MEASURES OF EXCHANGE RATE VOLATILITY

Literature on exchange rate volatility has made use of different methods to measure volatility. In general, the future behavior of an economic variable is uncertain since the probability of future events cannot be determined, \textit{a priori}. Thus, future volatility of an economic variable is seen as a stochastic process that evolves over time with a random and a deterministic component (see Crawford and Kasumovich, 1996 and Carruth, et. al. 2000). Though there are four alternative ways to generate exchange rate volatility namely historical volatility, implied volatility, conditional volatility, and stochastic volatility. This section outlines some of the measures utilized as proxies for exchange rate uncertainty in assessing the effects of exchange rate volatility on FDI. Table - 1 shows the summary of different measures of generating volatility applied in empirical literature.
### TABLE - 1
SUMMARY OF DIFFERENT MEASURES OF EXCHANGE RATE UNCERTAINTY

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Measure of Exchange Rate Volatility</th>
<th>Used in following research papers</th>
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</table>
| 1.     | Absolute percentage change of the exchange rate, i.e.,  

\[
V_t = \left( e_t - e_{t-1} \right) / e_{t-1}
\]

where, \( e_t \) is the spot exchange rate; and \( t \) refers to time.  
Beiley and Tavlas (1991); Gopinath, et. al. (1998) and Martin, et. al. (1999). |
| 2.     | Average absolute difference between the previous forward and the current spot rate, i.e.,  

\[
V_t = \sum_{i=1}^{n} (f_{t-1} - e_i) / n
\]

where, \( f_t \) is the forward rate.  
Hooper and Kohlhagen (1978). |
| 3.     | Moving average of the standard deviation (MASD) of the exchange rate. For example, as used by Koray and Lastrapes (1989):  

\[
V_t = \left( \frac{1}{m} \sum_{i=1}^{m} (Z_{t+i-1} - Z_{t+i-2})^2 \right)^{1/2}
\]

where, \( Z \) is the log relative price of foreign consumer good in terms of U.S. consumer goods; and \( m=12 \).  
Cushman (1985 and 1988); Koray and Lastropes (1989); Chowdhury (1993); Campa (1993); Goldberg and Kolstad (1995); Chakrabarti and Scholnick (2000); Revil and Quere (2001); Gorg and Walkin (2002); Pain and Welsum (2003); Bouoiyour and Rey (2006); and Lin, et. al.(2006). |
| 4.     | Long run exchange rate uncertainty measured as:  

\[
V_t = \max X_{t-1}^{r} - \min X_{t-1}^{r} + \left[ 1 + \frac{\left( X_t - X_{t}^{p} \right)^2}{X_{t}^{p}} \right]
\]

where, \( X_t \) is the nominal exchange rate at time \( t \); \( \max X_t^{r} \) and \( \min X_t^{r} \) refer to maximum and minimum values of the nominal exchange rate over a given time interval of size \( k \) up to time \( t \); and \( X_t^{p} \) is the 'equilibrium' exchange rate.  
| 5.     | Auto regressive conditional hetroscedasticity (ARCH) models  

\[ y_t = X_t \beta + \varepsilon_t \]

\[ \sigma_t^2 = \alpha_0 + \omega_1 \varepsilon_{t-1}^2 + \omega_2 \sigma_{t-1}^2 + \ldots + \omega_m \sigma_{t-m}^2 \]

where, \( \varepsilon_t \sim N(0, \sigma_t^2) \); \( \varepsilon_t^2 \) is the squared residuals; \( \gamma_i \) are the ARCH parameters.  
Pozo (1992); Food (1998); Darby, et. al. (1999); Ozbay (1999); Amuedo-Dorantes and Pozo (2001); Crowley and Lee (2003); Athukorala and Patirana (2003); Lin, et. al. (2006); Becker and Hall (2007); and Vita and Abbott (2007). |
| 6.     | \( Vol_t^{i} = \text{var} \left( \frac{c_t}{p_t} \right) - \text{var} \left( \frac{c_t \beta_t}{p_t} \right) \)  
| 7.     | The coefficient of variation of real exchange rate  
Unata and Kavai (2000); Quere and Fontagne (2001); and Revil and Quere (2001). |
| 8.     | Auto regressive integrated moving average (ARIMA)  

\[
\text{Min} \sum_{t=1}^{T} e_t^2 + \lambda \sum_{t=1}^{T} \left( g_t - g_{t-1} \right)^2 - \left( g_{t-1} - g_{t-2} \right)^2
\]

where, \( y_t \) is the time series; \( g_t \) is the growth component, \( e_t \) is the cyclical component. The parameter \( \lambda \) is a positive number, which penalises variability in the growth component series.  
In the literature, both conditional and unconditional measures of volatility have been largely used as proxy for exchange rate volatility. One of the methods to measure exchange rate uncertainty through the average absolute difference in the previous forward and current (nominal) exchange rate (Cushman 1983, and Hooper and Kohlhagen 1978) is justified on the grounds that it captures the difference between expected (future) and realized exchange rates. That is, information on expected exchange rate is contained in the forward rate. This measure assumes that previous deviation from expectations can be used as a predictor for current exchange rate movements. Hence, previous average ‘forecast errors’ is utilized to determine current exchange rate dynamics. Dell’ariccia (1999) opined the benefit of such a measure is that in countries with target zones, it is able to capture that part of uncertainty which tends to maintain the official parity.

Peree and Steinherr (1989) argued that the appropriate measure for uncertainty should capture medium/long-run (nominal) uncertainty since short-term risk can be hedged. Additionally, they stated that in international trade both variations in the exchange rate, like the largest spread in exchange rate over the past few years, and the deviation from the ‘equilibrium’ exchange rate is followed in order to capture the misalignment of exchange rate. A disadvantage of the measure is that if country inflation rates permanently deviate from each other and nominal exchange rates are used as an instrument to uphold purchasing power parity then the measure exaggerates uncertainty.

The most frequently used measure of uncertainty is the moving average of the standard deviation (MASD) of the percent change in the exchange rate (Chowdhury, 1993). This specification of exchange rate uncertainty, an unconditional measure, is
commonly used in the literature like Goldberg and Kolstad (1995) and Cushman (1985 and 1988). An advantage of MASD measure is that it has the characteristic of having a value of zero, when the exchange rate exhibits a constant trend (Dell’ariccia 1999). Additionally, it would also place greater weight on observations that are outliers.

Chowdhury (1993) supported the use of MASD measure, since it incorporates the temporal variation in the degree of changes in the exchange rate. Smaghi (1991) argued in favour of using the measure since it is able to represent ‘higher frequency’ variations in the exchange rate, but argued against the use of moving averages which incorporate many lag length. He argued that while MASD smooths out the series, and it is unjustified since exchange rate movements do not exhibit such autocorrelations. Further, he argued that measures of uncertainty should be conditional on the distribution of exchange rate, and as such, do more to disaggregate unexpected from the expected exchange rate volatility. Moreover, Kroner and Lastrapes (1993) argued that such measures are ‘ad hoc’ since they arbitrarily set forth the condition on volatility without regard to how it is generated.

In contrast, MASD measure employed provides with only a naïve forecast of expected volatility by assuming that economic agents simply use average volatility over the past year to forecast future volatility.

The standard deviations are time variant, but not conditional on previous observations. Authors who calculated the standard deviation of exchange rate (Kenen and Rodrik 1986) have been criticized, because this procedure does not take into account expectations of future exchange rates. Hence, an appropriate exchange rate risk measure should capture the unexpected deviations of the current spot exchange.
rate from its expected value, i.e., the past forward exchange rate. Therefore, fluctuations in exchange rates should not be considered as a risk as long as they can be anticipated by the market participants. With this measure, it is assumed that the expectation of exchange rate in each and every past period is equal to the actual average, such that expectations are correct on average. While the moving standard deviation captures the variability of the real exchange rate, it is not the best proxy for uncertainty, defined as the expected variability in the exchange rate.

Udomkerdmongkol, et. al. (2006) applied Hodrick-Prescott (1997) filter method to measure exchange rate volatility. It is a mathematical tool used in macroeconomics, especially in real business cycle theory. It is used to obtain a smoothed non-linear representation of a time series, one that is more sensitive to long-term than to short-term fluctuations. The adjustment of the sensitivity of the trend to short-term fluctuations is achieved by modifying a multiplier $\lambda$. The Hodrick-Prescott filter is quite simple to implement.

However, it has potentially large drawbacks. One would like a filter to generate estimates of the cycle which are close to the actual values for the cycle. Unfortunately, the HP filter is optimal in this sense only under two fairly restrictive assumptions. First, the data must, a priori, be known to have an I(2) trend. Otherwise, the filter will generate shifts in trend growth rates when they don’t exist in the raw data. If instead there are only one-time permanent shocks to the level of trend, or a constant (split) trend growth rate, or both, then the H-P filter distorts the cyclical properties and the higher moments of the data in a significant way.

Second, the H-P filter is optimal only if the cycle consists of white noise i.e., $\text{Normal} \sim (0, \sigma^2)$ or if the identical dynamic mechanism propagates changes in the trend
growth rate and in the innovations to the business cycle component. And third, the filter has misleading predictive outcome when used dynamically since the algorithm changes the past state of the time series to adjust for the current state regardless of the size of lambda used.

Another measure of exchange rate uncertainty based on conditional volatility developed by autoregressive conditional heteroskedasticity (ARCH) model of Engle (1982), later on generalized as GARCH (Generalized ARCH) by Bollerslev (1986). This model is to generate expected volatility in a series conditional on past behavior. As Pozo (1992) and others have noted, exchange rate series can be characterized by “volatility clustering”. Essentially, successive changes appear not to be independent-large changes in exchange rate are preceded by large changes while small changes are preceded by small changes. In this scenario, the assumption of a constant variance of the series is inappropriate, since the variance would be time-dependent, a form of heteroskedasticity exist in time series analysis.

Further, as Enders (1995) explains if exporters are concerned about exchange rate behaviour during the time of the contract, they will be interested in the forecast of exchange rate movements and the uncertainty of the accuracy of these forecasts. Therefore they are interested not only in the conditional mean but also the conditional variance of the series. Hence, there has been a recent surge in interest in modeling and forecasting conditional volatility of exchange rate behaviour. When studying uncertainty, the conditional should be a better measure because it captures the unexpected volatility (Crawford and Kasumovich 1996). Therefore, ARCH/GARCH models have been used by many studies that focus on volatility, as they generate the conditional variance of a variable. However, Chowdhury (1993, p. 701) concludes
that, “since there is no unique way to measure exchange rate uncertainty, empirical research on its effects has generally used some measure of exchange rate variability as a proxy for uncertainty”.