium relationship even though they may deviate from the equilibrium in the short run. Due to these issues, Engle and Granger (1987)[13] developed cointegration test method to analyze the relationships among non-stationary variables.

If two or more variables are linked to form an equilibrium relationship spanning the long run, these variables are said to be cointegrated. In fact, one variable drags the other over the period and hence, both of them share the same movement. Fig. 7 shows the movement of two cointegrated time series.

4.4.1. Johansen cointegration test

Addressing weaknesses in the Engel−Granger methodology, Johansen (1988) and Johansen and Juselius (1990)[14,15] have developed improved cointegration tests models. The Johansen (1988)[14] version is widely used and has been incorporated in various econometric software. This test method is based on the relationship between the rank of matrix and its characteristics roots. We have a generalized model with *n* variable vectors:

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[h] See Gujarati (1995)[11] for detailed discussion.
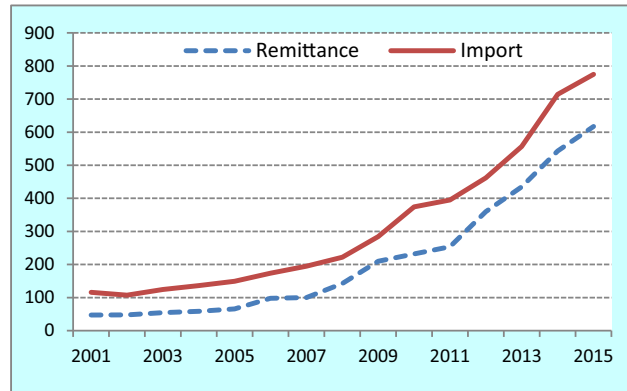[i] See Sims and Sachs (1982)[12] for details.

Fig. 7. Remittance and import in Nepal.

$$x_t = A_1 x_{t-1} + \varepsilon_t, \tag{14}$$

so that

$$\Delta x_t = A_1 x_{t-1} - x_{t-1} + \varepsilon_t \tag{15}$$

$$= (A_1 - I) \ x_{t-1} + \varepsilon_t \text{ can be written as}$$

$$= \prod x_{t-1} + \varepsilon_t \tag{16}$$

where,

x_t and ε_t are (n.1) vectors

$A_1 =$ an (n.n) matrix of parameters

$I =$ an (n.n) identity matrix

$\Pi = A_1 - I$

We test the rank of $A_1 - I$ matrix. If the rank of $A_1 - I$, that is, the rank of $\Pi = 0$, then we say sequences are unit root processes. If rank of $\Pi = k$ then we say the series is stationary and if rank of $\Pi < k$, also known as reduced rank, then there exists cointegration. Hence, the intuition is if we have 3 variables in cointegration tests, the maximum rank of Π can be less than three (if $k = 3$, cointegration rank<3 and maximum cointegration relation is only two).

4.5. Error correction models

If the variables are I(1) and there exists a cointegration relationship, then Error Correction Model (ECM) can be derived. Consider the following bivariate relationship.

$$Y_t = \mu + \beta_1 X_t + \varepsilon_t \tag{17}$$

Based on the representation theorem of Engle and Granger (1987),[13] we establish a link between the cointegration and Error Correction Model (ECM) by transforming Eq. (17).

Cointegration equation between Y_t and X_t are as follows:

$$\varepsilon_t = Y_t - \mu - \beta_1 X_t \tag{18}$$

The Error Correction Models for Y_t and X_t are as follows:

$$\Delta Y_t = \mu_Y + \alpha_Y \varepsilon_{t-1} + \sum_{h=1}^{l} a_{1h} \Delta Y_{t-h} + \sum_{h=1}^{l} b_{1h} \Delta X_{t-h} + u_{Yt} \tag{19}$$

$$\Delta X_t = \mu_X + \alpha_X \varepsilon_{t-1} + \sum_{h=1}^{l} a_{2h} \Delta Y_{t-h} + \sum_{h=1}^{l} b_{2h} \Delta X_{t-h} + u_{Xt} \tag{20}$$

where, u_{Yt} and u_{Xt} are stationary white noise processes for some number of lags l. The model can be further advanced in multivariate case in a similar way.

The coefficients in the cointegration equation give the estimated long-run relationship among the variables and coefficients on the ECM describe how deviations from that long-run relationship affect the changes on them in next period. The parameters α_Y and α_X of Eqs. (19) and (20) measure the speed of adjustment of X_t and Y_t, respectively towards the long-run equilibrium.

4.6. ARDL models

Johansen cointegration test cannot be applied directly if variables of interest are of mixed order of integration or all of them are not non-stationary, as this method requires all the variables to be I(1). An autoregressive distributed lag (ARDL) model is an ordinary least square (OLS) based model which is applicable for both non-stationary time series as well as for times series with mixed order of integration.[16,17] This model takes sufficient numbers of lags to capture the data generating process in a general-to-specific modeling framework.

A dynamic error correction model (ECM) can be derived from ARDL through a simple linear transformation. Likewise, the ECM integrates the short-run dynamics with the long-run equilibrium without losing long-run information and avoids problems such as spurious relationship resulting from non-stationary time series data.

To illustrate the ARDL modeling approach, the following simple model can be considered:

$$y_t = \alpha + \beta x_t + \delta z_t + e_t \tag{21}$$

The error correction version of the ARDL model is given by:

$$\Delta y_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \sum_{i=1}^{p} \delta_i \Delta x_{t-i} + \sum_{i=1}^{p} \varepsilon_i \Delta z_{t-i} + \lambda_1 y_{t-1} + \lambda_2 x_{t-1} + \lambda_3 z_{t-1} + u_t \tag{22}$$

The first part of the equation with β, δ and ε represents short run dynamics of the model. The second part with λs represents long run relationship. The null hypothesis in the equation is $\lambda_1 + \lambda_2 + \lambda_3 = 0$, which means non-existence of long run relationship.

4.7. Causality test

If two variables Y and X is cointegrated, then there may exist any of the 3 relationships: a) X affects Y, b) Y affects X and c) X and Y affect each other. The first two show unidirectional relationship while the third shows bidirectional relationship. If two variables are not cointegrated, then one does not affect the other and are independent. To determine the pattern of such relationship, Granger (1969)[18] has developed causality test method. If current and lagged values of X improve the prediction of the future value of Y, then it is said that X 'Granger causes' Y. The simple model of Granger causality is as follows:

$$\Delta Y_t = \sum_{i=1}^{n} \alpha_i \Delta Y_{t-i} + \sum_{j=1}^{n} \beta_j \Delta X_{t-j} + u_{1t} \tag{23}$$

$$\Delta X_t = \sum_{i=1}^{n} \lambda_i \Delta X_{t-i} + \sum_{j=1}^{n} \delta_j \Delta Y_{t-j} + u_{2t} \tag{24}$$

Eq. (23) shows that the current value of ΔY is related to the past values of itself and the past values of ΔY. Similarly, Eq. (24) postulates that ΔX is related to the past values of itself and that of ΔY.

The null hypothesis in Eq. (23) is $\beta_j = 0$ which means, "ΔX does not Granger cause ΔY". Similarly, the null hypothesis in Eq. (24) is $\delta_j = 0$, and states "ΔY does not Granger cause ΔX." The rejection or non-rejection of the null hypothesis is based on the F-statistics.

5. Diagnostic tests of the time series model

To make the estimated model robust and unbiased, we need to determine the fitness of the model through checking goodness of fit statistics and conducting diagnostics tests.

5.1. Goodness of fit

A rough impression of the robustness of estimated regression coefficients can be made by examining how well the regression line explains the data, whether there is a serial correlation in residuals and whether the overall model is

significant, among others. Goodness of fit test values is displayed together with the estimated coefficients by almost all types of software.

Common tests for goodness of fit include R^2, which shows a correlation in bivariate case and hence the value closer towards 1 is considered to be better. In a multivariate regression, adjusted R^2 is chosen instead of R^2. R^2 increases with the increase in the number of variable while adjusted R^2 increases only when the new variable improves the prediction power. Durbin Watson (DW) statistics indicate whether there is an autocorrelation in residuals. If the value of DW is near to two, then model is considered to be 'autocorrelation free'.

5.2. Diagnostics tests

Diagnostic tests tell us about the robustness of estimated coefficients. Diagnostic test statistics are generally not reported automatically by software and thus should be estimated separately. Type of the diagnostic test depends upon the modeling technique being utilized. However, the most common types of diagnostics tests are lag structure, co-efficient diagnostics and residual diagnostics. Residual diagnostics is the most crucial part of diagnostic tests in economic modeling since the regression models try to minimize errors (or residuals). The error terms must be white noise (independently and identically distributed, *i.i.d.*). Residual diagnostics examine whether the error terms are *i.i.d.* Lagrange multiplier (LM) test, correlogram, and heteroskedasticity test are the major test methods for residual diagnostics. The stability diagnostics examine whether the parameters of the estimated model are stable across various sub-samples of the data.

The diagnostics tests have been discussed in detail in Annex 1.

6. Analyzing the money–price relationship in Nepal: an example

6.1. Theoretical background

Classical and neoclassical economists believe that over-supply of money leads to an increase in price level. The most famous quantity theory of money by Fisher (1922)[19] has expressed the money–price relationship as follows:

$$MV = PT \tag{25}$$

where, M denotes money supply, V refers the velocity of money, P is the average price level and T indicates the total volume of transaction of goods and services in an economy. The modern quantity theory of money (QTM) believes that the firm specific cost increase cannot be inflationary as long as they are not related to, or accommodated by, increases in the money supply. The relationship can be expressed as:

$$MV = PY \tag{26}$$

In the above equation, if output of the economy, Y, and the velocity of money V are given, then increase in M will proportionately increase P.

In the developing countries like Nepal, where the supply side bottlenecks are also a big issue, demand side inflation may be dominated by structural constraints. This paper empirically analyses the money–price relationship in Nepal by following the econometric framework discussed in the preceding sections of this paper.

6.2. Data and unit root test

In line with the methodological framework discussed above, Nepal's money–price relationship is analyzed with due consideration to the properties of time series. We include the monthly series of Nepalese consumer price index (CPI), nominal effective exchange rate (NEER), broad money (M2) in Rs. million, and Indian CPI (CPII) from January 2000 through April 2014. The graphical plots of the series are presented in Annex 2.

From the graphs shown in Annex 2, we can figure out the possible non-stationarity in Nepalese CPI, Indian CPI and M2 but cannot determine the nature of the non-stationarity. In the case of NEER, it looks like a stationary series but cannot be sure about it.

The unit root test on the monthly series of CPI, M2, NEER and CPII at level data and as transformed series by taking log, first difference and including intercept and both trend and intercept was carried out separately on the three popular test methods: ADF, PP and KPSS as discussed in Section 3.1. The unit root test results are presented below in Table 1.

The ADF tests for stationarity shows that all the four variables are non-stationary at the level data as well as at log transformation. The level series of NEER and CPII becomes stationary at first difference. Nonetheless, even at the first difference, CPI and M2 are non-stationary. But M2 becomes stationary at first difference after taking log. None of the series is trend stationary since all of them were still non-stationary after the inclusion of time trend in the ADF test equation. CPI variable is found non-stationary even at the first difference with and without the log. However, CPI is stationary at 5 percent at first difference if both trend and intercept is included in ADF test equation.

The Philips−Perron (PP) test results also show that all the variables are non-stationary (Table 2). Results are consistent with ADF test results.

The KPSS test for stationary also shows the similar results of non-stationarity of all the series at level (with and without taking logs). Nonetheless, the test results are different at first difference. Although CPI and log(CPI) both were non-stationary at first difference (without trend) in ADF Tests, KPSS test reports that log(CPI) is stationary but CPI is not at the first difference. Both of them were stationary at first difference in PP tests. In case of M2, both M2 and log(M2) were non-stationary in KPSS tests even at first difference but log(M2) was stationary at PP as well as in ADF tests (at first difference). M2 at first difference was stationary only in PP tests. Surprisingly, although log(CPII) was stationary at first difference in ADF and PP tests, it is not stationary in KPSS tests (Table 3).

As shown in Table 4, although non-stationary property can be confirmed by any of the available test methods, sometimes the way we make those variables stationary and retest for confirmation might show inconsistent results. Usually, we have to be careful on those variables that cannot be stationary even at the first difference and those at the borderline of decision points. One good way might be choosing the property that has been repeated or are similar in various test results.

6.3. OLS model estimation

Following the methodology illustrated in Section 3, we should not estimate OLS model as unit root tests show that all the variables included in our model are non-stationary. However, for comparison purpose, we conduct following OLS regression using the log data in order to measure elasticity.

$$log(CPI_t) = \alpha + \beta_1 log(M2_t) + \beta_2 log(CPII_t) + \beta_3 log(NEER_t) + \varepsilon_t \tag{27}$$

The estimates of Eq. (27) are:

$$log(CPI_t) = \frac{-0.97*}{(5.75)} + \frac{0.106*log(M2_t)}{(4.04)} + \frac{0.776*log(CPII_t)}{(13.28)} + \frac{0.14*log(NEER_t)}{(3.37)} \tag{28}$$

Adj. $R^2 = 0.999$, F-stat: 12040. DW Stat: 0.686. *: significant at 5 percent or lower level.

Table 1
ADF tests results.

Variable	Intercept				Trend and intercept			
	Level		First difference		Level		First difference	
	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value
CPI	2.252	1.000	−0.996	0.754	−0.004	0.996	3.689	0.026
log(CPI)	1.375	0.999	−1.953	0.307	−2.150	0.514	−2.722	0.229
M2	4.6176	1.000	−0.653	0.854	0.904	0.999	−6.679	0.000
log(M2)	2.147	0.999	−12.160	0.000	−1.399	0.858	−12.576	0.000
NEER	−1.456	0.553	−10.736	0.000	−1.162	0.914	−10.805	0.000
log(NEER)	−1.441	0.561	−10.845	0.000	−1.139	0.918	−10.916	0.000
CPII	5.149	1.000	−9.498	0.000	0.566	0.999	−7.613	0.000
log(CPII)	3.748	1.000	−10.406	0.000	−1.177	0.911	−7.605	0.000

Table 2
Philips–Perron tests results.

Variable	Intercept				Trend and intercept			
	Level		First difference		Level		First difference	
	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value
CPI	3.705	1.000	−10.755	0.000	−1.130	0.920	−12.232	0.000
log(CPI)	2.541	1.000	−13.249	0.000	−2.535	0.311	−18.626	0.000
M2	7.46	1.000	−12.359	0.000	1.351	1.000	−14.187	0.000
log (M2)	1.662	0.999	−13.917	0.000	−1.352	0.871	−14.265	0.000
NEER	−1.127	0.704	−10.657	0.000	−0.928	0.949	−10.777	0.000
log (NEER)	−1.127	0.704	−10.819	0.000	−0.944	0.948	−10.876	0.000
CPII	3.892	1.000	−9.603	0.000	−0.587	0.978	−10.422	0.000
log (CPII)	2.541	1.000	−13.249	0.000	−2.535	0.311	−18.626	0.000

Table 3
KPSS test results.

Variable	LM Statistics KPSS tests			
	Intercept Critical value @ 5% = 0.463		Trend and intercept Critical value @ 5% = 0.146	
	Level	First difference	Level	First difference
CPI	1.579	0.732	0.417	0.032
log(CPI)	1.638	0.461	0.405	0.112
M2	1.519	1.385	0.415	0.108
log(M2)	1.647	0.527	0.347	0.102
NEER	0.466	0.267	0.342	0.072
log(NEER)	0.471	0.261	0.344	0.073
CPII	1.537	1.235	0.412	0.051
log(CPII)	1.604	0.696	0.411	0.061

Note: For not rejecting null, i.e., the variable to be stationary, LM-Stats should be smaller than the critical values and vice versa.

Table 4
Comparison of results of three unit root test methods.

Variables	ADF	PP	KPSS
CPI	Non-stationary at first difference	Non-stationary at first difference	Stationary at first difference
log(CPI)	Non-stationary at first difference	Stationary at first difference	Stationary at first difference
M2	Non-stationary at first difference	Stationary at first difference	Non-stationary at first difference
log(M2)	Stationary at first difference	Stationary at first difference	Non-stationary at first difference
CPII	Stationary at first difference	Stationary at first difference	Non-stationary at first difference
log(CPII)	Stationary at first difference	Stationary at first difference	Non-stationary at first difference

Without considering the time series properties of the data, the level data estimates show robust-looking result with high adjusted R^2 values, significant F-stat among others and all variables being significant. But the preliminary observation of non-stationarity of these series might have given spurious estimates. This can be shown by the lower value of DW-Stat (0.686) even lower than the R^2 values. Also, the Adjusted R^2 value very close to 1 (0.999) is believed to have spurious relation. Further to this, if we plot the residuals of the model, we won't get the sum zero, which violates the OLS assumptions (Annex 3 Figure A5).

6.4. VAR model estimation

The VAR models of those four variables using level data with two lags can be represented as follows:

$$log(CPI_t) = \alpha_1 + \beta_1 log(CPI_{t-1}) + \beta_2 log(CPI_{t-2}) + \beta_3 log(M2_{t-1}) + \beta_4 log(M2_{t-2})$$
$$+\beta_5 log(CPII_{t-1}) + \beta_6 log(CPII_{t-2}) + \beta_7 log(NEER_{t-1}) + \beta_8 log(NEER_{t-2}) + \varepsilon_t \tag{29}$$

$$log(CPII_t) = \alpha_2 + \gamma_1 log(CPI_{t-1}) + \gamma_2 log(CPI_{t-2}) + \gamma_3 log(M2_{t-1}) + \gamma_4 log(M2_{t-2})$$
$$+\gamma_5 log(CPII_{t-1}) + \gamma_6 log(CPII_{t-2}) + \gamma_7 log(NEER_{t-1}) + \gamma_8 log(NEER_{t-2}) + \varepsilon_t \tag{30}$$

$$log(M2_t) = \alpha_3 + \lambda_1 log(CPI_{t-1}) + \lambda_2 log(CPI_{t-2}) + \lambda_3 log(M2_{t-1}) + \lambda_4 log(M2_{t-2})$$
$$+\lambda_5 log(CPII_{t-1}) + \lambda_6 log(CPII_{t-2}) + \lambda_7 log(NEER_{t-1}) + \lambda_8 log(NEER_{t-2}) + \varepsilon_t \tag{31}$$

$$log(NEER_t) = \alpha_4 + \delta_1 log(CPI_{t-1}) + \delta_2 log(CPI_{t-2}) + \delta_3 log(M2_{t-1}) + \delta_4 log(M2_{t-2})$$
$$+\delta_5 log(CPII_{t-1}) + \delta_6 log(CPII_{t-2}) + \delta_7 log(NEER_{t-1}) + \delta_8 log(NEER_{t-2}) + \varepsilon_t \tag{32}$$

The estimates of the VAR model (Eqs. (29)−(32)) are obtained as follows:

$$log(CPI_t) = -0.39^* + 0.82^*log(CPI_{t-1}) - 0.20^*log(CPI_{t-2}) + 0.14^*log(M2_{t-1}) - 0.09log(M2_{t-2})$$
$$+0.65^*log(CPII_{t-1}) - 0.36^*log(CPII_{t-2}) - 0.21log(NEER_{t-1}) + 0.26^{**}log(NEER_{t-2}) \tag{33}$$

$$log(CPII_t) = -0.10 - 0.03log(CPI_{t-1}) + 0.01log(CPI_{t-2}) - 0.006log(M2_{t-1}) + 0.04log(M2_{t-2})$$
$$+1.13^*log(CPII_{t-1}) - 0.18^*log(CPII_{t-2}) - 0.04log(NEER_{t-1}) + 0.05log(NEER_{t-2}) \tag{34}$$

$$log(M2_t) = -0.20 + 0.08log(CPI_{t-1}) + 0.09log(CPI_{t-2}) + 0.84*log(M2_{t-1}) + 0.14log(M2_{t-2})$$
$$+0.13log(CPII_{t-1}) - 0.25log(CPII_{t-2}) - 0.44*log(NEER_{t-1}) + 0.49*log(NEER_{t-2}) \tag{35}$$

$$log(NEER_t) = 0.05 - 0.05log(CPI_{t-1}) - 0.003log(CPI_{t-2}) + 0.04log(M2_{t-1}) - 0.04log(M2_{t-2})$$
$$-0.06log(CPII_{t-1}) - 0.09log(CPII_{t-2}) + 1.18*log(NEER_{t-1}) - 0.20*log(NEER_{t-2}) \tag{36}$$

*significant at 5% or lower level of significance, **significant at 10% level of significance.
Adjusted R^2: 0.99 for CPI, CPII, M2 and 0.96 for NEER.

The VAR estimates of the level data also show robust-looking result with high adjusted R^2 values, significant F-stat among others. But the LM test stat shows the autocorrelation in residuals (we reject null hypothesis for up to 2 lags with LM Stat 56.26 and p-value 0.000). Likewise, the correlogram spikes also cross the benchmark line.

6.5. Cointegration test

The unit root tests show that all the series included in the money−price model are I(1). In this case, the series might be cointegrated which, if not addressed, may result in spurious estimates. This has been shown by the test results of OLS and VAR models presented in the preceding sections. Hence, we conduct Johansen cointegration test employing monthly series of log(CPI), log(CPII), log(M2) and log(NEER). The test results given by the EViews software are presented in Table 5.

The software reports two different types of test statistics: Trace statistics and maximum eigenvalue statistics. The calculation process of rank of the matrix slightly differs between them. The trace statistics tests for the null hypothesis of k cointegrating relations against the alternative hypothesis of k−1. On the other hand, the maximum eigenvalue statistics tests for the null hypothesis of r cointegrating relations against the alternative of r+1. In both methods, we proceed sequentially from r = 0 to r = k−1 until we fail to reject the null hypothesis. Both methods in general show the similar decisions on number of cointegration relations. In case both methods show conflicting results, there is a convention of interpreting the result based upon the economic logics and purpose of the study.

With this process, the unrestricted cointegration rank tests based on trace statistics and maximum eigenvalue both indicate that there exists one cointegration relationship. However, it is relatively weak since we reject the null hypothesis only at the 10 percent level of significance. Still, with the logic that Nepal's inflation might have cointegrated with Indian inflation (as graphical plots indicate), we can assume one cointegration relation.

Besides the number of cointegrating vectors, Johansen cointegration test also jointly estimates the long-run and short-run relationships of the variables incorporated in the model. The long-run estimates are called Beta relations while short-run estimates are Alpha relations. However, the beta coefficients are only identified when some restrictions are imposed in VECM to normalize the relationship amongst the variables.

The results of the Johansen cointegration relations are presented in Table 6.

The Johansen cointegration test results indicate that all the three variables have significant positive impact on inflation in the long run. The magnitude of impact (the coefficient) of Indian inflation is largest while that of money supply and exchange rate are almost similar. The short run relation statistics show a significant positive impact on inflation of its lag values and a negative impact of money supply.

6.6. Error correction models (ECMs)

Based on the Johansen test result of one cointegrated relation, we estimate an error correction model (ECM) as described in Section 4.5.

To identify the number of optimal lags, we can run normal unrestricted VAR and check for optimal lag lengths of the series. In our case, the optimal lag length is three as indicated by FPE, AIC and HQ criterion (Table 7).

The cointegration and error correction equation of the *LNCPI, LNCPII, LNM2* and *LNNEER* can be estimated as given below. The VECM approach estimates the long run relationship (with cointegration equation) first and then the short run relationships for each of the variables (error correction equations).

Cointegration Equation:

$$\varepsilon_t = LNCPI_t - \phi - \beta_1 LNCPII_t - \beta_2 LNM2_t - \beta_3 LNNEER_t \tag{37}$$

ECM for Nepal's CPI:

$$\Delta LNCPI_t = \mu_{LNCPI} + \alpha_{LNCPI}\varepsilon_{t-1} + \sum_{h=1}^{3} a_{1h}\Delta LNCPI_{t-h} + \sum_{h=1}^{3} b_{1h}\Delta LNCPII_{t-h} + \sum_{h=1}^{3} c_{1h}\Delta LNM2_{t-h}$$
$$+ \sum_{h=1}^{3} d_{1h}\Delta LNNEER_{t-h} + u_{LNCPIt} \tag{38}$$

ECM for Indian CPI:

$$\Delta LNCPI - I_t = \mu_{LNCPI\_I} + \alpha_{LNCPI\_I}\varepsilon_{t-1} + \sum_{h=1}^{3} a_{2h}\Delta LNCPI_{t-h} + \sum_{h=1}^{3} b_{2h}\Delta LNCPII_{t-h} + \sum_{h=1}^{3} c_{2h}\Delta LNM2_{t-h}$$
$$+ \sum_{h=1}^{3} d_{2h}\Delta LNNEER_{t-h} + u_{LNCPI\_It} \tag{39}$$

ECM for Nepal's Broad Money (M2):

Table 5
Johansen cointegration test results.

Unrestricted cointegration tank test (Trace)					Unrestricted cointegration rank test (Maximum eigenvalue)				
Hypothesized no. of CE(s)	Eigenvalue	Trace statistics	0.05 Critical value	Prob.	Hypothesized no. of CE(s)	Eigenvalue	Statistic	Critical value	Prob.
None*	0.203	67.036	47.86	0.00	None*	0.203	37.36	27.58	0.002
At most 1	0.109	29.673	29.80	0.05	At most 1	0.109	19.13	21.13	0.093
At most 2	0.049	10.541	15.49	0.24	At most 2	0.049	8.33	14.26	0.346
At most 3	0.013	2.213	3.84	0.12	At most 3	0.013	2.21	3.84	0.137

* Rejection of hypothesis at 5 percent significance level.

Table 6
Johansen cointegration relations results.

Coefficient	Estimates	Standard error
Long-run (Beta) relations		
$LNCPII_t$	0.72[b]	0.079
$LNM2_t$	0.13[b]	0.035
$LNNEER_t$	0.125[b]	0.056
Short-run (Alpha) relations		
$\Delta\log(CPII)_t$	0.055	0.056
$\Delta\log(NEER)_t$	0.049	0.038
$\Delta\log(M2)_t$	−0.16[a]	0.090
$\Delta\log(CPI)_t$	0.49[b]	0.065

[a] Significant at 10 percent level.
[b] Significant at 5 percent or lower level.

$$\Delta LNM2_t = \mu_{LNM2} + \alpha_{LNM2}\varepsilon_{t-1} + \sum_{h=1}^{3} a_{3h}\Delta\Delta LNCPI_{t-h} + \sum_{h=1}^{3} b_{3h}\Delta LNCPII_{t-h} + \sum_{h=1}^{3} c_{3h}\Delta\Delta LNM2_{t-h}$$
$$+ \sum_{h=1}^{3} d_{3h}\Delta LNNEER_{t-h} + u_{LNM2t} \tag{40}$$

ECM for Nominal Effective Exchange Rate (NEER):

$$\Delta LNNEER_t = \mu_{LNNEER} + \alpha_{LNNEER}\varepsilon_{t-1} + \sum_{h=1}^{3} a_{4h}\Delta LNCPI_{t-h} + \sum_{h=1}^{3} b_{4h}\Delta LNCPI\_I_{t-h} + \sum_{h=1}^{3} c_{4h}\Delta LNM2_{t-h}$$
$$+ \sum_{h=1}^{3} d_{4h}\Delta LNNEER_{t-h} + u_{LNNEERt} \tag{41}$$

The estimates of the coefficients of Eqs. (37–41) obtained through EViews 8 are given in Table 8[j]. The long-run relationships indicate that the contemporaneous impact of Indian CPI is about 68 percent to Nepal's CPI whereas broad money supply (M2) and nominal effective exchange rate (NEER) account about 15 percent and 10 percent respectively. All the coefficients of cointegration equation are significant at 5 percent or lower level of significance.

The short-run equilibrium coefficient of ECM (α_s) indicates that M2 helps correcting the disequilibrium of Nepal's inflation whereas exchange rate and Indian inflation does not. The coefficient for LNM2 is 0.18 and significant at 10 percent level, indicating some level of control of the central bank over inflation both in the short and long-run.

The diagnostics test results show a robust VECM estimates. The residual plot of regressors and the cointegration equation shows a random zero mean disturbances. Likewise, the inverse roots of AR lie randomly inside the circle. The LM test does not reject the null hypothesis of no autocorrelation in residuals up to three lags (Annex 4).

6.7. Autoregressive distributed lag (ARDL) model

As mentioned earlier, we estimated the determinants of Nepal's consumer price index (CPI) by including broad money supply (M2), Indian CPI (CPII) and nominal effective exchange rate (NEER) in the model. The Johansen test indicated a weak cointegration relation. On the other hand, graphical plots of CPI and CPII show a common trend, indicating a cointegration relation. Thus, it would not be wise to take first difference and estimate models as it may ignore the long run relationship. In this case, ARDL model can capture both long-run and short-run relation of the cointegrated variables. Hence, ARDL model discussed in 4.6 has been employed to revisit the money—price relationship in Nepal. Following is the model used with data in log (LN) form:

$$LNCPI_t = \alpha + \beta LNM2_t + \chi LNNEER_t + \delta LNCPII_t + e_t \tag{42}$$

The error correction version of the above model is as follows:

[j] The order of the variables has been set as decreasing order of exogeneity: LNCPII, LNNEER, LNM2 and LNCPI.

Table 7
VAR lag order selection criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
1	1992.727	NA	2.96e-16	−24.404	−24.099[a]	−24.280
2	2016.836	45.837	2.68e-16	−24.504	−23.894	−24.256
3	2045.989	53.986	2.28e−16[a]	−24.666[a]	−23.751	−24.295[a]
4	2057.528	20.799	2.41e−16	−24.611	−23.391	−24.116

LR: Likelihood ratio; FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz criterion; HQ: Hannan−Quinn criterion.
   [a] Optimal lag length.

$$\Delta LNCPI_t = \varepsilon_0 + \sum_{i=1}^{p} \phi_i \Delta LNCPI_{t-i} + \sum_{i=1}^{p} \varphi_i \Delta LNM2_{t-i} + \sum_{i=1}^{p} \gamma_i \Delta LNNEER_{t-i} + \sum_{i=1}^{p} \eta_i \Delta CPII_{t-i}$$
$$+ \lambda_1 LNCPI_{t-1} + \lambda_2 LNM2 + \lambda_3 LNNEER_{t-1} + \lambda_4 LNCPII + u_t \tag{43}$$

Above models were estimated on Microfit. The ARDL (1,0,0,1) model was selected based on Akaike Information Criterion (Table 9).

The long-run estimates of ARDL (Eqs. (42) and (43)) show that M2 and CPII are the determinants of inflation in Nepal. According to the test results, one percent change in money supply (M2) brings a change of about 0.27 percent in inflation while one percent change in Indian inflation leads to a change in Nepal's inflation by 0.43 percent. However, NEER does not seem to affect the inflation.

The diagnostic tests for the ARDL estimates indicate a white noise *i.i.d.* error terms with Homoskedasticity and normality. The null hypothesis of Lagrange multiplier test of residual serial correlation cannot be rejected, the functional form is fine, error terms distributed normally and the null hypothesis for homoskedastic error terms cannot be rejected (Annex 5).

6.8. Granger causality tests

As described in Section 4.7, the Granger causality tests show pairwise relationship, which may be one-way or two-way relationship or no relationship. To justify the inclusion of variables in the model, validate cointegration relation and know the direction of the relationship, this test serves as a complement. The summary results of the Granger causality test are presented in Table 10.

In a nutshell, the Granger causality test confirms that all the variables (CPII, NEER and M2) included in the model influence the CPI. These relationships are also theoretically valid and no other problems such as endogeneity are observed.

Table 8
Cointegration and EC estimates of Eqs. (37−41).

Coefficient	Estimates	t-stats	Equation No.
Long-run cointegration estimates			
φ	−0.965	−	Eq. 37
β_1 (LNCPII$_t$)	0.682[a]	−8.20	
β_2 (LNM2$_t$)	0.150[a]	3.997	
β_3 (LNNEER$_t$)	0.097[b]	−1.709	
Short-run ECM estimates			
α_{LNCPI}	−0.462[a]	−5.968	Eq. 38
α_{LNCPII}	−0.106[a]	−2.516	Eq. 39
α_{LNM2}	0.18[b]	1.728	Eq. 40
α_{LNNEER}	−0.052	−1.172	Eq. 41

   [a] Significant at 5 percent or lower level.
   [b] Significant at 10 percent level.

Table 9
ARDL test statistics.

Coefficient	Estimates	t-stats
Long-run estimates (Eq. (41))		
α (Constant)	−1.386**	
β (LNM2)	0.268**	2.935
λ (LNNEER)	0.130	0.795
δ (LNCPII)	0.432**	2.106
Short-run estimates (Eq. (42))		
ΔConstant	−0.414*	−1.80
ΔLNM2	0.80**	2.558
ΔLNNEER	0.039	4.178
ΔLNCPII	−0.008	2.653
Adjusted R^2		0.99
DW stat		2.15
F-stat. F(5, 162)		3316

*Significant at 10 percent level.
**Significant at 5 percent level.

Table 10
Granger causality tests.

Pair	Null hypothesis	F-Stat/(p-value)	Explanations
1	CPII does not Granger cause CPI	24.729 (0.000)	Only first hypothesis is rejected. It shows that Indian inflation has a
	CPI does not Granger cause CPII	0.8509(0.428)	unidirectional relationship with Nepal's inflation.
2	NEER does not Granger cause CPI	3.658(0.027)	Only the first hypothesis is rejected. This indicates that there exists a
	CPI does not Granger cause NEER	1.066(0.346)	unidirectional relationship of NEER with CPI.
3	M2 does not Granger cause CPI	6.089(0.002)	Only the first hypothesis is rejected. It means that there is an unidirectional
	CPI does not Granger cause M2	1.957(0.144)	relationship of M2 with CPI.
4	NEER does not Granger cause CPII	0.609(0.545)	We do not reject both null hypotheses. This indicates that there is no
	CPII does not Granger cause NEER	0.964(0.383)	relationship between NEER and CPII.
5	M2 does not Granger cause CPII	1.1823(0.309)	As both hypotheses are not rejected, we can infer that M2 and CPII are
	CPII does not Granger cause M2	1.684(0.188)	independent from each other.
6	M2 does not Granger cause NEER	1.196(0.304)	Second hypothesis is rejected. It shows that NEER affects M2 but M2 does
	NEER does not Granger cause M2	7.962 (0.000)	not affect NEER.

6.9. Summary results of different models

Nepal's money−price relationship has been modeled following the methodological framework described in Section 4 of this paper. Different models provide different coefficients of relationships as shown in Table 11.

Table 11
Summary results of estimated models.

Model	Variables incorporated	Estimates	Remarks
OLS	CPI, CPII, M2, NEER (Monthly 2000 Jan−2014 Apr)	M2 = 0.106 Adjusted R^2 = 0.99 DW = 0.686	Estimates are significant but DW stat is lower than R^2 value. It shows that the model is spurious.
VAR		M2 = 0.14 Adjusted R^2 = 0.99 LM Stat: 58 p-value: 0.00	Estimates are significant but we reject the null hypothesis of no autocorrelation in residuals.
Johansen cointegration		Long run: M2 = 0.13 Short run: M2 = −0.16	Shows one cointegration equation but relatively weak (we reject null at 10%)
ECM		Long run: M2 = 0.15 Short run: M2 = 0.18 LM stat: 13.06 p-value: 0.667	Estimates are significant and robust
ARDL		Long run: M2 = 0.27 Short Run: ΔM2 = 0.80 Adjusted R^2 = 0.99 DW = 2.15	Estimates are significant and robust.
Granger causality		A unidirectional relationship: M2 affects CPI but CPI does not affect M2.	

As discussed above, various methods report different coefficients on the impact of money on consumer price inflation in Nepal. OLS test results suggest that one percent change in M2 will lead to 0.11 percent change in CPI. According to VAR results, one percent change in M2 brings a change of 0.14 percent in CPI. However, model fitness indicators show that these results are spurious. This is due mainly to the non-stationarity of the variables included in the model. Johansen cointegration test shows that long-run coefficient of M2 is 0.13, while coefficient of M2 estimated by VECM is 0.15. According to ARDL model test results, coefficient of M2 is found to be 0.27 indicating that one percent change in M2 leads to 0.27 percent change in CPI.

7. Summary and conclusion

The unique features possessed by time series data create difficulty in method selection process while analyzing the relationship among economic variables. The autoregressiveness, stationarity, trends, cycles, seasonality and structural breaks are the most common properties of time series. These properties should be duly accommodated or addressed to make the models robust. Specifically, researchers must be aware of spurious relationship among variables. This paper suggests a general framework for time series analysis which could help in avoiding spurious regression and obtaining robust results.

Unit root test is the starting point for time series analysis. Based on the results of the unit root test, methods and models should be selected for the analysis. It is suggested that OLS, VAR or other similar models be used if all the variables are stationary. However, these models may provide spurious relationship if all or some variables are non-stationary. The diagnostics test is the significant part of time series analysis to identify spuriousness and robustness.

Johansen cointegration test method is employed when all the variables included in the model are nonstationary. In the case of mixed variables, i.e., some variables stationary but others nonstationary, Johansen cointegration method cannot be used. In such a case, ARDL models are appropriate. ARDL models also can be employed using all nonstationary variables.

Nepal's money price relationship is analyzed following the methodological framework suggested in this paper. The framework greatly helps in choosing appropriate test methods for data analysis. Analysis of the money–price relation employing ARDL model shows that in the long-run, money supply affects consumer price inflation by 27 percent. Based on the model fitness statistics, we can argue that this estimate is robust and reliable compared to the estimates given by other methods.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jfds.2017.11.001

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