Forecasting Remittance Inflows in Bangladesh

A thesis Presented by

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1 Introduction

In Bangladesh remittance plays the role of central force in the economy by Contributing in Import payment, pays foreign loans and development sector. Bangladesh is the eighth biggest remittance recipient country in the world. Remittance inflows contributed around 8.2% of the GDP in 2014, which more than offset the trade balance. As of 2015, remittance inflows stood over $15 billion. According to (world bank, 2016), international migrants' remittances provide a lifeline for millions of households in developing countries at more than three times the size of development aid and migrants hold more than $500 billion in annual savings. Together, remittances and migrant savings offer a substantial source of financing for development projects that can improve lives and livelihoods in developing countries.

Remittances undoubtedly help fuel the global economy. They alleviate poverty, feed, help educate and support millions of families all over the world. Increasingly they also provide a pathway to financial inclusion for some of the over 2 billion unbanked adults worldwide - for many, receiving a remittance is the first regular, recorded financial transaction that they make[1]. Remittances into developing countries are indeed less volatile than private capital and even more stable than FDI and remain relatively stable even during large shocks. Remittances lead to an appreciation of the real exchange rate, accompanied by the deterioration of the current account (Ratha, 2003). The short-run consequences of remittances are a blessing. The increase in imports (financed by remittances) increases the state's revenues from import tax and VAT on imports. The real exchange rate appreciation facilitates the servicing of public debt. Since liabilities of most developing governments are primarily dollar-denominated, the appreciation reduces the overall value of public debt. The inflow of foreign currency facilitates the accumulation of foreign reserves by the central bank (Gherbovet, n.d.). So to proper utilize the use of remittance and to estimate the possible appreciation or depreciation of domestic currency we need to forecast remittance flow.

ARIMA Model was used to Forecast Remittances as a Major Source of Foreign Income to Nigeria (Adedokun, 2013). In another study ARIMA and exponential smoothing models were used to describe econometric estimation of money transfers associated with remittances in Moldova (Gherbovet, n.d.). Besides a simple model using two approaches as matrix based approach and elasticity based approach used to forecasting migrant remittances during the global financial crisis (world bank, 2012). But there were many limitations of ignoring other important variables which may effect to the flow of remittance.

Although it is thought that multivariate study is a better option for forecasting, but from some studies like oil forecasting models it is seen that multivariate does not forecast better always

[1] http://blogs.worldbank.org/peoplemove/remittance-reality-getting-3-and-beyond

than univariate models. In multivariate model we need to add other variable with remittance. The problem is due to the different behavioral impact for different variables. In this case we need to be aware of these issues. The real life reason for this is that in real life market does not follow what is said in literature or theoretical models. So it gets complicated in using multivariate models.

The reason behind choosing univariate modeling is that it is the simplest method to forecast by univariate modeling. Where the future values only depend on the previous values of that one variable. Literature shows that univariate model is the best method for forecasting time series data. (Gherbovet,n.d.) Worked with two ways of forecasting using regression and times series analysis and discussed that in case of regression approach for modeling the relationship between a scalar dependent variable and one or more explanatory variables, most of the models gave wrong forecasting results as compensation equation from IMF report (IMF, 2012).

In this study we experimented with different univariate models to choose the best fitted model for the remittance flow of Bangladesh. We played with different categories of models rather than using only a general form like only exponential smoothing but different types of exponential smoothing including damped trend, and other models which are not yet used for forecasting remittances. It is not possible to exactly forecast remittance by using a forecasting model, but an approximate idea can be found from this forecasting.

In the later parts of the study we will try to explain this by using a multivariate model using VAR and compare the results from that of univariate results.

1.2 Motivation of the study

There are many empirical analyses on remittance, where remittance is used both as an independent and dependent variable(s). So far, no study has considered studying a forecasting model of remittance inflows. We fill this gap in the literature by examining both univariate and multivariate forecasting models of remittance, in the context of Bangladesh. We are forecasting remittance inflows as forecasting key economic variables is of high interest to any policymaking, knowledge of trend and cycle in remittance is crucial to understanding the behaviour of remittance and forecasting is an interesting academic exercise. Through learning-by-doing, sophisticated forecasting models may be developed over time.

1.3 Impacts of remittance in economy

Common effects of remittances are found from micro evidence as income insurance by playing as an anti-poverty role. It works as a means for investment by contributing higher investment in education and healthcare. In the macro perspective, it works as a source of foreign exchange reserve if transferred through formal channels. It stimulates aggregate demand and hence economic growth through increased consumption, demand for local goods or services and job creation. It helps to increase bilateral trade in home and host countries. It also affects price level in the presence of a weaker monetary control.

Table 1: Impacts of migrants' remittances on economy

	For	**Against**
	Impacts of remittances' at micro level	
As a social insurance	Plays the role as a powerful anti-poverty role. A 10 percent increase in the remittance flow from every remitter will lead to a decrease in 3.5 percent people under poverty	Create a culture of dependency and deepens the vulnerabilities of recipients
As a means for investment	Contributes for higher investment in health care and add value to local human capital by ensuring improved investment in education	Does not necessarily leads to long-term investment as it is usually spent on consumption
	Impacts of remittances' at a macro level	
As a source of revenue for local government	Increase national income if remittances are transferred through formal channels	
Impact on national economy	Boost local economies by stimulating consumption, demand for local goods or services through multiplier effect and fostering job creation	remittances impact positively on GDP growth when the financial markets are relatively underdeveloped
Impact on trade	Helps in import payment	Large remittance flows could lead to currency appreciation, with negative consequences on exports and increase the propensity to import more
As a financial tool	Act as substitute to other financial means such as credit and insurance. Raise domestic savings and improve financial intermediation	May reduce the recipients' likelihood to work, and increase the private consumption of imported goods instead of financing domestic investments or savings
Impact on price		Rise in inflation with weaker

level		monetary control
Impacts on inequalities		Aggravate regional inequalities between receiving and non-receiving areas. Increase inequality between international and internal migrants alike between migrants and non-migrants

2 Literature Review

Silva and Rajapaksa (2014) uses a variety of parametric and nonparametric forecasting techniques in R to analyze and evaluate Sri Lanka's energy consumption forecasts for electricity, petroleum, coal and renewable electricity. They use annual time series using net Consumption data from 1980–2010 and applied SSA model for forecasting and compare the results against the popular benchmarks of ARIMA, ETS, HW, TBATS, and NN. On average, the SSA model is found to be best for energy consumption forecasting in Sri Lanka whilst the Neural Networks model is second best.

Athanasopoulos G. at all (2011) Forecasts tourist arrivals using time-varying parameter by combining two models STSM and TVP and create a new model, the TVP-STSM which is employed for modeling and forecasting quarterly tourist arrivals to Hong Kong from four key source markets: China, South Korea, the UK and the USA. Quarterly data is used for the period 1985 to 2008, within which the data from 1985 to 2004 are employed for model estimation and the rest are used for forecasting comparisons. The empirical results shows that the TVP-STSM outperforms all seven competitors named CSM, TVP, BSM, ADLM, SARIMA, Naïve 1 and Naïve 2 including the basic and causal STSMs and the TVP model for one to four-quarters-ahead ex post forecasts and one-quarter-ahead ex ante forecasts.

Nakamura (2005) evaluates the usefulness of neural networks for inflation forecasting. In a pseudo-out-of-sample forecasting experiment using quarterly U.S. data the U.S. GDP deflector from 1960 to 2003. He uses a fixed scheme pseudo-out-of-sample forecasting approach to compare the NN and AR models. He finds that neural networks outperform univariate auto-regressive models on average for short horizons of one and two quarters.

Less work has done on remittance on Bangladesh till date and most of them are regarding the relationship between remittance flow and growth of GDP. Siddique (2010) investigates the causal link between remittances and economic growth in three countries, Bangladesh, India and Sri Lanka, by employing the Granger causality test under a VAR framework Using time series data over a 1975 to 2005 period, they found that growth in remittances does lead to economic growth in Bangladesh. In India, there seems to be no causal relationship between growth in remittances and economic growth; but in Sri Lanka, a two-way directional causality is found; namely economic growth influences growth in remittances and vice-versa.

Barua (2007) Identified macroeconomic determinants of inflow of workers' remittances in the context of Bangladesh. He used a balanced panel dataset of bilateral remittance flows from 10 major host countries (of Bangladeshi migrants') to Bangladesh over the 1993 to 2005 period. He found that income differential between host and home country is positively correlated with the inflow of remittances. Inflation differential between home and host country is also found to be negatively correlated with the inflow of remittances, indicating that higher inflation in home country relative to host country may have exerted some negative effect on workers' remittances. Devaluation of domestic currency or (increase in exchange rate) appeared to be positively correlated with the flow of workers' remittances in Bangladesh.

Only one work has done on forecasting remittances (World Bank, 2012) by adopting a simple model for forecasting remittances which is based on two approaches. One is remittance matrix based approach and another is elasticity based approach. In matrix based approach it is assumed that remittance flow will change at the same rate as income of migrants change in the host country. On the other hand the elasticity based approach recognizes that remittances can grow faster than the income of host country .which suggests the elasticity may be more than one. It may happen due to other facts of remittances like improved technologies and falling costs to send remittances increase in migrant stocks.

Elasticity based approach is more broadly accepted and applied in recent works for forecasting remittances where there is a lack of official data on remittances. This is indeed a good work for forecasting remittances and performed well in estimation remittances in global financial crisis but the model is quite complicated and there is some limitation on the models like ignoring the feature return migration which is a risk factor for remittances. The actual returns turned out to be smaller in the crisis period which suggests that there need a high frequency data, and they ignored the effect of exchange rate movements, response of falling costs of remittances which may have significant effect on investment decision of remittances.

These issues highlighted the need for forecasting remittances in developing countries where it has proved to be a lifeline to poor and policy makers. This in turn reflects that an improved methodology is needed to better forecast the remittance flows in Bangladesh.

3 Data

The sources of data are IMF and Bangladesh bank. The data span is from 1980 first quarter to 2014 fourth quarter expressed in million US \$. Our main variable is worker remittances for Bangladesh. The reason behind choosing quarterly data other than monthly or yearly data is that, monthly data from 1980 is not available and if used, there were more volatility, which is not our focus in this study. In case of using yearly data, the observations would be very less and if used, the seasonal fluctuations would be rounded and seasonality will not be found in that case.

For the multivariate model three variables are used a) a measure of global real economic activity from kilian(2009)[2], b)oil price and c) remittance flow. Global economic activity data has taken from Kilian's website and oil price data was taken from Federal Reserve of St. Louis[3].

3.1 Methodology[4]

Different forecasting methods used including ARIMA (different variations), Exponential smoothing (including various variations), Artificial neural network, BATS (Box-Cox transformation of ARMA, trend, seasonality), STL (Seasonal and Trend decomposition using Loess), hybrid forecast and other naïve tests for univariate forecasting. For multivariate forecasting a Vector Autoregression (VAR) model is used using three variables, a measure of global real economic activity, oil price and remittance flows. The whole estimation is done in **R** using **forecast** package.

Mean forecast method assumes the forecasts of all future values equal to the mean of the historical data. The forecasts can be given by:

$$\hat{y}_{T+h} = \bar{y} = \frac{y_1 + \cdots y_T}{T} \qquad (1)$$

Where $\hat{y}_{T+h}$ is a short-hand for the estimate of y_{T+h} based on the historical data $y_1, \ldots, y_T$

Naive forecast is about setting all forecasts to be the value of the last observation. Here the forecasts of all future values are set to be y_T, where y_T is the last observed value in the previous equation. By the same approach **Seasonal Naïve method**, assumes the forecast is to

[2] http://bwl.univie.ac.at/fileadmin/user_upload/lehrstuhl_ind_en_uw/lehre/ws1011/SE_Int._Energy_Mgmt/Buchner.pdf

[3] https://www.stlouisfed.org/

[4] This section draws heavily on Hyndman and Athanasopoulos (2013)

be equal to the last observed value from the same season of the time period. The forecast for time y_{T+h} can be written as:

$$y_{T+h-km} \qquad (2)$$

Where m= seasonal period,$k = \left[\frac{h-1}{m}\right] + 1$ and $[u]$ denotes the integer part of u.

ETS method automatically chooses a model by default using the AIC, AICc or BIC. It can handle any combination of trend, seasonality and damping Produces prediction intervals for every model ensures the parameters are admissible. Each model has an observation equation and transition equations, one for each state (level, trend, seasonal).

Exponential smoothing forecasts are calculated using weighted averages where the most weight is given in most recent observation. The equation can be written as:

Exponential smoothing model:

$y_{T+1} = \alpha y_T + \alpha(1-\alpha)y_{T-\mathbf{1}} + \alpha(1-\alpha)^2 y_{T-\mathbf{2}}+..$, **(3)**

Trend Component		Seasonal Component N (None)	A (Additive)	M (Multiplicative)
N	(None)	N,N	N,A	N,M
A	(Additive)	A,N	A,A	A,M
A_d	(Additive damped)	A_d,N	A_d,A	A_d,M
M	(Multiplicative)	M,N	M,A	M,M
M_d	(Multiplicative damped)	M_d,N	M_d,A	M_d,M

Where $\mathbf{0} \le \boldsymbol{\alpha} \le \mathbf{1}$ is the smoothing parameter. The one-step-ahead forecast for time $T+1$ is a weighted average of all the observations in the series $y_1, \dots, y_T$. The rate at which the weights decrease is controlled by the parameterα.

For any α between 0 and 1, the weights attached to the observations decrease exponentially as we go back in time. If α is small (i.e., close to 0), more weight is given to observations from the more distant past. If α is large (i.e., close to 1), more weight is given to the more recent observations. At the extreme case where $\alpha = 1$, $\hat{y}_{T+1} = y_T$ and forecasts are equal to the naïve forecasts.

Simple exponential smoothing method is used for forecasting data with no trend or seasonal pattern. This can be expressed as:

$$\hat{y}_{t+1} = l_t \qquad 4)$$

$$l_t = \alpha y_t + (1-\alpha) l_{t-1} \qquad (5)$$

Holt's (1957) linear trend method is about allowing a trend in simple exponential smoothing to forecast time series. It involves one forecasting equation and two smoothing equations:

$$\boldsymbol{\hat{y}_{t+h} = l_t + h b_t} \qquad (6)$$

$$\boldsymbol{l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1})} \qquad (7)$$

$$\boldsymbol{b_t = \beta^*(l_t - l_{t-1)} + (1-\beta^*) b_{t-1}} \qquad (8)$$

Where $\boldsymbol{l_t}$ denotes an estimate of the level of the series at time$t$, $\boldsymbol{b_t}$ denotes an estimate of the trend (slope) of the series at time t .

Holt's exponential trend model assumes that the level and the slope are to be multiplied rather than added. It is given by:

$$\boldsymbol{\hat{y}_{t+h} = l_t b^h{}_t} \qquad (9)$$

$$\boldsymbol{l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1})} \qquad (10)$$

$$\boldsymbol{b_t = \beta^* \frac{l_t}{l_{t-1}} + (1-\beta^*) b_{t-1}} \qquad (11)$$

Where $\boldsymbol{b_t}$now represents an estimated growth rate (in relative terms) which is multiplied rather than added to the estimated level.

Holt's damped trend method by Gardner and McKenzie (1985)[5]. In conjunction with the smoothing parameters α and β^*(with values between 0 and 1 as in Holt's method), this method also includes a damping parameter $0 < \varphi < 1$

Additive Holt damped equation:

Observed series $\boldsymbol{y_{t+h} = l_t + (\varphi + \varphi^2 + \cdots + \varphi^h) b_t}$ (12)

Level $\boldsymbol{l_t = \alpha y_t + (1 - \alpha)(l_{t-1} + \varphi b_{t-1})}$ (13)

Gradient $\boldsymbol{b_t = \beta^*(l_t - l_{t-1}) + (1 - \beta^*)\varphi b_{t-1}}$ (14)

Here, If $\boldsymbol{\varphi}$**=1**the method is identical to Holt's linear method. For values between 0and 1, $\boldsymbol{\varphi}$ dampens the trend so that it approaches a constant sometime in the future.

Holt winter's method is used to capture seasonality. The Holt-Winters seasonal method comprises the forecast equation and three smoothing equations — one for the level $\boldsymbol{l_t}$, one for trend$\boldsymbol{b_t}$, and one for the seasonal component denoted by $\boldsymbol{s_t}$, with smoothing parameters $\boldsymbol{\alpha}$, $\boldsymbol{\beta^*}$ and $\boldsymbol{\gamma}$.

Holt winters additive equation:

Observed series $\boldsymbol{\hat{y}_{t+h} = l_t + h b_t + s_{t-m+h_m}}$ (15)

Level $\boldsymbol{l_t = \alpha(y_t - s_{t-m}) + (1 - \alpha)(l_{t-1} + b_{t-1})}$ (16)

Gradient $\boldsymbol{b_t = \beta^*(l_t - l_{t-1}) + (1 - \beta^*) b_{t-1}}$ (17)

Seasonality $\boldsymbol{s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + 1 - \gamma) s_{t-m}}$ (18)

Here m denotes the period of the seasonality, the method of seasonality depends on the seasonal variation being constant or proportional to the level of the series respectively to additive or multiplicative.

STL method is a very versatile and robust method for decomposing time series with any type of seasonality.

Auto arima function combines unit root tests, minimization of the AICc and MLE to obtain an ARIMA model. The algorithm follows different steps to determine the values for p, q and d. The best model (with smallest AICc) is selected from different combinations.

A simple ARIMA (1, 1, 1,) is

$$\boldsymbol{y_t = \alpha + \rho y_{t-1} + \theta_{\varepsilon_{t-1}} + \varepsilon_t}$$

[5] https://www.otexts.org/fpp/7/4

In addition to this **Log** has taken in ARIMA to reduce variability.

Artificial neural networks (ANN) are parallel, distributed information processing computational models which draw their inspiration from neurons in the brain.

BATS model includes Box-Cox transform, ARMA errors, Trend, and Seasonal components. It is supplemented with to indicate the Box-Cox parameter, damping parameter, ARMA parameters (p and q), and the seasonal periods. The BATS model is the most obvious generalization of the traditional seasonal innovations models to allow for multiple seasonal periods.

Hybrid forecast is used to combine the forecast results generated from auto.arima(), ets(), nnetar(), stlm(), and tbats(). This can be combined with equal weights or weights based on in-sample errors from these models.

3.2 Model selection criteria

We evaluated forecast accuracy using training and test sets by considering how well the model performs on new data that were not used when fitting the model. For choosing models, we used a portion of the available data for fitting, and used the rest of the data for testing the model. Then the testing data is used to measure how well the model is likely to forecast on new data.

Here we used MASE to select the best fitted model for the forecasting of the remittance flow of Bangladesh. Because Scaled errors were proposed by Hyndman and Koehler (2006) as an alternative to using percentage errors when comparing forecast accuracy across series on different scales. They proposed scaling the errors based on the *training* MAE from a simple forecast method.

The *mean absolute scaled error* is simply

$$MASE = mean(|q_j|)$$

The result is independent of the scale of the data. A scaled error is less than one if it arises from a better forecast than the average one-step, naïve forecast computed in sample. Conversely, it is greater than one if the forecast is worse than the average one-step; naïve forecast computed in-sample.

4 Empirical Results

Figure 1: Remittance inflows in Bangladesh (million US$)

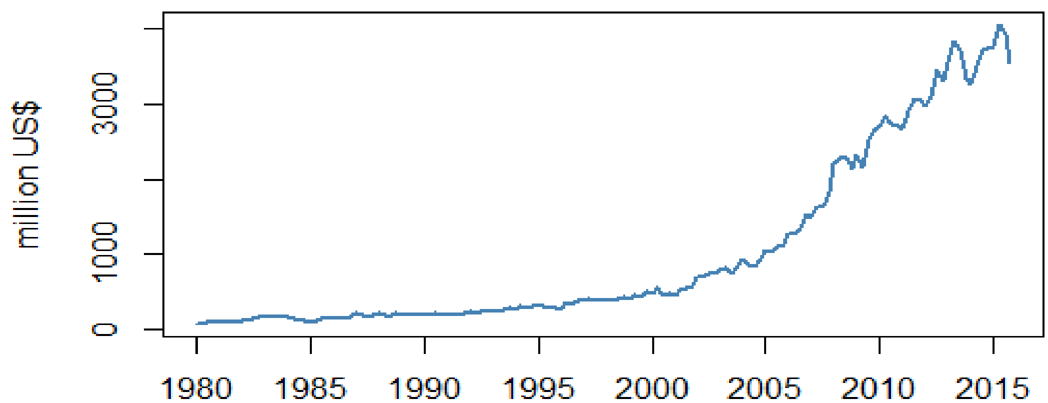
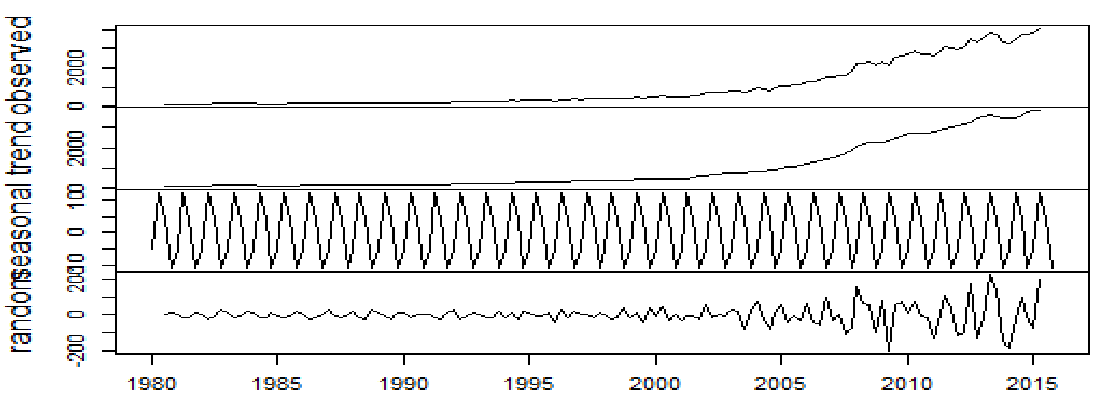


Figure 2: Decomposition of remittance inflows in Bangladesh (million US$)



4.1 Descriptive statistics (remittance)

Table 2: descriptive statistics and unit root tests

Table 1: Descriptive statistics and unit root tests

Statistics	1981–1990	1991–2000	2001–2010	2011–2015	1980-2015
Average ($M)	154.44	331.64	1439.22	3424.81	1012.83
CV	0.23	0.29	0.53	0.11	1.17
AAGR (%)	7.16	9.65	19.66	5.95	11.59
Q-test	90.52***	167.41***	195.14***	21.60***	1929.65***
Normality	8.04**	3.38	8.48***	1.08	21.65***
DF-GLS					-2.401
KPSS					0.322**

The sample period is 1980Q1–2015Q4. CV denotes coefficient of variation. AAGR refers to annual average growth rate. Q-test refers to the Ljung and Box (1978) test statistic for autocorrelation. Normality is a test of normality based on D'Agostino et al. (1990) and Royston (1991). DF-GLS (and KPSS) refer to unit root (and stationarity) tests by Elliott et al. (1996) and Kwiatkowski et al. (1992), respectively. ***: p-value < 0.01; **: p-value < 0.05.

Table 2 shows selected descriptive statistics for (original) remittance inflows at different time intervals. From 1980 to 2000, both the level and variance of remittance inflows were low, indicating a period of low but stable remittance base. The AAGR (annual average growth rate) in the first two decades of the sample reflect the low base of inflows at that time. The decade of 2001 to 2010 clearly marks a big success for the country's remittance income. On average, remittance inflow in each quarter exceeded $1.4 billion without a commensurate increase in volatility (as indicated by the value of coefficient of variation). As a result, the growth accelerated to an AAGR of nearly 20% in that decade. Over the past years, the level of remittance inflows continued to increase, well in excess of average annual inflow of $14 billion. Moreover, these inflows were much less volatile than they used to be. The relatively modest AAGR of 5.95% reflects a high base effect following a 20% growth in the previous decade. Over the entire sample period, remittance inflows grew at an AAGR of 11.59% (in nominal terms). The large, positive and significance autocorrelations (indicated by the Q-test) for quarterly lags indicates that remittance inflows show sign of persistence.

Inflows are the mass movement of temporary migrant workers to a larger number of countries across the globe (Mamun and Nath, 2010). Normality is rejected for the entire sample, although more recent data suggest normality. The last two rows in Table 2 shows the results of the DF-

GLS unit root test of Elliott et al. (1996)[6] and the stationary test of Kwiatkowski et al. (1996)[7]. Both tests allow a constant and a linear trend as deterministic components in the test regressions. Optimal lag length for the DF-GLS is chosen using the modified AIC procedure of Ng and Perron (2001)[8], while KPSS test uses an automatic bandwidth selection procedure as described in Hobijn et al. (1998)[9]. At the 5% significance level, the critical value of the DF-GLS test is -2.952, implying that the null hypothesis of a unit root cannot be rejected. Similarly, the 5% level critical value for the KPSS test is 0.146, suggesting that we can reject the null hypothesis of stationarity. All in all, the results of both tests indicate that the (log) of remittance inflows exhibits a unit root process or, equivalently the series is nonstationary.

To shed light on the analysis that follows, Figure 2 plot a decomposition of remittance inflows over the entire sample period. Such decomposition offers an intuitive way to identify the relative importance of different components (i.e., trend, seasonality, error) in the underlying data. Some remarks are in order. The top panel of Figure 2 plots the original data, which shows that after a full in the rest two decades, remittance inflows picked up steadily by the early 2000s. Since then, there is a strong upward trend in remittance inflows, as evident by the second plot labeled as trend in Figure 2. The seasonal factor exhibits a regularly repeating pattern, implying that an additive model is useful for decomposing the observed data. The random component shows sharp fluctuations in remittance inflows in recent years. Possible explanations include movements of local currency against currencies in destination countries, changes in migration flows, cyclical changes in income in destination countries, among other factors. Based on a survey of 217 migrant households in Bangladesh, Sugiarto et al. (2010a) document adverse micro-level impact of the global financial crisis on employment opportunities abroad and remittance receipts. At the macro-level, however, Sugiarto et al. (2010a) find that the impact of recent global economic turmoil on Bangladesh's remittance income was rather temporary.

4.2 Univariate forecasting

The forecasting is conducted by splitting the sample into two periods. Where “training” set included the data from 2000 to 2013 and the “test” set included from 2014 to 2015. In order to evaluate the forecasting accuracy of alternative (univariate) models, we used different forecast accuracy measures namely ME, RMSE, MAE, MPE, MAPE, MASE, ACF1 and

[6] http://www.ssc.wisc.edu/~bhansen/718/ElliottRothenbergStock.pdf
[7] http://www.stat.yale.edu/~lc436/papers/Caner_Kilian.pdf
[8] http://www.columbia.edu/~sn2294/pub/ecta01.pdf
[9] http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.224.9518&rep=rep1&type=pdf

Theil's U. among all these measures we selected the best fitted model based on MASE as it is independent to different scales of data.[10]

Table 3: Accuracy measure in test data

Forecasting model	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	Theil's U
Holt damped test	-0.01	0.05	0.04	-0.12	0.47	***0.24***	0.08	0.79
Hybrid test	-0.06	0.08	0.06	-0.70	0.70	***0.36***	0.15	1.27
BATS test	0.01	0.07	0.06	0.10	0.75	***0.38***	0.08	1.06
S. Naive test	0.02	0.07	0.06	0.25	0.79	***0.40***	0.52	1.16
STL test	-0.08	0.11	0.08	-1.02	1.02	***0.52***	0.15	1.75
ARIMA test	-0.09	0.11	0.09	-1.06	1.06	***0.54***	0.22	1.85
ES test	0.10	0.12	0.10	1.19	1.26	***0.65***	0.37	2.07
Naive test	0.10	0.12	0.10	1.19	1.26	***0.65***	0.37	2.07
ARIMA test (log)	-0.11	0.14	0.11	-1.39	1.39	***0.71***	0.29	2.35
ANN test	0.12	0.14	0.13	1.49	1.53	***0.78***	0.34	2.49
Holt Winters test	-0.13	0.14	0.13	-1.59	1.59	***0.81***	0.22	2.40
Holt linear test	-0.13	0.15	0.13	-1.61	1.61	***0.82***	0.25	2.53
ETS test	-0.13	0.15	0.13	-1.61	1.61	***0.82***	0.25	2.53
Holt ES test	-0.15	0.17	0.15	-1.84	1.84	***0.94***	0.27	2.84
linear trend test	-0.37	0.37	0.37	-4.48	4.48	***2.29***	0.27	6.23
Mean test	0.95	0.95	0.95	11.51	11.51	***5.89***	0.37	16.01

Best fitted model:

Here we can see the best selected model is Holt damped model for forecasting remittance flow in Bangladesh for the selected time period. It is seen that it has the lowest MASE 0.24 compared to other forecasting models. It is also the best fitted model based on other accuracy measures.

[10] http://robjhyndman.com/papers/foresight.pdf

Holt's damped method (results):

Smoothing parameters:

Alpha = 0.7579

Beta = 1e-04

Phi = 0.98

Initial states:

l = 6.1322

b = 0.059

Sigma: 0.0739

Figure 3: Comparison between Holt damped in sample forecast and actual data (in log value)

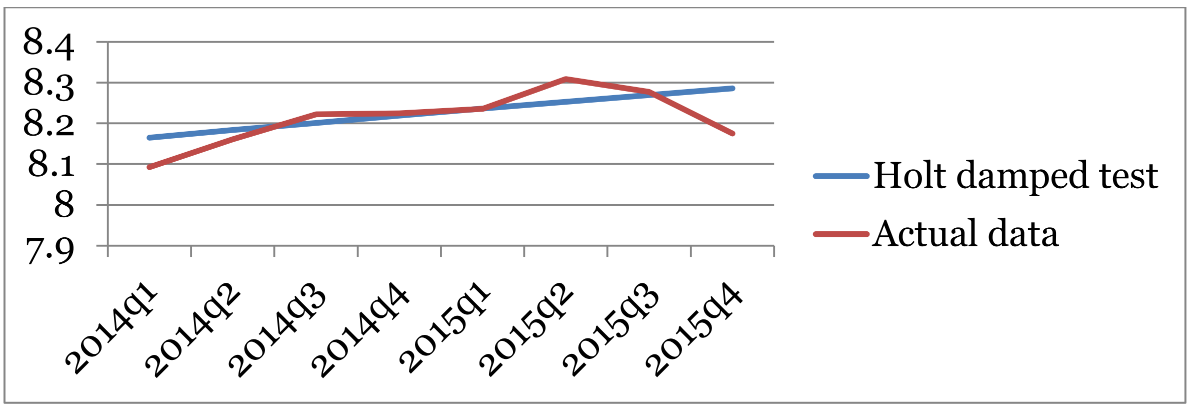


Figure 4: Out of sample forecast of Holt's damped trend method

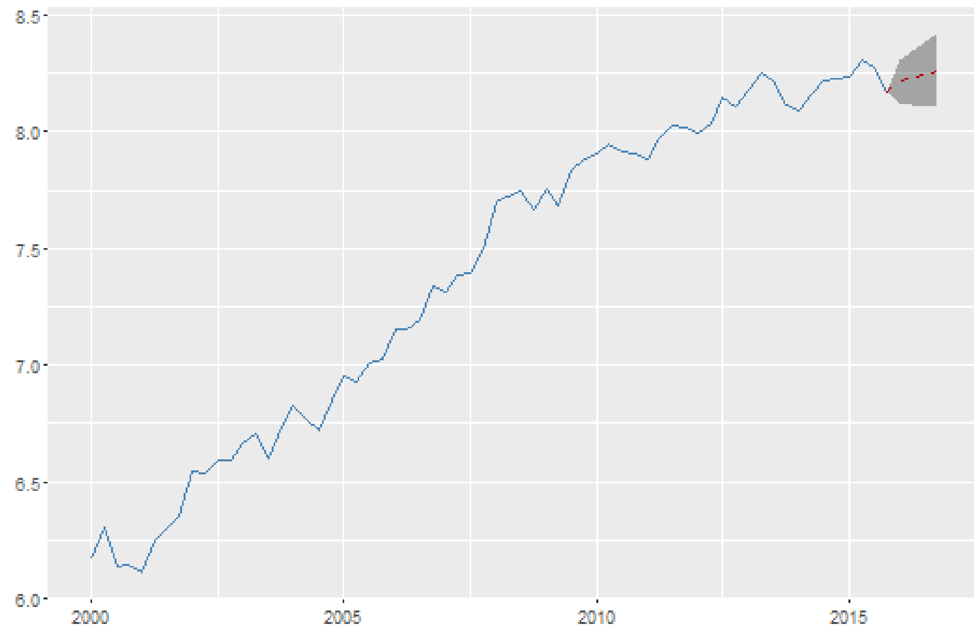
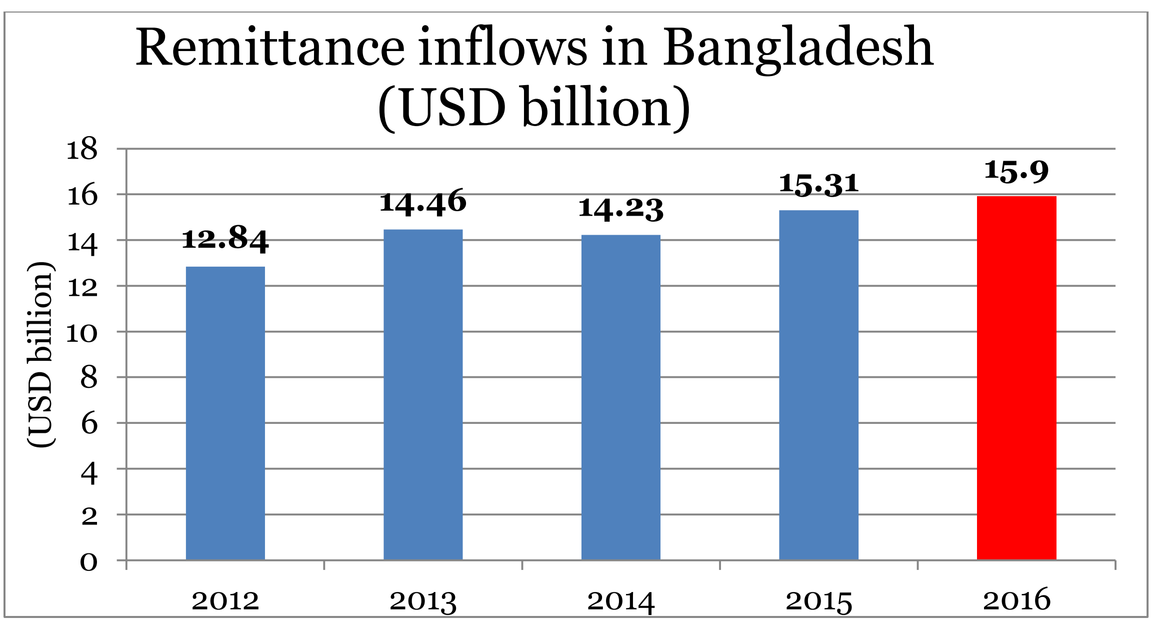


Figure 5: Actual data from 2012 to 2015 and forecast for 2016 by Holt damped (in USD billion)



4.3 Robustness check

If the window is changed in the ratio of 80% and 20% for training and test data set as suggested by Rob J Hyndman it is seen that the top model remains Holt damped. This reveals the robustness of the model. It is needed to specify that the window 2013 matched well with all the models (which have been used for the final result). It is needed to specify that if the window is set to 2010, it matched very well with only Holt damped model but not with other models. As a result it is seen that the result of MASE for Holt damped in this window decreased but for other models it increased compared to the 2013 window. It may be explained that the Holt damped model works well with all different combinations of windows.

4.4 Multivariate forecasting

Choice of the variables: three variables are chosen for the multivariate forecasting of remittance flow of Bangladesh. Global economic activities and price of oil. It is assumed that global oil price, global economic activity and remittance flow related to each other. As the destination of most of the migrants are middle east (oil exporting) countries, so the fluctuation global oil price may affect the construction works in those host countries, (which is very much correlated to global oil price) employment generation in construction sector (where most of the Bangladeshi migrants are construction workers), may directly affect the job loss and decreased flow in remittance.

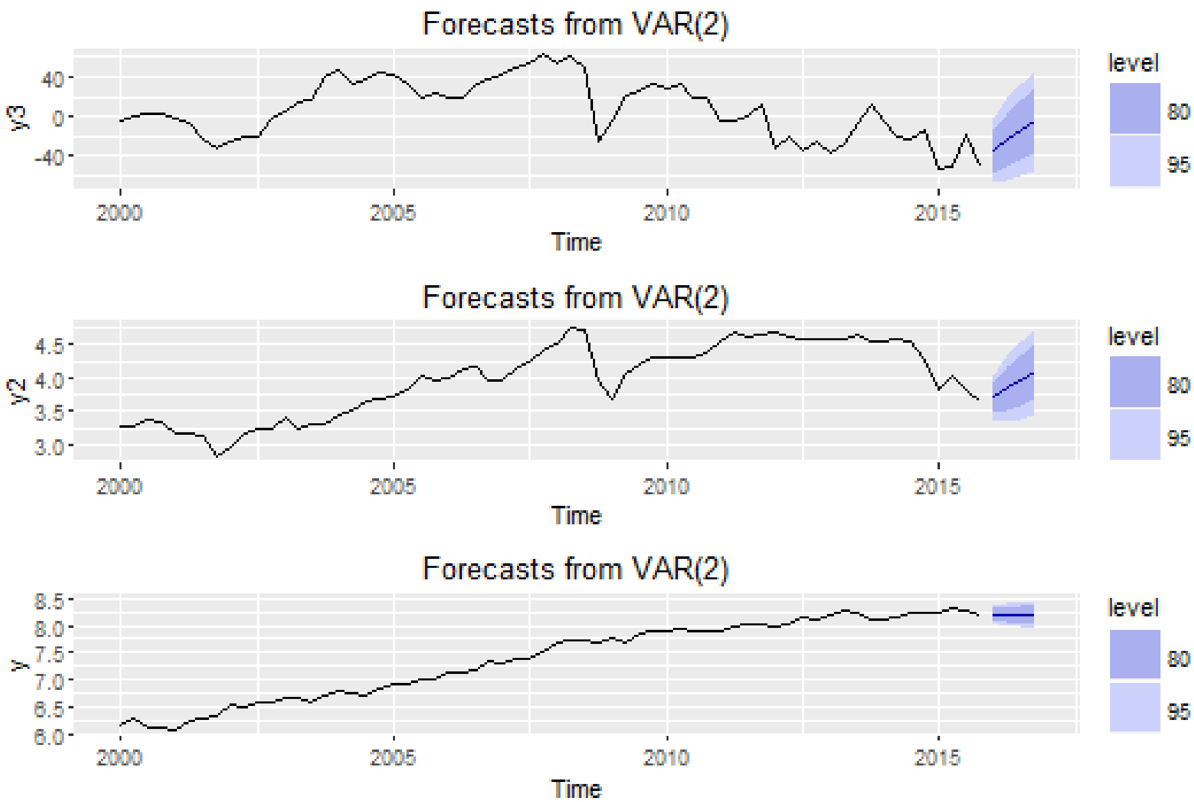
Model selection:

A three variable VAR model is selected for the forecasting. The empirical model uses natural logarithm of global oil price (loilp), global economic activity (gea) and natural logarithm of remittance flow of Bangladesh (lremit). Our var model is based on data for gea= (loilp,lremit). Lag length is selected to two periods. The reduced form VAR (2) is given by

$$\begin{bmatrix} gea_t \\ loil_t \\ lremit_t \end{bmatrix} = \mu + \beta_1 \begin{bmatrix} gea_{t-1} \\ loil_{t-1} \\ lremit_{t-1} \end{bmatrix} + \beta_2 \begin{bmatrix} gea_{t-2} \\ loil_{t-2} \\ lremit_{t-2} \end{bmatrix} + e_t$$

Where μ is a 3×1 vector of intercepts, β_1 and β_2 are 3×3 matrics of parametres and e_t is the 3×1 IID errors with mean 0 and covariance$\sum$.

Figure 6: Forecasts from VAR (2) model

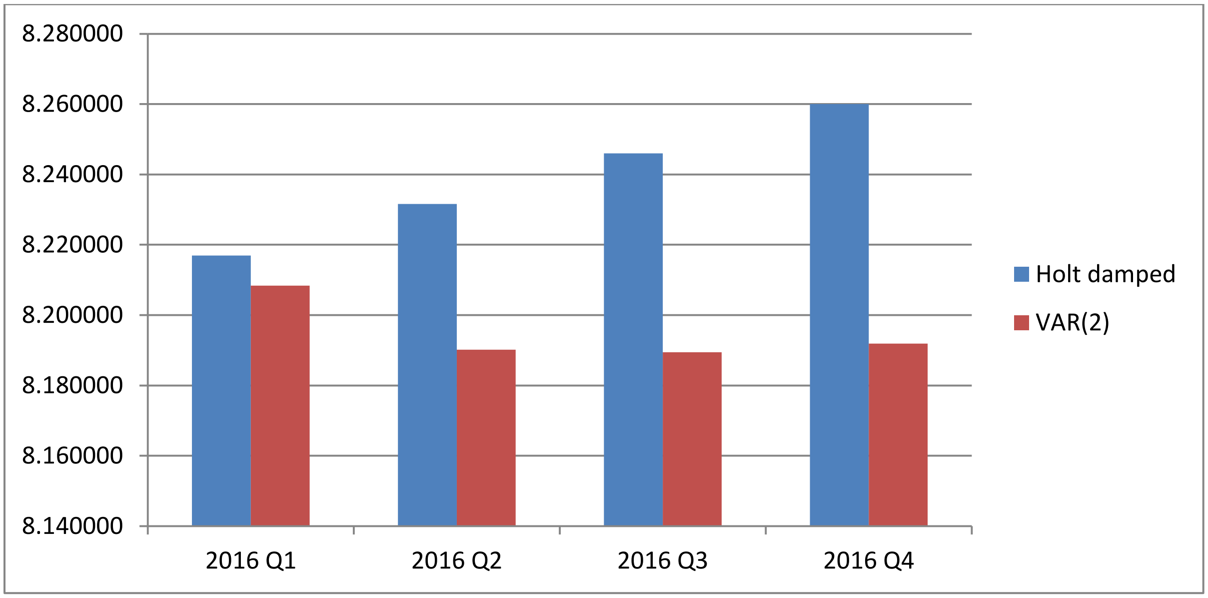


Notes: herey_3, y_2, y and denotes gea, loil and lremit respectively

Table 4: Forecast comparison between Holt damped and VAR (2)

Quarter	Holt damped	VAR(2)
2016 Q1	8.216918	8.208374
2016 Q2	8.231581	8.190129
2016 Q3	8.245951	8.189450
2016 Q4	8.260034	8.191885

Figure 7: Comparison among Holt damped, combined and multivariate forecast for out of sample (in log value)



Here we will compare the out-of-sample forecasts from VAR with that of Holt's damped method. It is seen that remittance flow of Bangladesh for the four quarters of 2016 is over estimated in holt damped model, whereas forecasting from VAR(2) is decreasing, which goes with the real scenario of remittance flow for the first quarter of 2016.

Table 5: Point Forecast of lremit for next four quarters

Quarter	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2016 Q1	8.208374	8.112320	8.304428	8.061472	8.355276
2016 Q2	8.190129	8.065470	8.314787	7.999480	8.380777
2016 Q3	8.189450	8.040908	8.337992	7.962275	8.416625
2016 Q4	8.191885	8.022093	8.361677	7.932211	8.451560

Note: values in natural log

Further analysis from the upper and lower limit suggests the same interpretation as VAR (2) forecast explains the real flow of remittance in forecasting periods. From the lower 95 level value for quarter 1, 2016, the estimated decrease of remittance flow of that period is close to that of actual decrease of remittance for the same period. This explains the robustness of multivariate forecasting over that of univariate models.

4.5 Limitations of the study

There are limitations of the study regarding using more variables in multivariate model along with different approaches of multivariate forecasting. An additional aspect may be studied by analyzing the impact of structural changes of the economy in different time periods.

5 Conclusion

Remittance plays a big role in our economy, yet to date no effort is given to build a forecasting model for remittance.This research fills this gap. Recent advances in time series econometrics made forecasting exercise much easier. By using different univariate models and a multivariate model for forecasting the remittance flow of Bangladesh, it is found that multivariate models forecasts better hat univariate models, as fluctuations in remittance flow in Bangladesh not only affected by its own previous values but also with global indicators like global economic activity and global oil price. This study may be extended through studying different remittance receiving countries in different regions.

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