Exchange rate volatility: Trader's beliefs and the role of news

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Abstract

The study of financial market volatility has focused on the unexpected and expected components of news (Vortelinos, 2015; Omrane and Hafner, 2015). We incorporate the role of biases arising from the 'availability' of recent outcomes to the traders, in influencing trading decisions. The theory of heuristics (Tversky and Kahneman, 1974) is used to build on the theory of trader's biases which helps to understand the reasons behind market volatility. Empirically the model is tested with five minute data on USD/INR and time stamped news from the US and Indian markets. We find that volatility is likely to be in higher ranges with increase in trader's biases, corresponding to unexpected news component. GARCH analysis of returns of average bid-ask rates shows that unexpected news, expected news and bias corresponding to expected news lead to increased volatility.

Keywords: Exchange rate volatility, Unexpected and expected news, Trader's biases

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Section 1: Introduction

The association of exchange rate volatility to macroeconomic news announcements is supported by strong empirical evidence (Vortelinos, 2015; Omrane and Hafner, 2015, Bessembinder, 1994). Economic literature shows that macroeconomic announcements and news events have a positive impact on the market volatility (Bessembinder, 1994; Fleming and Remolona, 1999; Evans and Lyons, 2005, 2008; Omrane & Hafner, 2015). However, while both asymmetric information and the rise in inventory costs can explain the exchange rate volatility (Fleming and Remolona, 1999, Chari, 2007), role of trader's perceptions formed by past market movement has remained largely unexplored. We add to the understanding of market volatility by incorporating the role of heuristics (Tversky and Kahneman, 1974) in explaining trader's behaviour. Following Tversky and Kahneman (Ibid) work on heuristics, we introduce the concept of "Bias" to explain the behaviour of participants in the financial markets. Bias reflects perceptions arising from the 'availability' of recent outcomes, and looks at the influence of previous exchange rate movement in response to news, in determining trading decision making. The unexpected and expected components of a news event, and the market movement in response of it create likely scenarios ("available" to the trader instantaneously based on recent past experience) in the minds of the traders, which in turn dominate the decisions made in the current period. We find that, instead of the new set of factors that can influence exchange rate movement, the experience of the prior movement has a determining influence on market volatility.

Empirically the theory is tested with reference to the Indian foreign exchange market which have seen sharp volatility is recent past. We examine the impact of three factors, macroeconomic news, trader's biases and technical analysis indicators[1], on volatility of movement for the Indian rupee for a period of three months, 24th May, 2017 to 24th August, 2018. Time stamped exchange rate data is taken at the high frequency level of five minutes to understand market heterogeneity better. The time stamped macroeconomic news announcements from India and the United States markets

[1] At any particular moment in the market, there would be traders trading on fundamentals as well as chartists, trading on the basis of chart movements. We incorporate chartist's perceptions through the difference between price and 10 period average prices, a technical analysis indicator.

is availed collated from the Thomson Reuters Eikon database and cover news related to inflation, growth, industry, government and central banks.

We find that news events and trader's biases have a statistically significant positive impact on market volatility. The expected component of news and trader's biases evolving from their past experiences lead to an increase in market heterogeneity while unexpected news shock leads to a slight fall in volatility.

The role of both asymmetric information and the rise in inventory costs have been discussed with regard to exchange rate volatility (Fleming and Remolona, 1999, Chari, 2007). However, the reaction of traders to the macroeconomic news is better understood in the context of psychology of human decision making under uncertainty. While participants have information on the likely factors influencing exchange rate behaviour, the news announcements majorly do not lead to a clear view emerging on the exchange rate movement as macroeconomic fundamentals are interpreted by different people in different ways. The previous exchange rate movement in this case forms a guide to traders for the exchange rate behaviour in the immediate future, who form trading decisions accordingly.

The paper contributes to the economic literature in two major ways. First, the theoretical framework adds on to the understanding of market volatility, by incorporating the influence of trader's bias, (arising out of perceptions created by past market movements) on market heterogeneity. Secondly, the volatility of USD/INR pair is analyzed with the use of high frequency data and time stamped news. While the Indian rupee has experienced volatile market conditions in the recent past, to the best of our knowledge, such a study has not been attempted to understand the reasons behind the market volatility.

The rest of the paper is organized as follows. Section 2 discusses the theoretical background and Section 3 gives the methodology and data. Section 4 presents and discusses the results.

Section 2: Theoretical background

The advent of new information in financial markets is a catalyst for action. The impact of such information in the form of macroeconomic news on market volatility is an essential feature of the financial market analysis. There is strong empirical evidence of the link between macroeconomic news and volatility in financial markets, including foreign exchange markets (Bessembinder, 1994; Fleming and Remolona, 1999; Hartmann, 1999; Galati, 2000; Evans and Lyons, 2005, 2008; Omrane & Hafner, 2015 and Vortelinos, 2015). As foreign exchange markets may take a considerable period to absorb news (Evans and Lyons, 2005), the impact of a news will include the 'instantaneous' change in the exchange rate, and the induced changes over time (Evans and Lyons, 2008).

What happens in financial markets following the arrival of macroeconomic news? Fleming and Remolona (1999) show that macroeconomic announcements have the greatest impact on bid-ask spreads in the shortest time frames and the sharp change in bid-ask spread following a macroeconomic announcement is irrespective of trading. A macroeconomic news essentially leads to a revision of expectations regarding the price movement among market participants. News is a medium for participants in financial markets to make sense of economic fundamentals. With the arrival of news therefore, an opportunity presents itself before the trader to initiate or revise his trades. The reaction of the market participants to the changed macroeconomic fundamentals is thus reflected through the quote given for trading.

In microstructure theory, bid ask spreads represent order processing costs, asymmetric information costs and inventory carrying costs (Bessembinder, 1994). The act of market making imposes on interbank dealers the need to either maintain liquidity in terms of currencies themselves or provide liquidity to counterparties by trading at given rates immediately. This "provision of immediacy" leads to opportunity costs of holding liquid inventory (Bessembinder, Ibid). The inventory carrying costs, in this model, explain to a large extent the variation in exchange rate with news.

Asymmetric information reflect the widening of spreads as participants face more 'informed' traders. In the presence of a more informed trader with insider information will lead to a rise in bid-ask spreads by existing participants to protect against the lack of information (Fleming and Remolona, 1998). Galati (2000) points out that the presence of inventory carrying cost and information asymmetry is more important than the order processing costs in explain the widening of bid ask spreads, as typically order processing costs are small in foreign exchange markets.

Fleming and Remolona (1999) mark the two stages of adjustment to macroeconomic news– the release of new information leads to widening of spreads as the market makers look at inventory costs. This change is sharp and instantaneous and leads to fall in trading volume as market makers withdraw from trading. In stage two, trading increases with volatility remaining high as there is "residual disagreement among investors about what the just released information means for prices" (Fleming and Remolona, 1999).

The above point is corroborated studies on market volatility. For example, market participants may have an imprecise estimate of fundamentals with precise estimate of exchange rate targets (Evans and Lyons 2002). Dreger and Stadtmann (Ibid) points out that exchange rate expectation differs across market participants. Heterogeneity comes from the use of different models or different provisions in the same model and different interpretations of fundamental and technical indicators (Dreger & Stadtmann 2008; Chari 2007).

Why do traders not form uniform view-points on the market movement to be expected? While fundamental factors should make every market participant should have a similar view of exchange rate movement, it does not happen so. We incorporate the concept of biases inherent in our judgments (Tversky and Kahneman, 1974), to the financial markets for a better understanding of the process of increased volatility. Tversky and Kahneman, Ibid, talk of the availability bias where people assess the "probability of an event by the ease with which instances or occurrences can be brought to mind" (pp.1127). This also means that recent occurrences is likely to be "relatively more available than earlier occurrences"(pp.1127).

How does this apply to financial markets? Every time as a new set of information and news comes, the trader is to objectively analyse the old and new trades with reference to the new information. However since traders are exposed to market happenings every day they will carry "availability" of likely scenarios of exchange rate movement in their minds, depending on the unexpected and expected components of news. In the decision-making process therefore, these likely scenarios (" available" to the trader instantaneously), dominate the decision made in the current period. The trader thinks she's completely objective in analyzing a new set of information but it is far from so. In an interesting take, Tversky and Kahneman, Ibid, point out that "subjective probability of traffic accidents rises temporarily when one sees a car overturned by the side of the road"(pp.1127). All these point out to the role of available past scenarios in guiding decision-making even with a new set of information available. The forecasting of market movement now comes from the possible set of past experiences or available solutions to the trader.

Further, while expert's intuitions are effects of prolonged practices, professional intuitions do not all arise from the experience. "When confronted with the problem of choosing a chess move or deciding whether to invest in a stock, the machinery of intuitive thought does the best it can (Kahnemann,2011 . p.12)." If the problem at hand is very complex and no skill solutions available, thus the answer that comes to mind will be the easier one and may not be the right one. Intuitive heuristics in a different situation involves a answering an easier question without noticing substitution (Kahnemann, 2011). The solutions available to the trader therefore dominate the decision making in this case. If there are inherent bias in reaction of participant's to market events, the widening of spread may not be determined simply by information asymmetry and costs. It is thus possible to use the theory of heuristics to better explain the decision-making of traders under uncertainty.

The analysis of volatility in foreign exchange markets incorporates an understanding of what happens in a particular trading scenario. At any point of time in the market, we can conceive of the participants being composed of traders who trade on the basis of fundamentals and traders who are 'chartists' or trade on the basis of technicals. It is plausible to think of most traders using a combination of both, so that each trading decision considers the 'fundamental' factors as well as the signals generated from technical analysis. Technical analysis strategies are commonly used by traders for trading decision making (Menkoff & Taylor, 2007). The popularity of technical analysis comes from the fact that traders concur on the profitability of technical analysis strategies, in spite of the deep academic distrust of it and a host of empirical studies have shown that technical analysis is indeed profitable and generates excess returns, eschewing the academic negation of it (Pinches, 1970, Menkoff & Taylor, Ibid, Saacke, 2002).

As traders evaluate the new information set, and take the trading decision, they are unknowingly influenced by the past set of solutions (or market movements experienced) available to them. Thus the trades are influenced not only by news and by the element of surprise in the news, but also by the biases inherent in the trading decision, which comes from the influence of past market action on traders. These biases we refer to as perceptions in our model of spot market volatility.

To understand the impact of news and perceptions (biases) on volatility of exchange rate, we conceive of a trading scenario where the market participants use both fundamental and technical analysis to take trading positions, in addition to intervention news. The first order condition for optimal choice of the present period spot rate following Chari (2007) is given as:

$P_0 = b_1 + b_2\breve{\varepsilon_p} + b_3\breve{\varepsilon_t} + b_4\breve{\varepsilon_I}$……………………………………………………….(1)

Where $\breve{\varepsilon_p} \cong N(0, \tau_p)$ is the trader's prior about the fundamentals or news, $\breve{\varepsilon_p} \cong N(0, \tau_t)$is the trader's prior about the technicals and $\breve{\varepsilon_p} \cong N(0, \tau_I)$ is the trader's perceptions resulting from the interaction of past exchange rate movements with expected and unexpected news component.

τ_p , τ_t , τ_I are measures of precision, with variance being the inverse of precision. With the incorporation of the these factors, the variance of spot rate can be written as

$$\sigma_{P_0}^2 = b_2^2\sigma_{\check{\varepsilon}_p}^2 + b_3^2\sigma_{\check{\varepsilon}_t}^2 + b_4^2\sigma_{\check{\varepsilon}_I}^2 + 2b_2b_3\sigma_{\check{\varepsilon}_{pt}}^2 + 2b_2b_4\sigma_{\check{\varepsilon}_{pI}}^2 + 2b_3b_4\sigma_{\check{\varepsilon}_{tI}}^2 \ldots\ldots\ldots\ldots\ldots\ldots(2),$$

In the second equation, the variance terms depends on speculator's prior precision on fundamentals, technical indicators or the perceptions or biases manifested in the trading decisions.

Using the above model, we can conceive of the stages of the reaction of market participants to a random news shock. Following Chari (2007) we develop a timeline to understand this adjustment process.

T= -1: Market participants have specific views on the exchange rate depending on the available information on the fundamentals and/or signals from technical indicators, most commonly trend following ones. In the period preceding the arrival of news, market participants have updated their perceptions depending on the previous movement in the market.

1. At T= 0: News arrives in the market, which has an unexpected and an expected component. The markets react to the unexpected and expected components with an update of the prior and a change in trading positions if required. However, more than the present information set available to the market participant, the previous market move in response to the unexpected and expected components of news guide the trader in decision making. The trader's decision making is influenced and biased by the past set of solutions available of them, and this influences the present market move.
2. At T= 1: Volatility is likely to increase as market participants react to the intervention by widening bid-ask spreads. However, how much volatility will increase will depend on how much the market had moved previously to the unexpected component of the news, as this influences the trading decisions today.
3. $T \rightarrow \infty$ The greater the prior reaction of market to the news, the more the participants are likely to react in the present scenario expecting the past movement to be a guide for the present. This process get repeated with every news shock in the market.

In this paper, we incorporate both the news as well as the trading bias to understand better how volatility develops in the market. The formal model therefore looks at the unexpected and expected components of news as well as an interaction of exchange rate movement in the recent past with the unexpected and expected components of news, representing the way past solutions will bias the trader in the present decision-making.

Section 3: Data and methodology

To understand the impact of intervention on volatility as reflected in the bid-ask spreads, we look at the difference between average bid-ask spread (DELAVG) between consecutive periods. The exchange rate data is taken at a high frequency level of five minutes. The change in average bid-ask spread serves as a proxy for volatility as bid–ask spread in the current period reflects dealers' expectations of current volatility (Chari 2007). As the news data is available with a gap of thirty minutes, we map the exchange rate data to the news data, by taking the average of bid and ask rate over a thirty minute period.

The use of bid-ask spread as a proxy for volatility is based on economic literature supporting a positive association between spread and volatility (Bollerslev and Melvin, 1994; Hartmann, 1999; Galati, 2000; Bjønnes and Rime, 2003 and Osler et al. 2011).The seminal work of Bollerslev & Melvin (1994) emphasize the link between bid-ask spreads and volatility. Bollerslev & Melvin (Ibid) point out why, in response to greater uncertainty regarding the future spot rate, there is a widening of the bid-ask spread, instead of both the bid and the ask moving in the same direction. The theoretical model developed in this paper with liquidity and information-based trades, as also the empirical analysis, show that the spread, in equilibrium, is positively related to the standard deviation of exchange rate. Bollerslev & Melvin (Ibid) further contend that while in a more general model with 'endogenous information acquisition', the proportionality between spread and standard deviation may fail to hold, the results (of the positive association between volatility and spread) remain generally valid (p.359). Galati (2000) finds evidence supporting the positive relationship between spread and volatility for emerging market nations, including India, linking it to the rise in inventory costs.

Why should the dealers widen the bid-ask spread as a response to market uncertainty? To understand this, we need to consider the information access to market participants. Given that select market participants will have access to private information, dealers try to guard themselves against this information asymmetry by raising the spreads, so that spreads are inversely related to information content (Bjønnes and Rime 2003, Osler et al. 2011). Bid-ask spreads reflect reaction of dealers to adverse selection problem, informational risk and inventory risk (Naranjo & Nimalendran 2000; Pasquariello 2006 & Chari 2007).

Looking at the range in the variable DELAVG, we divide it into buckets, arriving at the categorical dependent variable (CAVG) with values 1, 2, and 3 for three main volatility ranges. The range of variable DELAVG is 0-0.6 but we identify from the frequency distribution, three main buckets for the volatility variable[2]. These are less than 0.05, 0.05 to 0.1 and more than 0.1: taking other buckets with smaller ranges would dilute the main aim of classifying low, medium and high volatility ranges. The frequency distribution of DELAVG (continuous) and the categorical variable (CAVG) is presented in Table 1.

The exchange rate data as well as intervention and other news data for the study is availed from Thomson Reuters Eikon database[3], which gives time stamped tick-by-tick bid-ask exchange rate data and news reports. The exchange rate data is collected at 5 minute level and averaged for six period to get the half-hourly dataset that corresponds to the news data. The news reports feature in the Economic Monitor of the Eikon database. The news reports cover the following categories: external sector, inflation, Government, labor, growth and central banking. The time-stamped news data is collated with the exchange rate date.

The data on news from all the categories is compiled together date wise and mapped to the exchange rate data. A key problem is mapping the news data is news releases in US market typically happens in non-market hours for rupee. In this case, we have to map the news on rupee to the next immediate exchange rate data available as the market opens. For example, the news at Indian time 11 pm (US market hours) is in non-market hours and mapped to the exchange rate data at 9 am on opening. The logic behind this is that the news in the aftermarket hours impacts the exchange rate movement immediately as the market opens the next day. Table 2 shows the representative news data. For example, on 24 Aug 2017, (19.30 pm: Indian local time) indicator Existing Home Sales ' is declared, with polled and actual values.

One of the core problems to be addressed in analyzing the impact of news on volatility is the issue of endogeneity. As the volatility in exchange rate movement in turn impacts economic policy decisions (especially intervention by central banks), as reflected in news, the cotemporaneous determination of volatility and news cannot be ruled out. Here the use of high frequency data in

[2] We recognize the loss of information from the conversion of continuous to discreet (categorical) variable but the differentiation into high medium and low volatility buckets is crucial for the Logit analysis used in the paper. To keep the information loss as minimal we increase the number of categories (three) (Pasta, 2009).

[3] Thomson Reuters.

the intra-day frame helps us to address the endogeneity issue. The use of intraday data can address the endogeneity issue as the time taken for central bank intervention in response to an increase in volatility is likely to be less than the intraday frame under study (Neely, 2005, Chari, 2007). Chari (Ibid) points out this would be especially true for high-frequency data as volatility at high frequency level is unlikely to impact intervention in the same time frame. This study using high-frequency data assumes that the central bank takes at least five minutes to react to the volatility and intervene, ruling out the contemporaneous determination of volatility and exchange rate.

Section4: Empirical model

Modelling exchange rate volatility in a microstructure framework, we assume that there are expected and unexpected components of the news, which impacts exchange rate movement in different ways. The difference between actual macroeconomic variable values and the forecasted (poll) values representing the market expectation of the macroeconomic variable represents the unexpected component of news. The expected and unexpected (surprise) element of the news is analyzed separately to see its impact on volatility. Following standard literature (Vortelinos, 2015; Omrane and Hafner, 2011), we define the variable representing unexpected news component as difference between the expected (poll) and actual (realized) macroeconomic variable values. The standard methodology followed to address the problem of difference in units of measurement is to divide the news surprise by standard deviation of differences to get the standardized variable $S_{ca,t}$, representing unexpected (surprise) component of news of indicator category ca at time t.

$$S_{ca,t} = \frac{Actual_{\,ca,t} - Expected_{\,ca,t}}{\sigma_{ca,t}};$$

Where

Actual $_{ca,t}$ = Actual / Realized value of the macroeconomic variable from category (ca) at time t

Expected $_{ca,t}$= Poll value of the macroeconomic variable from category (ca) at time t;

$\sigma_{ca,t}$= Standard deviation of differences between Actual and expected values for category ca. The expected news component is calculated separately with reference to the difference between actual and unexpected as a ratio of the actual macroeconomic value.

To incorporate the trader's perceptions regarding the past exchange rate movement relative to the news (expected and unexpected components) in the past, we introduce two new variables, Bias 1 and Bias 2. In each time period, we can think of the trader being biased by the response of exchange rate to news in the immediate past, so that if in the previous period markets have demonstrated volatility in response to a news, the trader will expect a similar movement. Bias 1 & 2, at time t, represents the interaction of unexpected and expected news, of time t-1, with returns in time t, given by Log (R_t/ R_{t-1}). The variables therefore underline the perceptions created in the minds of the traders by movement of the exchange rate in response of the previous news and its unexpected and expected components. Technical analysis is represented by the difference between the price at period t, P_t and the 10-period moving average of the price, a commonly used indicator by chartists (Murphy, 1999).

A. Ordered Logit Model:

The ordered Logit model estimates the relation between an ordered and categorical dependent variable (difference in bid ask spreads, CAVG) and a set of independent variable as given in equation 3.

$CAVG_i$= F (BIAS, $NEWS_i$)…………………(3)

Which can be written as:

$$CAVG_i = b_1UNEXPECTED_i + b_2EXPECTED_i + b_3BIAS_{1_i} + b_4BIAS_{2_i} + b_5TA_i + \varepsilon_i$$

The dependent variable in our model is CAVG, which is categorized into 1,2, or 3 according to the range, the frequency distribution of which is given in table 1 The ordered categories are now estimated as a linear function of independent variables. The dependent variables in this model are unexpected and expected news component (Unexpected and Expected respectively), Biases (1 & 2), reflecting the interaction of exchange rate movement with the expected and unexpected components respectively and technical analysis indicator operationalized by difference between price and ten-period moving average (TA). The bias variable thus represents the returns with reference to past surprises and news expectations.

The ordered Logit model looks at the determinants of volatility being in different categories. It is suitable given the non-normal frequency distribution of CATV and the variable DELAVG (histograms in Graph 1 & 2). As seen from Table 3, the model is statistically significant at 5% level of significance and shows that both unexpected and expected news components have statistically significant impact on the volatility as proxied by the bid-ask spread over time. Importantly, we find there is a statistically significant, positive and large impact of Bias 1 (reflecting the perception of the traders created by past exchange rate movement in response to unexpected market shocks). However, the present period unexpected shock do not lead to an increase in volatility, suggesting that the past movement influences trader's perceptions more than the immediate shock in news. The expected components of news leads to a slight increase in volatility, as trader's respond to news itself. The other variables do not have any statistically significant impact on volatility.

As we can see from the Tables, marginal effects show that Bias 1 reduces greatly the probability of volatility being in the lower ranges and the probability of volatility being in the middle and upper ranges. Similarly, unexpected component increases the probability of volatility being in the lower range and reduces the probability of volatility being in the middle or high range.

The marginal effects confirm that the expected news also increases the chance of volatility being in higher ranges.

B. GARCH estimation

We analyze the impact of news and participant perceptions on exchange rate volatility for the data using a GRACH framework. In this case, we look at the exchange rate returns and probe the change in exchange rate with time and the factors which impact them. For the GARCH model, the data test the null hypothesis that intervention has no effect on exchange rate volatility. The basic regression model with GARCH (1, 1) errors is

$$R_t = \alpha_0 + \alpha_1 UNEXPECTED_t + \alpha_2 EXPECTED_t + \alpha_3 TA_{1_t} + \alpha_4 BIAS_{1_t} + \alpha_5 BIAS_2 + \varepsilon_t \qquad \ldots\ldots\ldots\ldots (5)$$

$$\varepsilon_t | I_{t-1} \sim N(0, h_t) \qquad \ldots. (6)$$

$$h_t = \delta_0 + \delta_1 UNEXPECTED_t + \delta_2 EXPECTED_t + \delta_3 TA_{1_t} + \delta_4 BIAS_{1_t} + \delta_5 BIAS_2 + \varphi\varepsilon_{t-1}^2 + \delta h_{t-1}$$

………….. (7)

Where,

LUSDINR= Log returns of average of bid and ask rate

UNEXECTED=Unexpected component of the news

EXPECTED=Expected component of news

EXT=Surprise element of news

$BIAS_1$= Interaction term of unexpected component of news with exchange rate returns

$BIAS_2$= Interaction term of expected component of news with exchange rate returns

TA= Difference between price and ten-period moving average Equation (5) measures the effect of news and bias on exchange rate changes; equation (6) states that regression residuals will be modeled as a GARCH process; and equation (7) describes the conditional variance. Returns and other variables subject to unit root tests [Augmented Dickey-Fuller (ADF)]. Before running the

GARCH model, the appropriateness of using GARCH is tested by regressing log returns on the set of independent variables and testing for ARCH effects, rejecting the null hypothesis of no ARCH effects at 5 % level of significance (Table 4 a), as also confirmed by Graph 3 showing standardized residuals. Table 4 (b) reports the coefficients of the conditional mean and conditional variance equations for the GARCH model, for the model.

The conditional mean equation shows that both expected and unexpected news, as well as the increased gap between moving average and price leads to a small depreciation in the USD/INR market. The GARCH analysis confirms our finding from the Logit. We see that Bias 1 has a large and statistically significant positive impact on volatility. Expected news also contributes to increased volatility but unexpected news leads to a small reduction in volatility. TA and Bias 2 (representing perceptions of market participants out of the market movement in response to expected news) do not have any statistically significant impact on volatility.

Section5: Discussions and Conclusion

The study looks at the contribution of news and traders biases on exchange rate volatility. Out paper contributes to the growing empirical evidence of the link between macroeconomic news and volatility in financial markets, including foreign exchange markets (Bessembinder, 1994; Fleming and Remolona, 1999; Hartmann, 1999; Galati, 2000; Evans and Lyons, 2005, 2008; Omrane & Hafner, 2015 and Vortelinos, 2015).However, it also goes on to question what leads to the volatility on the market? While the role of unexpected and expected components of news have been explored in economic literature (Omrane & Hafner, 2015 and Vortelinos, 2015), news by itself do not contribute to volatility. The unexpected and expected components of news make the trader form perceptions of market movement. Incorporating the theory of heuristics (Tversky and Kahneman, 1974), we underline that the biases created by perceptions means traders are likely to refer to the recent past solutions available for the trading decision making. This means that the trader refers to the past movement of the market in response of the news (expected and unexpected) and forms his trading decision. Expectedly, we find a large significant impact of bias 1, or perceptions created by past movements, that have occurred in response to unexpected news, on the market volatility.

The ordered Logit model shows that both unexpected and expected news components have statistically significant impact on the volatility. There is a large and statistically significant, positive impact of Bias 1 (which gives the perception of the traders created by past exchange rate movement in response to unexpected market shocks) on market heterogeneity. The marginal analysis in the Logit framework confirm our findings showing probability of volatility being in upper ranges increases with increase in Bias 1 but falls with increase in unexpected component of market news.

The GARCH analysis also extends strong support to our findings from the Logit. Bias 1 has a large and statistically significant positive impact on volatility as also, Expected component of news. Unexpected news leads to a small reduction in volatility. TA and Bias 2 (representing perceptions of market participants out of the market movement in response to expected news) do not have any statistically significant impact on volatility. This showcases an interesting aspect of market behaviour. As the news comes in, the unexpected and expected components in news influence the market heterogeneity, but in immediately following periods, the traders are much influenced by the movement that happened in the market in response to unexpected shocks.

Our paper extends the understanding of why news leads to an increase in volatility for the foreign exchange markets. Market participants are closely influenced by past market movements in framing their trading decisions. While a new information set is available in any time frame, it is difficult to not refer to what has happened in the past while trading. More precisely how the markets have reacted earlier on response of a market shock (unexpected component of news) is very important in guiding the market participant.

Empirical literature shows that market heterogeneity comes from the use of different and different interpretations of fundamental and technical indicators (Dreger & Stadtmann 2008; Chari 2007), While the same set of factors should move the market in a similar fashion, it does not happen so.A likely reason, according to this paper, is the availability bias where people assess the "probability of an event by the ease with which instances or occurrences can be brought to mind". This means that every time as a new set of information and news comes, the market participant does not take the trading decision with reference to the new information only. In the decision-making process therefore, past likely scenarios (" available" to the trader instantaneously) dominate. The forecasting of market movement now comes from the possible set of past experiences or available solutions, especially the experience of how the markets have moved earlier in response to a market shock. The perception formed by market participants on the basis on how the markets in the pasts have reacted to unexpected news shock, contribute majorly to market volatility.

Tables and Graphs

Table 1: Frequency distribution of CAVG

Bin	*Frequency*	*Percentage %*	*Cumulative %*
1	*905*	*83.41*	*83.41*
2	*140*	*12.90*	*96.31*
3	*40*	*3.69*	*100.00*
1	*905*	*83.41*	*83.41*

Source: Author's calculations

Table 2: Sample news from Eikon database

RIC	**Local Start Date**	**Local Time**	**Country**	**Indicator Name**	**Reuters Poll**	**Actual**
USEHS=ECI	24 Aug 2017	19:30	United States	Existing Home Sales	5.57M	5.42M
USEHSP=ECI	24 Aug 2017	19:30	United States	Exist. Home Sales % Chg	0.9%	-1.5%
USDGN=ECI	25 Aug 2017	18:00	United States	Durable Goods	-6.0%	-6.8%
USDGXT=ECI	25 Aug 2017	18:00	United States	Durables Ex-Transport	0.4%	0.5%
USNDXA=ECI	25 Aug 2017	18:00	United States	Nondefe Cap Ex-Air	0.3%	0.4%

Source: Thomson Reuters Eikon database

Table 3: Results of Ordered logistic regression

Number of obs = 1073
LR chi2(4) = 15.07
Prob > chi2 = 0.0101
Log likelihood = -557.58639
Pseudo R2 = 0.0315

VARIABLES	COEF.	STD. ERR.	Z	P>|Z|
TA	0.854	1.225	0.700	0.486
BIAS2	569.934	432.946	1.320	0.188
BIAS1	697.172	267.398	2.610	0.009*

UNEXPECTED	-0.585	0.311	-1.880	0.060***
EXPECTED	0.458	0.172	2.660	0.008*
/CUT1	1.674	0.090	1.497	1.850
/CUT2	3.466	0.184	3.106	3.826

, **, * denote statistical significance at the 1 per cent, 5 per cent and 10 per cent levels respectively*

MARGINAL EFFECTS AFTER OLOGIT				
Y= PR(CAVG=1) (PREDICT, OUTCOME(1)) = 0.83847249				
VARIABLE	DY/DX	STD. ERR	Z	P>|Z|
TA	-0.1156796	0.16523	-0.7	0.484
BIAS2	-77.18983	58.048	-1.33	0.184
BIAS1	-94.42239	35.811	-2.64	0.008*
UNEXPECTED	0.0791734	0.04145	1.91	0.056***
EXPECTED	-0.0620179	0.02301	-2.7	0.007*
Y= PR(CAVG=2) (PREDICT, OUTCOME(2)) = 0.13043972				
VARIABLE	DY/DX	STD. ERR	Z	P>|Z|
TA	0.090	0.129	0.700	0.486
BIAS2	60.023	45.902	1.310	0.191
BIAS1	73.423	28.477	2.580	0.010**
UNEXPECTED	-0.062	0.032	-1.900	0.058***
EXPECTED	0.048	0.018	2.630	0.009*
Y= PR(CAVG=3) (PREDICT, OUTCOME(3)) = 0.03108778				
VARIABLE	DY/DX	STD. ERR	Z	P>|Z|
TA	0.026	0.036	0.710	0.480
BIAS2	17.167	12.466	1.380	0.168
BIAS1	21.000	8.135	2.580	0.010**
UNEXPECTED	-0.018	0.010	-1.850	0.064***
EXPECTED	0.014	0.005	2.660	0.008*

, **, * denote statistical significance at the 1 per cent, 5 per cent and 10 per cent levels respectively*

Table 4: Results of the GARCH estimation

Unit root test

Variable	Test statistic value	1% critical value	5% critical value	10% critical value
Log (Exchange rate)	0.334	-3.43	-2.86	-2.57
UNEXPECTED	-128.164	-3.43	-2.86	-2.57
EXPECTED	-1271.447	-3.43	-2.86	-2.57
EXT	-38.262	-3.43	-2.86	-2.57
BIAS 1	-55.913	-3.43	-2.86	-2.57
BIAS 2	-8.474	-3.43	-2.86	-2.57
BIAS 3	0.334	-3.43	-2.86	-2.57
	H0: no ARCH effects vs. H1:ARCH(p)			
LM test for autoregressive conditional heteroskedasticity (ARCH)				
	lags(p)	chi2	df	Prob > chi2
Event 1	1	3.413	1	0.0647***
	H0: no ARCH effects vs. H1:ARCH(p)			

*, **, *** *denote statistical significance at the 1 per cent, 5 per cent and 10 per cent levels respectively*

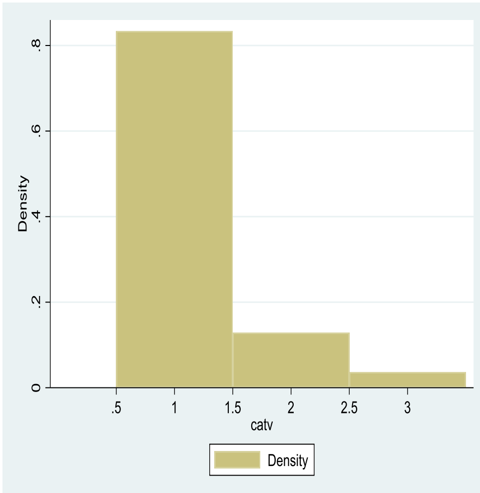
Table 2 (b): Results of GARCH estimation

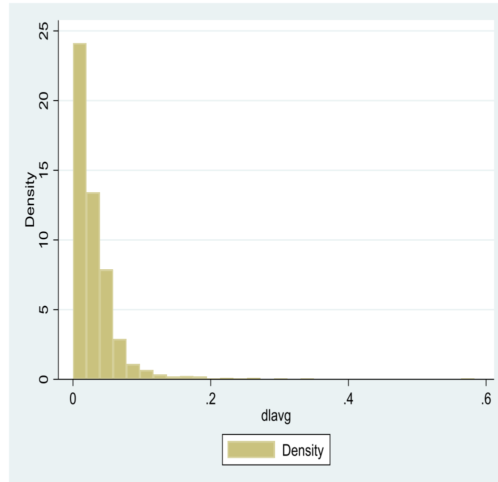
	Coef.	Std. Error	z	P>z
UNEXPECTED	0.0001	0.000	1.990	0.046 **
EXPECTED	0.000	0.000	0.800	0.423
BIAS 1	-0.014	0.215	-0.070	0.947
BIAS 2	0.029	0.152	0.190	0.848
TA	0.004	0.000	9.310	0.000 *
_cons	0.000	0.000	-0.520	0.600
HET				
UNEXPECTED	-0.545	0.205	-2.660	0.008 *
EXPECTED	0.305	0.119	2.580	0.010 **
BIAS 1	538.504	122.451	4.400	0.000 *
BIAS 2	470.694	628.301	0.750	0.454
TA	0.995	5.733	0.170	0.862
_cons	-16.478	0.757	-21.760	0.000 *
ARCH L1	0.215	0.065	3.300	0.001 *
GARCH L1	0.486	0.197	2.460	0.014 *

*, **, *** *denote statistical significance at the 1 per cent, 5 per cent and 10 per cent levels respectively*

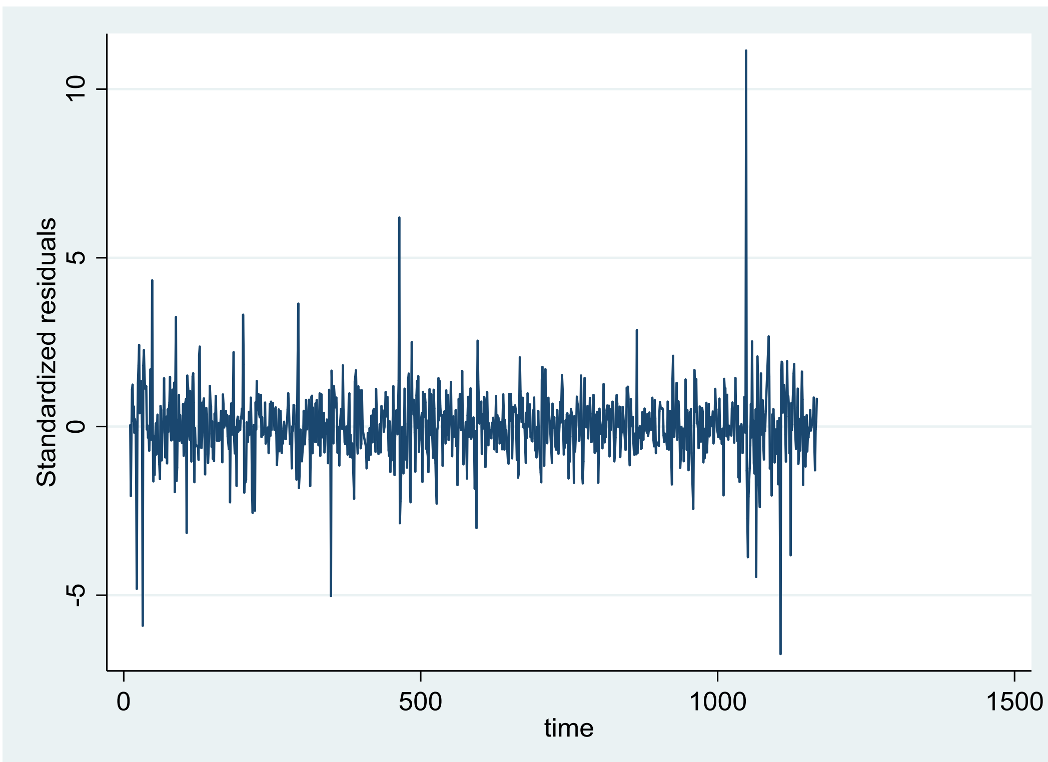
Graph1: Histogram CATV

Graph 2: Histogram DELAVG





Graph 3: Post estimation: ARCH effects



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