

Examining Volatility of Interbank Rate in Nepal

Suman Neupane*

Abstract

This paper attempts to examine volatility pattern of interbank rate of Nepal using daily and monthly data. The empirical results show significant variation in volatility during the period of study. It depicts the clustering of large and small variances of interbank rate. Moreover, as the sum of ARCH and GARCH coefficients are greater than unity in the daily interbank rate, shocks are highly persistent in the interbank market. However, the SLF of NRB has been observed to lower the persistence of shocks, as the sum of ARCH and GARCH coefficients decreases when effect of SLF and repo are introduced in the model. It depicts that SLF and repo of NRB has been effective to lower the persistence of shocks on daily interbank market, but it increased the mean of conditional volatility. The other important finding of the study is that mean conditional volatility is highest in February and lowest in August.

I. INTRODUCTION

Interbank rate is an interest rate at which banks borrow and lend their funds in the money market for short term. It is an overnight lending of one bank to another. Most importantly, it contains information whether the market is tight or excess of liquidity. The rate gives essential signals for central bank to understand the money market condition.

In liberal economy, the interbank rate (IBR) is closely linked with other interest rates in the market. Therefore, many central banks implement monetary policy in such a way that the interbank rate does not deviate much from the central bank's policy rates. Understanding volatility of interbank rate is important for the central bank to identify whether the pressure on interbank rate arises from demand side, supply side or exogenous factors and whether intervention in market is required or it dies out automatically.

* Assistant Director, Research Department, Nepal Rastra Bank, email: neupsuman@gmail.com

Remarks: The views expressed in this paper are those of author and do not necessarily represent those of the Nepal Rastra Bank

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Van't Dack (1999) observes that most central banks favor a smooth trend in key short-term interest rates and are willing to act towards reducing volatility. This is because volatile interest rates are often seen as obscuring policy signals, while more orderly market conditions are often seen as promoting a more rapid and more predictable transmission of monetary policy. Also, less volatile interest rate conditions are seen as helpful for financial institutions in better management of their exposure to market risks. Gray, Hoggarth and Place (2000) argue that central banks consider volatility in short-run interest rates to be potentially harmful to the economy; so they choose to smoothen the change in the price of money whenever possible.

Recent developments in financial econometrics suggest the use of nonlinear time series structures to model the attitude of investors toward risk and expected return. Therefore, in comparison to linear OLS models, which are based on the assumptions of constant mean and variance, autoregressive conditional heteroscedasticity (ARCH) models are advanced in forecasting conditional volatility of high frequency financial time series. Campbell and MacKinlay (1997) argue that it is both logically inconsistent and statistically inefficient to use volatility measures that are based on the assumption of constant volatility over some period when the resulting series moves through time. In the case of financial data, viz. stock returns, interest rates, inflation etc., the large and small errors tend to occur in clusters, i.e., large returns are followed by more large returns, and small returns by more small returns. In such case, ARCH models are widely applicable to forecast the volatility of series.

Moreover, as Bera and Higgins (1993) remarked that a major contribution of the ARCH literature is the finding that apparent changes in the volatility of economic time series may be predictable and result from a specific type of nonlinear dependence rather than exogenous structural changes in variables.

Against the above background, the purpose of this study is to analyze the persistence of shocks in IBR volatility in Nepal for daily and monthly interbank market. The ARCH and generalized ARCH (GARCH) methods have been applied to measure the volatility using high daily and monthly IBR series. The significance of applying ARCH family models are that they are simple and easy to handle, they take care of clustered errors, nonlinearities, and more appropriately forecast the high frequency time series. Therefore, an important application of ARCH and GARCH models are to measure and forecast the time-varying volatility of IBR, particularly data observed at high frequencies.

II. FACTORS AFFECTING VOLATILITY OF IBR

Volatility clustering is confirmed with the significant GARCH effect in monthly and daily IBR series. The variance is highly persistent and might have been driven by several factors.²

² This is based on the conclusion from analysis of later sections.

Interbank rate in Nepal is one of the market clearing rates. Fluctuations in the interbank rate arise mainly from supply and demand for liquidity in the money market. However, as the central bank is a monopolist in terms of supplying reserves, it can directly affect equilibrium. The demand and supply of liquidity position are affected through open market operations (OMO), foreign exchange interventions, refinance facility of central bank on one hand, and market forces, seasonal factors, commercial banks' cash requirements to meet their daily payment obligations and other factors like cash holding propensity of the people or expectations on the other. The factors influencing demand and supply conditions of bank reserves also influence the IBR, which are briefly discussed below.

Reserve Requirements: Banks are required to hold a percentage of reserves at Nepal Rastra Bank (NRB) as determined by the reserve ratio of deposit liabilities. The reserve requirement acts as a tool for liquidity management via two channels: reserve ratio and reserve maintenance period. Firstly, NRB, generally through monetary policy, may alter the liquidity position of the market through changing required reserve ratios.

Secondly, reserve maintenance period, is a provision for banks to comply with the reserve requirement over a given period on average. When the maintenance period is changed then the volatility of short-term interbank rates would likely to be change. In Nepal, cash reserve requirement is calculated as a proportion of average level of deposit liabilities held over a week, called reserve computation period. The calculated amount must be satisfied on average over a reserve maintenance period, which is also a week. The reserves maintenance period follows the reserves calculation period with two weeks lag.³ On the other hand, statutory liquidity requirement are calculated on monthly average basis with lag in between calculation and maintenance period.

Hamilton (1996) and Prati and others (2001) observe that in most countries, interest rate volatility rises systematically through the reserve maintenance period, increasing as settlement day approaches. Prati & et.al. (2001) finds the length of these periods varies from country to country, with the U.S. averaging over a two week period, while Japan and the Euro zone average over a month. Shahiduzzaman & Naser (2007) state that in Bangladesh, reserve requirement is calculated as a portion of average level of deposits held over a month called reserve computation period; the calculated amount must be satisfied on average over a reserve maintenance period, which is the next fortnight.

However, in China reserve requirements should be maintained on a daily basis. A day to day maintenance of reserve makes the market more volatile. Bartolini and Prati (2003) and Moschitz (2004) find that by not averaging reserves over some maintenance period, this additional trading to either borrow sufficient funds or lend surplus funds is required every day, thereby resulting in higher average volatility.

³ See, Circular No. 13/067 in. Unified Directives of NRB for banks and financial institutions. Website: http://bfr.nrb.org.np/directives/Directives--Unified_Directives_%2020067.pdf

Foreign Exchange Intervention: All other factors remaining the same, foreign exchange market interventions affect the liquidity position of banking system. As central bank purchases foreign currencies of banks, their liquidity in terms of domestic currency increases.

Government Budget: The other fundamental factor affecting short-term liquidity position is the government budgetary management. Government spending injects liquidity; and taxes and domestic borrowing pull out liquidity from the market. Antal J. & et. al. (2001) states the “international practice is divided among countries over the issue of whether the treasury should hold its account exclusively with the central bank or with commercial banks (as well). Whereas in Germany, Austria, the Netherlands and Finland the volatility of treasury account balances held with the central banks is so low that their effect is negligible, in Italy and Spain it is quite large, especially at tax payment dates. Taken together, the volatility of treasury account balances is the item among the so-called autonomous factors which tends to affect interbank liquidity the most”(p.23).

Lending, Cash Holdings and Other Factors: The central bank may increase supply of liquidity by direct lending to banks. The NRB lends at pre-determined refinance rate to banks for loans to sick industries, export credit, and rural development banks. On the other hand sometimes unexpected events like change in propensity to cash holding and fear of people with the government’s rule also affect the liquidity position in the banking system. Karki (2010) describes that in the fourth month, after the Dashani festival of 2009/10 liquidity declined and recorded a shortage of Rs. 1.9 billion because of the disappearance of higher denomination notes and interruption in supply chain management of NRB’s note delivery. Similarly, due to the uncertainty regarding Voluntary Disclosure of Income Scheme (VDIS) and provision of Government of Nepal of disclosing income source for more than Rs. 1 million’s transactions, people tended to hoard money themselves.

III. LIQUIDITY MANAGEMENT PRACTICE IN NEPAL

Nepal adopted a gradual liberalization policy since mid 1980s. Under the process of liberalization, the old NRB act is replaced by new Nepal Rastra Bank Act 2002, which provides independence to the central bank. Interest rate has been gradually liberalized⁴; controlled interest rate regime was completely abolished on August 31, 1989. In spite of the liberalization policy, considering the vulnerability to shocks bearing capacity of the economy, Nepal has adopted dual currency system – flexible exchange rate vis-à-vis convertible currency and fixed exchange rate with Indian currency.

The NRB Act, 2002 limits the objectives of monetary policy to maintain price, financial and external sector stability. The fixed exchange rate with Indian currency is a nominal

⁴ Maskay and Pandit (2010) divides time line of interest rate liberalization in four phases: pre interest phase, pre 1955, controlled interest rate phase 1956-1983, transitional interest rate phase 1984-1989, liberalized phase 1990-present.

anchor of monetary policy. Excess liquidity of financial system is chosen as an operating target of monetary policy with monetary aggregates as intermediate targets.

As interest rates are fully liberalized in Nepal, the NRB signals its policy stance either through bank rate, cash reserve ratio (CRR), or open market operation. Policy signals are given through changes in the bank rate and CRR in the annual announcement of monetary policy. However, Maskay and Pandit (2010) examine the impact of bank rate on market interest rate using annual data and finds that the bank rate in Nepal is ineffective in influencing the market rates. On the other hand, the medium-term policy instruments including outright sale and purchase auction as well as short-term policy instruments repo and reverse repo auctions of treasury bills are active in offsetting imbalances in liquidity mismatch in open market operations.

The Liquidity Monitoring and Forecast Framework (LMFF) has been made operational since fiscal year 2004/05. The LMFF supports open market operation (OMO) in order to monitor and forecast medium-term and short term (weekly) liquidity position of the economy. The quantity of outright sale or purchase and repo or reverse repo auctions in the secondary market is determined as per the recommendation of LMFF. Since fiscal year 2008/09 development banks and finance companies were also allowed to participate in open market operation (OMO)⁵, which increased the horizon of the liquidity market.

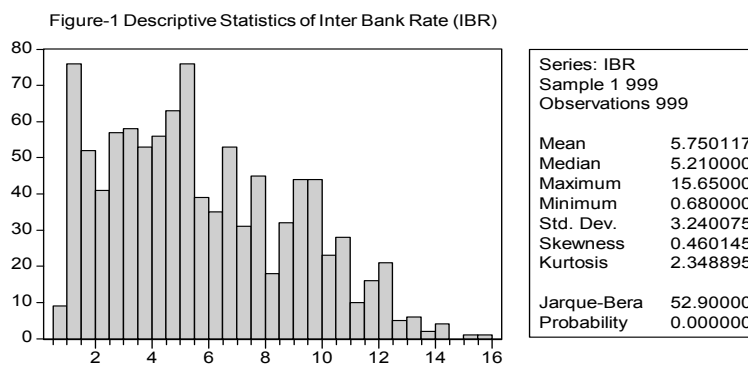
Banks and finance companies approach interbank market if they need immediate overnight liquidity or use standing liquidity facility (SLF) of central bank. The SLF can be used maximum for 5-days; it is fully collateralized and limited to 90 % of the collateral value. However according to IMF (2008) few banks are largely using SLF which has made the central bank the lender of first rather than last resort. Due to this backdrop, SLF rate is determined adding 3 % as penal rate at interest rate on the latest weighted average 91-days treasury bills rate or prevailing bank rate, whichever is highest⁶. As interest rate of SLF is higher than the market rate, banks first approach for fund in the market, and use central bank as a source of last resort.

⁵ Prior to this only commercial banks were the participant in OMO.

⁶ See, NRB (2010)

IV. DATA AND DESCRIPTIVE STATISTICS

The daily data of weighted average interbank rate (IBR)⁷ has a significant difference between its minimum and maximum rates. The market average IBR for the study period is



5.75 percent. The standard deviation of IBR series is 56 percent of its mean. The distribution of the IBR in Nepali money markets is described by skewness. Positively skewed IBR indicates that it has relatively long right tail i.e., distribution has relatively few high values. This denotes that IBR distribution is non-symmetric. On the other hand, the kurtosis value $2.35 < 3$ indicates that the distribution is platykurtic or relatively flat. The Jarque-Bera test firmly rejects normality implying that the daily IBR series is not normally distributed. Similarly, as depicted on Table 2 of Appendix 1, monthly IBR series shows that distribution is relatively peak. The Jarque-Bera test suggests that monthly IBR series is not normally distributed. The mean of monthly IBR is less than the mean of daily IBR.

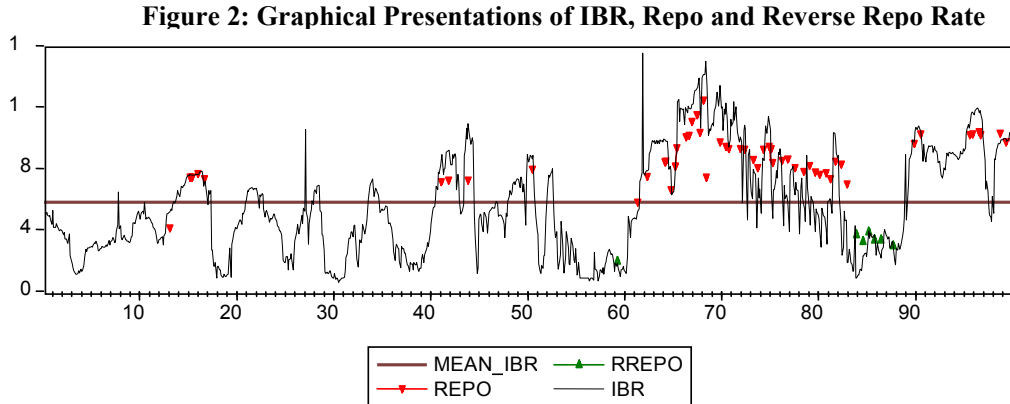
V. INTERACTION OF IBR WITH REPO AND REVERSE REPO

Figure 2 shows interaction of daily weighted average interest rate (IBR), repo and reverse repo rate of Nepali financial markets. The repo and reverse repo rate are the rate determined by the auction system of the NRB under its open market operation. However, interbank rate is market determined rate. All three rates IBR, repo, and reverse repo rate follow the same trend. Interbank rate is high when repo rate is high. On the other hand, interbank rate is low when reverse repo rate is low.

⁷ IBR series is available at Nepal Rastra Bank website:

http://www.nrb.org.np/cmfmrates_details.php?search=02

Note :Out of 999 observations, the missing 26 sample units are interpolated



However, as shown in Figure 2, repo and reverse repo may have a lag effect on the interbank rate. The interbank rate decreases after the introduction of repo and increases after the introduction of reverse repo. The introduction of repo by the NRB increases the supply of liquidity, which in turn eases the demand-supply gap for liquidity and drives the interbank rate down. On the other hand, reverse repo mops up the liquidity, which tends to increase the interbank rate. In addition, there are factors like government spending, seasonal factors, festivals, etc. that also force the interbank rate to rise or fall. The fluctuation of the interbank rate in Nepal depicts that the interbank rate in Nepal is volatile.

VI. METHODOLOGICAL FRAMEWORK

Engle (1982) invented the autoregressive conditional heteroscedasticity (ARCH) model to examine the volatility of inflation in the United Kingdom. However, besides inflation, the model has become an important econometric tool to measure the variability or volatility of all time series data. Green (2005) states that the ARCH model has proven to be useful in studying the volatility of inflation, the term structure of interest rates, the volatility of stock market returns, and the behavior of stock market returns, and the behavior of foreign exchange markets, to name but a few. Since its development, various extensions or modifications have been made in the ARCH model and named as GARCH, generalized autoregressive conditional heteroscedasticity, IGARCH, integrated generalized autoregressive conditional heteroscedasticity, ARCH-M, autoregressive conditional heteroscedasticity in mean, etc. These models are widely used in economic and financial time series to model the volatility.

The two most popular models of volatility clustering are ARCH and GARCH. Suppose that the autoregressive distributed lag, ADL (p, q), regression

$$Y_t = \beta_0 + \sum \beta_j Y_{t-j} + \sum \gamma_k X_{t-k} + u_t.$$

where Y_t and X_t are the variables, β_0 is a constant and β_p and γ_q are the coefficients, $j = 1, \dots, j$ and $k = 1, \dots, k$ are the number of lags, and u_t is the error term. In the ARCH model the error term is modeled as being normally distributed with mean zero and variance σ_t^2 , where σ_t^2 depends on past squared values u_t . Specifically, the ARCH model of order p , denoted as ARCH (p), is

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \dots + \alpha_p u_{t-p}^2$$

Where $\alpha_0, \alpha_1, \alpha_2, \dots, \alpha_p$ are unknown coefficients.

In the ARCH (p) process for unconditional variances to be finite and non-negative and satisfy the conditions of $\alpha_0 \geq 0$, $\alpha_i \geq 0$, and $0 \leq \sum \alpha_i \leq 1$ for all $i = 1, \dots, p$. Patterson (2002) explains that “testing for an ARCH (p) process is usually done with Lagrangian Multiplier (LM) principle and rejection of null hypothesis in favor of ARCH (p) with p ‘large’, rule of thumb $p \geq 3$, is suggestive of a GARCH process” (p. 742).

The generalized ARCH (**GARCH**) model extends the ARCH model to let σ_t^2 depend on its own lags as well as squared error. The GARCH (p, q) model is

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \dots + \alpha_p u_{t-p}^2 + \phi_1 \sigma_{t-1}^2 + \dots + \phi_q \sigma_{t-q}^2$$

Where $\alpha_0, \alpha_1, \dots, \alpha_p, \phi_1, \phi_2, \dots, \phi_p$ are unknown coefficients.

In the GARCH (p, q) process the conditions of $\alpha_0 \geq 0$, ϕ_j and $\alpha_i \geq 0$, and $0 \leq \sum \alpha_i + \sum \phi_j < 1$ for all $i = 1, \dots, p$, and $j = 1, \dots, q$ must be satisfied.

Moreover, in widely applied GARCH (1, 1) model, $\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \phi_1 \sigma_{t-1}^2$, estimations sometimes result in $(\alpha_1 + \phi_1) \approx 1$ or even $(\alpha_1 + \phi_1) > 1$. Engle and Bollerslev (1986) show that if $(\alpha_1 + \phi_1) \geq 1$, the conditional variance is persistent to the shocks. Similar to standard unit root process when $(\alpha_1 + \phi_1) \geq 1$ the GARCH (p, q) model is said to be integrated. This model, first developed by Engle and Bollerslev, is referred to an Integrated GARCH model, or an IGARCH model. Squared shocks are persistent, so the variance follows a random walk with a drift.

However, Nelson (1990) points out that the analogy with a random walk is not precise. He shows that even in IGARCH process the conditional variance is a geometrically decaying function of the current and past realizations of the u_t^2 sequence. As such, an IGARCH model can be estimated like any other GARCH model.

The GARCH model contains mean and variance equations, where the model of mean can contain explanatory variables. In addition, the specification of variance equation also allows for exogenous and dummy variables (D_t).⁸ Therefore, GARCH (1,1) specification can be modified as

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \phi_1 \sigma_{t-1}^2 + \lambda D_t$$

If it is found that $\lambda > 0$, it is possible to conclude that the shocks has increased the mean of conditional volatility.

⁸ See, Enders W. (2004), p.141 on the topic “Models with Explanatory Variables”

Therefore, with an application of ARCH and GARCH models this study concentrates in identifying the incidence of shocks and its persistence.

VII. EMPIRICAL ESTIMATES

The empirical analysis has been done using daily and monthly weighted average IBR. The daily IBR series includes 999 observations over the period of 17 July 2007 to 28 February 2011 and monthly IBR series includes 192 observations over the period February 1995 to January 2011⁹.

GARCH Model of Daily IBR

The ARCH(3), GARCH (1,1) with dummy and GARCH (1,1) without dummy in the variance equations are estimated for the IBR series to measure the conditional volatility.

The daily IBR series indicates volatility clustering and time-varying characteristics of volatility. The last two columns reported in the correlogram shown in Table 2 of Appendix 1 are the Ljung-Box Q-statistics and their p-values. The Q-statistic at lag k (lag length) is a test statistic for the null hypothesis that there is no autocorrelation up to order k. The values of Q statistics, ACF and PACF suggest the presence of autocorrelation and hence volatility clustering in the IBR series. They continue to decrease with the increase in the number of lags. The autocorrelation in the series dies out after 82 lags. The correlogram of the IBR series suggests the evidence of ARCH effects judging from the significant autocorrelation coefficients. In nutshell, the properties of IBR series are consistent with other financial times series; this indicates that interbank rate of Nepal is non-normal and exhibits 'ARCH effect'.

A test for the presence of ARCH in the residuals is calculated regressing the squared residuals on a constant and p lags. The correct number of lags in the model has been selected by using the sign of coefficients, AIC and SIC information criterion. The test can also be thought of as a test for autocorrelation in the squared residuals. The estimates and test-statistics of ARCH (3) model in Table 3 of Appendix 1 depicts the ARCH in IBR series.¹⁰ The non-negativity constraints of the coefficients have not been violated. ARCH models provide a framework for the analysis and development of time series models of volatility. However, the sum of ARCH coefficients in ARCH (3) exceeds unity; it indicates the high persistence of shocks in volatility of IBR.

Most recent empirical studies use GARCH model than ARCH as it is more parsimonious and avoids over-fitting. As stated earlier, ARCH (p) with p 'large', rule of thumb $p \geq 3$, is suggestive of a GARCH process.

The results of estimation and statistical verification of the GARCH (1, 1) with and without dummy variable are respectively shown in column third and fourth of Table 2 of

⁹ The difference in period for monthly and daily is because daily IBR is unavailable since 1995.

¹⁰ E-Views 4.1 software has been used to estimate all the test-statistics and equations.

Appendix I. The AR (1) parameters in the mean equation are significant in both the estimated models. The constant and coefficient of GARCH (1, 1) terms of variance equation of both equations are positive and significant. In addition, coefficients of dummy variables are positive in the variance equation of GARCH (1, 1) with dummy model.¹¹

The sum of ARCH and GARCH coefficients ($\alpha_1 + \phi_1$) = 1.23, which is greater than one, in GARCH (1, 1) model. As suggested by Engle and Bollerslev (1986) the conditional variance is highly persistent to the shocks; so, memory of shocks is remembered in the interbank liquidity market. On the other hand, the sum of ARCH and GARCH coefficients ($\alpha_1 + \phi_1$) = 0.63, in GARCH (1, 1) model with dummy variable indicates that the variance is relatively less persistent to the shocks as result of the repo and SLF in the liquidity market. However, the significant coefficients of dummies depict that the repo and SLF has increased the mean conditional volatility.

Interbank liquidity market of Nepal is volatile with high degree of persistence to the shocks, which has long memory in volatility. However, the open market operation of NRB has been very effective to decrease the long memory of shocks but has increased the mean of conditional variances.

Figure 3: GARCH Variances With and Without Dummy

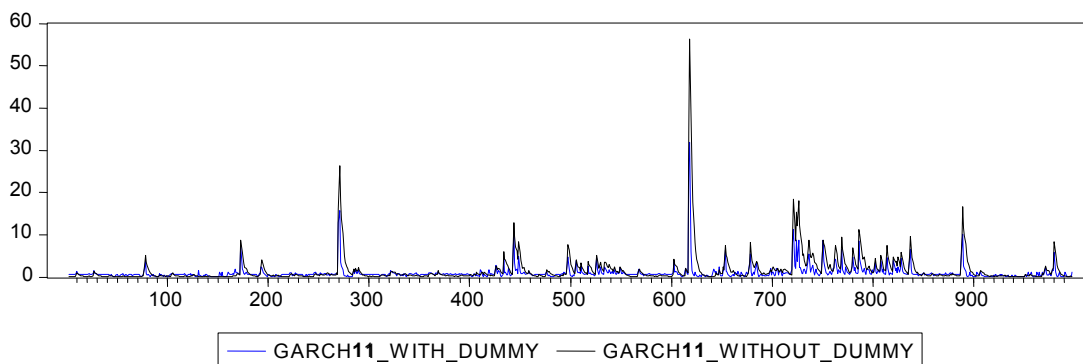


Figure 3 depicts the estimated GARCH variances of interbank rate of Nepal during the period 17 July, 2007 to 28 February, 2011. The series exhibits volatility clustering and time-varying characteristics of volatility. There is duration of time where the volatility is relatively high and relatively low which indicates volatility clustering during the study period. Statistically, volatility clustering implies a strong autocorrelation in the IBR series. Volatility clustering describes the tendency of large changes in interbank rate to follow large changes and vice versa. In other words, the current level of volatility tends to

¹¹ Two dummy variables are used which takes value 1 and 0 based on whether there is repo and SLF or not.

be positively correlated with the preceding periods. The conditional volatility in interbank liquidity market has increased in recent periods, and relatively high volatile in the middle, and relatively low in earlier sample period.

GARCH Model of Monthly IBR

The GARCH (1, 1) in the variance equations are estimated for the monthly IBR series to analyze the conditional volatility. The GARCH variance series shows the volatility clustering and time-varying characteristics of volatility.

The correlogram shown in Table 4 of Appendix 1 suggests the presence of autocorrelation and hence volatility clustering in the monthly IBR series. They continue to decrease with the increase in the number of lags, where the autocorrelation in the series dies out after 14 lags. Similar to other financial series, monthly IBR is non-normal and exhibits 'ARCH effect'.

The estimates and test-statistics of ARCH (2) model of monthly IBR is shown in second column of Table 6 in Appendix 1. The non-negative coefficients of ARCH models suggest volatility. However, the sum of ARCH coefficients in ARCH (2) is $0.76 < 1$ shows persistence of shocks in volatility of monthly IBR series.

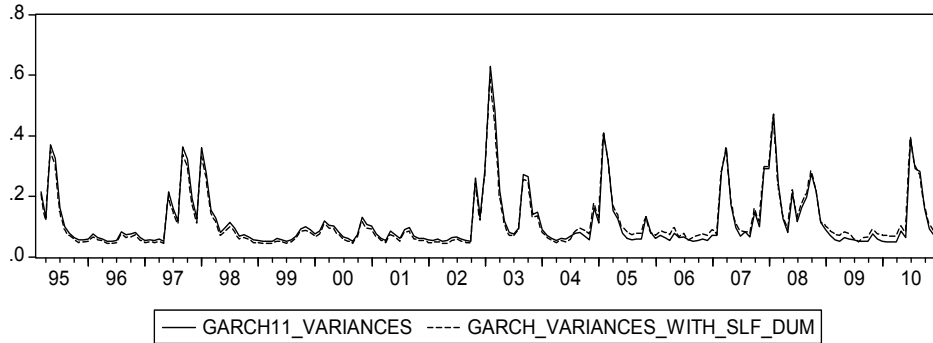
The estimates and statistical verification of the GARCH (1, 1), effect of SLF, and joint effect of repo and reverse repo on conditional variance are respectively shown in third, fourth and fifth column in Table 6 of Appendix 1. The AR (1) and constant parameters in the mean equation are significant in all estimated models. Similarly, the constant and coefficients of GARCH (1, 1) of variance equations are positive and significant in all the estimations. In addition, coefficient of SLF dummy (SLF_d) is positive and significant at 10 percent level of significance. However, the dummy coefficients of repo (repo_d) and reverse repo (rrepo_d) are insignificant even at 10 percent level of significance.

The sum of ARCH and GARCH coefficients ($\alpha_1 + \phi_1$) in the GARCH (1, 1) model with and without SLF dummy are respectively 0.76 and 0.74. During the sample period, SLF facility of NRB to banks has marginally decreased the persistence of shocks to IBR volatility.

Monthly weighted average interbank rate is volatile in Nepal. As the sum of GARCH coefficient is 0.76 i.e., less than unity, the effect of shocks to conditional volatility market dies out, but slowly. Figure 4 depicts the estimated GARCH variances of monthly IBR of Nepal during the period 1995 February to 2011 January. Similar to daily IBR series,

monthly series also exhibits volatility clustering and time-varying characteristics of volatility. There is duration of time where the volatility is relatively high and relatively

Fig 4: GARCH Variances With and Without SLF Dummy



low. The conditional volatility in interbank liquidity market is relatively high at the end of 2010.

Fig 5: GARCH(1,1) Variances By Month: 1995 Feb - 2011 Jan

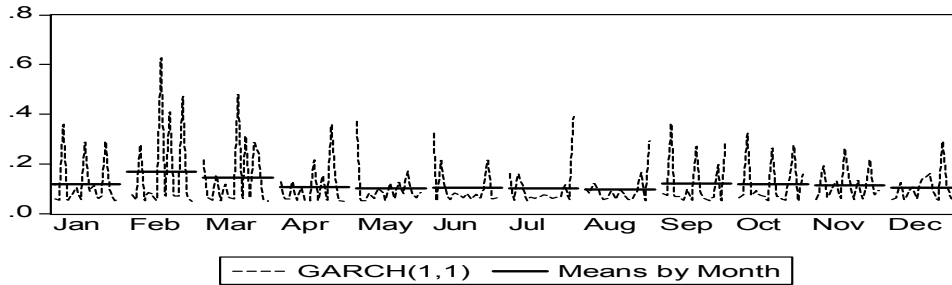


Figure 5 shows monthly average of GARCH variances. It indicates that interbank liquidity market is highly volatility during February and less volatile during August.

VIII. CONCLUSION

The study finds that the distribution of inter bank rate is non-normal and exhibiting significant time dependencies. The conditional volatility of IBR series has been modeled using ARCH (p) and GARCH (1, 1) model. The study shows that the IBR series depicts the evidences such as volatility clustering, time-varying conditional heteroskedasticity. The sum of ARCH and GARCH coefficients are higher, when there is no exogenous variable in the variance equation.

The parameter estimates suggest that volatility shocks are highly persistent in interbank market as the sum of ARCH and GARCH coefficients are greater than unity in daily IBR series. However, it is less than unity when the effect of repo and SLF are taken into

account. It depicts that NRB's intervention has been effective to lower the persistence of shocks on conditional volatility, but it has increased the mean of conditional volatility as the coefficient of dummy variable is significant. The monthly analysis of volatility in interbank market suggests seasonal effect in the volatility. The mean of conditional variances is highest in February and lowest in August.

In nutshell, the study revealed strong evidence of time-varying volatility; a tendency of the periods of high and low volatility to cluster; and high persistence of shocks on volatility of interbank lending market. Lastly, the study suggests that still there is room for in-depth analysis to measure the impact of reserve calculation period, day-wise effect, government spending, taxes, and external sector on volatility of interbank market.

REFERENCES

- Antal J. , Barabás G., Czeti T., Major J. 2001. “Liquidity Management Operations at the National Bank of Hungary”, Department for General Services and Procurement, National Bank of Hungary.
- Bartolini and Prati. 2003. “Cross-Country Differences in Monetary Policy Execution and Money Market Rates’ Volatility” *Staff Reports*, Federal Reserve Bank of New York, Staff Report No. 175
- Bera and Higgins. 1993. “ARCH Models: Properties, Estimation and Testing,” *Journal of Economic Surveys*, Vol. 7, pp. 305-366.
- Campbell, J. Y., Lo A. W., and MacKinlay, A. C. 1997. “The Econometrics of Financial Markets, Princeton”, New Jersey: Princeton University Press.
- Enders, W. 2004. *Applies Econometric Time Series 2nd Edition*, John Wiley & Sons (ASIA) Pte, Ltd. Singapore
- Engle, R. 1982. “Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation,” *Econometrica*, Vol. 50. No. 1, 1982, pp. 987-1007
- Engle, R.F. and Bollerslev, T. 1986. “Modelling the Persistence of Conditional Variance”, *Econometric Reviews*, Vol-5, pp. 1-50.
- Gray, S., Hoggarth, G. and Place J. 2000. *Introduction to Monetary Operations*, The Bank of England, Handbooks in Central Banking No 10
- Greene, H.G. 2005. *Econometric Analysis*, Fifth Edition, Pearson Education.
- Hamilton, James D. 1996. “The Daily Market for Federal Funds,” *Journal of Political Economy*, Vol. 104, No. 1, pp. 26–56 (Chicago, Illinois: University of Chicago Press).
- IMF. 2008. *Nepal Country Report*, IMF Country Report No. 08/182
- Karki P. 2010. “Ensuring a Smooth Liquidity Position through Open Market Operations”, *NRB News*, Year-4, Vol-20, Issue-II.
- Maskay, N.M., and Pandit, R. 2010. “Interest Rate Pass-Through in Nepal”, *Economic Review*, Occasional Paper, Nepal Rastra Bank, No.-22.
- Moschitz, J. 2004. “Determinants of the Overnight Interest Rate in the Euro Area,” European Central Bank, *Working Paper No. 393*, Frankfurt:European Central Bank.
- Nelson, D.B. 1990. “Stationarity and Persistence in the GARCH (1, 1) Model”, *Econometric Theory*, Vol. 6 pp. 381-334,
- NRB. 2010. *Monetary Policy-2010/11*, Nepal Rastra Bank, Central Office, Baluwatar, Kathmandu, Nepal.
- Patterson, K. 2000. *An Introduction to Applied Econometrics: A Time Series Approach*, Palgrave Publishers Ltd., New York.

- Porter, N. and Xu, T.T. 2009. "What Drives China's Interbank Market?" *IMF Working Paper*, WP/09/189, Asia Pacific Department, International Monetary Fund.
- Prati A., Bartolini L., and Bertola G. 2001. "The Overnight Interbank Market: Evidence from the G-7 and the Euro Zone," *FRB of New York Staff Report No. 135*, Federal Reserve Bank of New York.
- Shahiduzzaman M. and Naser M.S. 2007. "Volatility in the Overnight Money-Market Rate in Bangladesh: Recent Experiences" *Policy Note Series: PN 0707*, Policy Analysis Unit, Bangladesh Bank
- Shrestha, S.R. 2005. "Open Market Operations" *Nepal Rastra Bank in 50 Years*, Nepal Rastra Bank, Kathmandu, Nepal.
- Van 't dack, J. 1999. "Implementing Monetary Policy in Emerging Market Economies: An Overview of Issues", *BIS, Policy Papers No. 5*.

Appendix-1

Table 1	
Descriptive Statistics of Daily IBR	
Mean	5.75
Median	5.21
Maximum	15.65
Minimum	0.68
Std. Dev.	3.24
Skewness	0.46
Kurtosis	2.35
Jarque-Bera	52.90
Probability	0.00
Sum	5744.40
Sum Sq. Dev.	10477.00
Observations	999

Table 2						
Autocorrelation Function of Daily IBR						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
*****	*****	1	0.954	0.954	912	0.00
*****	*	10	0.709	0.073	6878	0.00
****		20	0.545	0.003	10808	0.00
***		30	0.413	-0.027	13085	0.00
***	*	40	0.331	-0.066	14481	0.00
**		50	0.271	0.045	15374	0.00
**		60	0.214	-0.034	15964	0.00
*		70	0.124	-0.056	16290	0.00
		80	0.016	-0.032	16333	0.00
		82	0.003	0.033	16333	0.00
		83	-0.002	-0.019	16333	0.00

Table 3			
Modeling Conditional Volatility of Daily IBR			
Dependent Variable: Inter Bank Rate (IBR)			
Mean Equations			
	ARCH(3)	GARCH(1,1)	GARCH(1,1) With Dummy
C	6.3217*	6.3848*	11.1218*
AR(1)	0.9863*	0.9883*	0.9855*
Variance Equations			
C	0.2475*	0.0171*	0.0781*
ARCH(1)	0.6332*	0.5518*	0.4453*
ARCH(2)	0.3002*	-	-
ARCH(3)	0.3727*	-	-
GARCH(1)	-	0.6783*	0.1852*
REPO_DUM	-	-	1.0931*
SLF_DUM1	-	-	0.4149*
R-Squared	0.9111	0.911	0.9107
Adjusted R-squared	0.9107	0.9107	0.9102
S.E. of Regression	0.9687	0.9689	0.9717
Sum Squared Resid	930.87	932.17	935.64
Log Likelihood	-1224.97	-1182.44	-1177.05
Durbin-Watson Stat	2.3027	2.304	2.289
Mean Dependent Var	5.7507	5.7507	5.7507
S.D. Dependent var	3.2416	3.2416	3.2416
Akaike Info Criterion	2.4669	2.3796	2.3728
Schwarz Criterion	2.4964	2.4042	2.4073
F-Statistic	2034.56*	2541.86*	1684.28*

Table 4 Descriptive Statistics of Monthly IBR		Table 5 Autocorrelation Function of Monthly IBR						
Mean	1.962	Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
Median	1.760	. *****	. *****	1	0.916	0.916	163.66	0.00
Maximum	4.500	. *****	. *	2	0.847	0.046	304.17	0.00
Minimum	0.600	. ****	.	8	0.385	-0.065	725.1	0.00
Std. Dev.	0.859	. ***	.	9	0.32	0.01	745.9	0.00
Skewness	0.912	. ***	*	10	0.255	-0.051	759.2	0.00
Kurtosis	3.156	. **	.	11	0.201	0.014	767.51	0.00
Jarque-Bera	26.833	. **	.	12	0.129	-0.166	770.93	0.00
Probability	0.000	. *	.	13	0.066	-0.006	771.84	0.00
Sum	376.773	.	.	14	0.015	0.003	771.89	0.00
Sum Sq. Dev.	140.959	.	.	15	-0.013	0.131	771.93	0.00
Observations	192	.	.	16	-0.053	-0.095	772.53	0.00

Table 6 Conditional Volatility of Monthly IBR				
Dependent Variable: Monthly IBR				
Mean Equations				
	ARCH(2)	GARCH(1,1)	GARCH(1,1) With SLF Dummy	GARCH(1,1) With repo & rrepo Dummy
C	1.537*	1.553*	1.513*	1.523*
AR(1)	0.911*	0.914*	0.919*	0.92*
Variance Equations				
C	0.041*	0.029*	0.024*	0.024*
ARCH(1)	0.302**	0.368*	0.347**	0.346*
ARCH(2)	0.459*			
GARCH(1)		0.392*	0.397*	0.42*
REPO D				0.018
RREPO D				0.012
SLF D			0.016***	
R-squared	0.85	0.85	0.85	0.85
Adjusted R-squared	0.84	0.85	0.84	0.84
S.E. of regression	0.34	0.34	0.34	0.34
Sum squared resid	21.22	21.19	21.2	21.19
Log likelihood	-41.52	-44.71	-43.68	-43.9
Durbin-Watson stat	2.08	2.09	2.1	2.11
Mean dependent var	1.96	1.96	1.96	1.96
S.D. dependent var	0.86	0.86	0.86	0.86
Akaike info criterion	0.49	0.52	0.52	0.53
Schwarz criterion	0.57	0.61	0.62	0.65
F-statistic	259.75*	260.18*	206.96*	171.65*

Note: *, ** and *** respectively represents significant at 1%, 5% and 10 level of significance