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Spillover-affect of Economic Policy Uncertainties on Equity Market in India : an empirical note

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Abstract:This paper empirically determined the impact of economic policy uncertainties on the Indian stock market. Taking advantage of a unique data set over the period 2004-2017 (14 yrs), we made use of Mixed data sampling (MIDAS) for our empirical assessment. The result showed that an increase in policy uncertainty impacted stock returns only if the extreme volatility was persistent. During regular volatile regimes other events, either political or corporate had a more significant impact on the equity market.

Keywords: Policy uncertainty, National Stock Exchange,, Differential regime model, MIDAS, GARCH

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1.0 Introduction

A recent volume of work has justified renewed interest in the economic impact of policy uncertainties [Bloom (2009)]. Empirical investigations have been carried out to examine the effect of policy shocks on a large set of economic indicators such as Industrial output, output gaps, growth, inflation (both core and headline), and (un)employment across nations [Fernandez-Villaverde et al. (2014)]. However, relatively little attention has been paid to the relationship between economic policy uncertainty (henceforth, EPU) and stock markets(Aurori,2016). Also, the bulk of what little work has been done has focused on the effects of uncertainty shocks on stock markets over, at best the last two or three decades [Antonakakis et al. (2013), Brogaard and Detzel (2014), Kang and Ratti (2015) and Liu L. and T. Zhang (2015)]. Emerging and vibrant markets like India lacks research in this domain.

Our paper contributes to this growing literature by providing an empirical exposition of the impact of policy uncertainty on the Indian stock market since 2004. Ourfindings may provide important implications for the policymakers to evaluate and understand the emerging economies like India, provide answer to some questions about the linkages between policy uncertainties, and return fluctuations (volatility) in the equity market.

Economic policy uncertainty refers to the non-zero probability of changes in the existing economic policies that determine the rules of the game for economic agents [Baker et al(2014)]. The effect of EPU on asset prices can run along many channels. First, policy uncertainty may change or delay important decisions taken by firms and other economic agents such as employment, investment, consumption, and saving decisions [Gulen and Ion(2014)]. Second, policy uncertainty may increase financing and production costs for the firms by affecting both supply and demand channels, intensifying disinvestment, and economic contraction [Julio (2002)]. Third, EPU may increase risks in financial markets in particular by reducing the value of protections provided by the government for markets [Pastor and Veronesi (2012)]. All these factors may reflect in the return distribution of the listed stocks in the market. We hypothise that the policy change impact market volatility.

Finally, economic uncertainty may also affect inflation, interest rate, and expected risk premiums [Pastor and Veronesi (2013)]. since the objective of the paper is to determine the segregated impact of EPU on Volatility only, we use difference in EPUas one of the regressand so that other factors are weeded out.

Our paper offers an original empirical investigation of the effects of EPU on the Indian stock market based on medium-term, but mixed frequency data of reconstituted price indexes over the period 2014-2017.

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The rest of the paper is organized as follows. Section 2.0 reviews the econometric specification. This is followed by a section on the data and the data generating process for the paper. Section 4.0 presents the estimates and empirical findings. Section 5.0 provides discussions of the results obtained. Section 6.0 concludes the paper.

2.0 **Econometric Specifications**

This section discusses the empirical specification related to the objective. The empirical specification holds importance as in an analysis of financial data we make use of daily data (inter/intraday) whereas for macroeconomic indicators monthly or quarterly data is available. We make use of mixed data sampling for our analysis.

Econometric analysis of MIDAS regressions was popularized in the seminal work in Ghysels, Sinko, and Valkanov (2006), Andreou *et al.* (2010), Bai, Ghysels, andWright (2013), Kvedaras and Račkauskas (2010), Rodriguez and Puggioni (2010), Wohlrabe (2009), among others.

MIDAS regression can also be viewed as a reduced-form representation of the linear projection which simplifies a state-space model approach. Bai *et al.* (2013) show that in some cases the MIDAS regression is a representation of the Kalman filter, It most cases, the model involves typically small approximation errors. Henceforth it has robust specification for our use.

The next section discusses the data sources and the differential regime for our analysis.

3.0 Data

To capture the degree of policy uncertainty, we use the news-based index available as detailed by Baker, Bloom, Davis, Wang (2013) and Baker, Bloom, and Davis (2014). This index was constructed as a scaled frequency count of news articles about India's policy related to economic uncertainty. The policy mattersaccounted for cover a variety of aspects including monetary, fiscal, tax, regulatory, international trade issues as well as political and economic reform.[2]

[2] Seven (English) newspapers were considered: The Economic Times, the Times of India, the Hindustan Times, the Hindu, the Statesman, the Indian Express, and the Financial Express. For each paper, a counter based on several news articles containing at least one term from each of three-term sets. The first set is uncertain, uncertainties, or uncertainty. The second set is the economic or economy. The third set consists of policy-relevant terms such as 'regulation', 'central bank', 'monetary policy', 'policymakers', 'deficit', 'legislation', and 'fiscal policy'.

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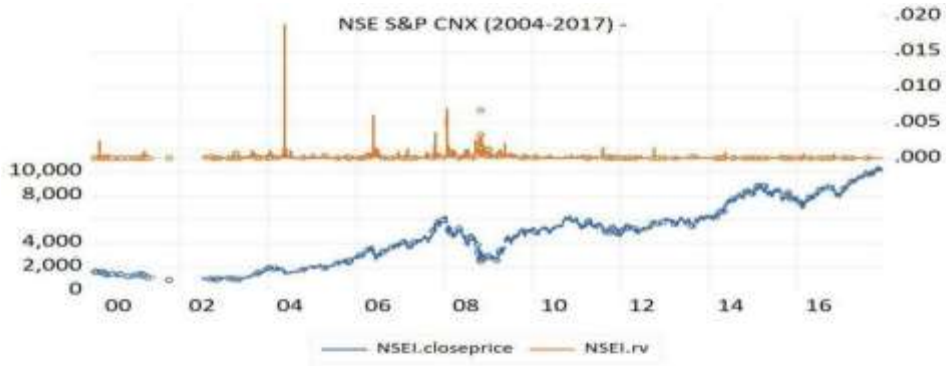
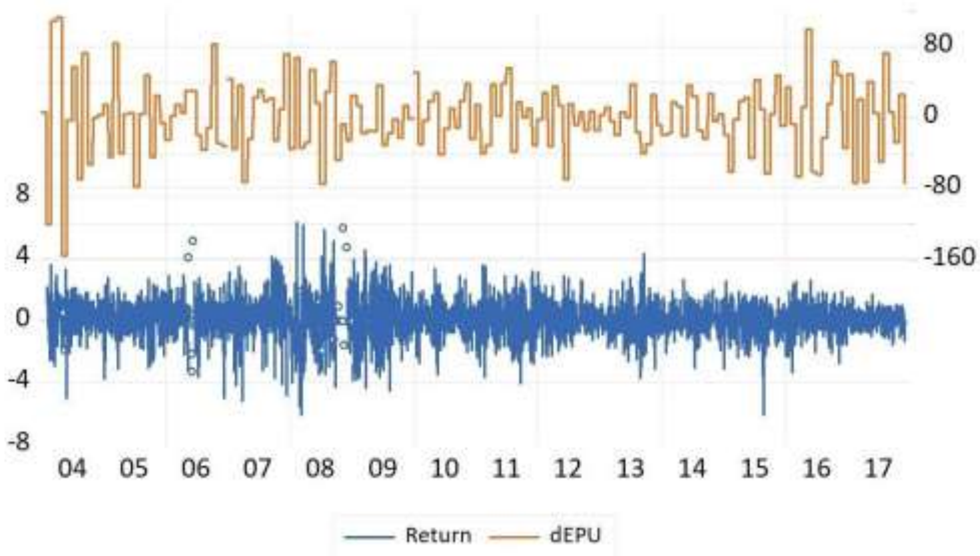
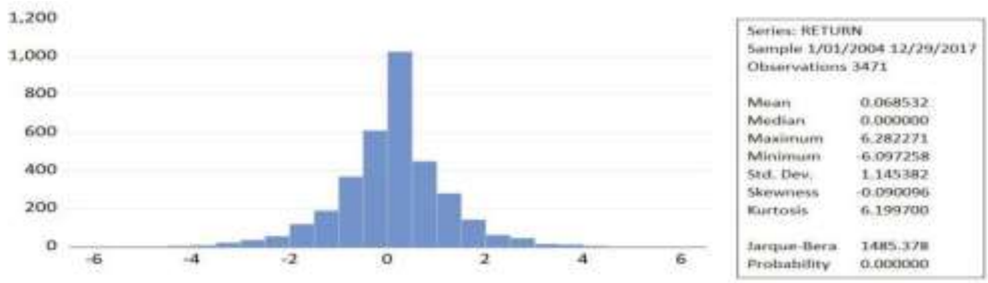


Figure3.1: ***Representation of NSE data indicating realized volatility and closing price (2004-17) (data source:****Heber G, Lunde A, Shephard N, Sheppard K (2009).)*

the two data strands used for our analysis are presented in Figure-2.





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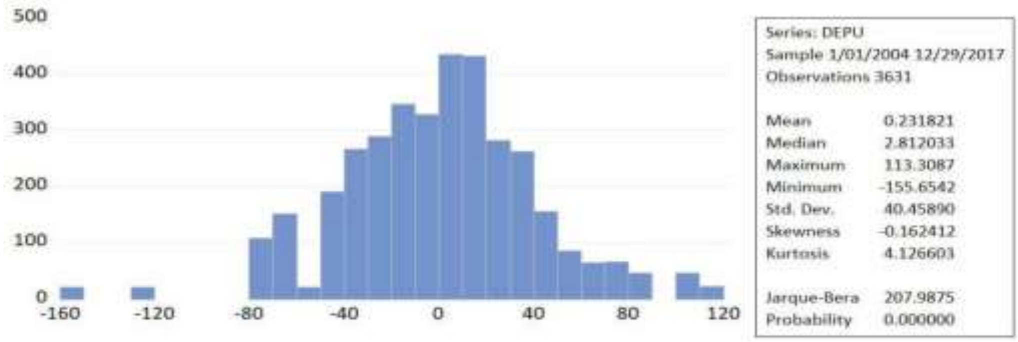

Figure: 3.2: ***Data Representation and description.*** *DEPU represents the change in n Economic policy uncertainty and Return represents the daily NSE Index return.*

The next section presents the empirical method adopted and tabulates the outcome for comparative ease.

4.0 Empirical Findings

In this section, we empirically determine whether economic policy uncertainty (EPU) affects NSE returns based on linear specifications where the model parameters are assumed to be time-invariant and thus they do not take into account possible structural breaks and regime changes that may create varying states of uncertainty in a regime-switching environment and affect the EPU stock market relationship. Therefore, it would be interesting to study the effects of EPU on stock markets under the differential regime as in Equation (1):

$$R_{i,t} = \alpha_{s_t} + \beta_{s_t} R_{t-1} + \gamma_{s_t} d(EPU) + \delta_{s_t} X + \varepsilon_{s_t} \tag{1}$$

Where,

$$\varepsilon_{s_t} \sim N(0, \sigma_{s_t})$$

, S_t is a discrete differential regime variable (1,2,3,4,…n) following an n-stage Markov process.

Also We tested for different specifications of the Markov switching model: two-regime models versus three-regime models with constant or regime-dependent variances. Our findings show that the three-regime dependent variance model (n=2) reproduces the data better than the other competing models. This three-regime specification allows us to represent market states by regular volatility which is characterized by GJR GARCH [3](1,1) model (Glosten L, R Jagannathan and D Runkle. (1993))following Sinha.,

3 NSE (Nifty) Descriptive Stats

- Q(1)[a:] 6.40(2-tailed,p-value=0.00);$Q^2(1)$[b:] 65.5(2-tailed,p-value=0.00)

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B (2006) and references therein, and extreme volatility regimes. The results of the model estimation are summarized in **Table -4.1.**

4.1 Why MIDAS Model

A regular regression model assumes that the regressor and the regressands data follow the same frequency and structure. This restricts is not always feasible in practice—for instance, in corporate finance or macroeconomics, where statistical releases occur on annual, quarterly, monthly and even daily frequencies. It becomes difficult tomeet the assumptions of a multiple regression model. Traditionally, to determine the estimation under such mixed frequency datasets , we used these data generating process (DGP) for our analysis:

The first approach was the sum/ mean of the higher frequency data into the lower frequency dependent variable. There were two main issue with this approach,(I)we implicitly applying equal weights to each high frequency value in the conversion. (ii)we loose good amount of information about the dynamics of the high frequency variable.

• Alternate model comprises of adding the individual components of the higher frequency data to the regression, allowing for a separate coefficient for each high frequency component. This is a complex model and increases the number of coefficients, which needed to be estimated.

MIDAS or Mixed frequency estimation allows for non-equal weights but reduces the number of coefficients by fitting functions to the parameters (parsimonious parameterization) of the higher frequency data.

The MIDAS model is :

- ARCH-LM statistic @ 1-lag:117.7;ACF[d] @ 1 lag for returns :0.078 (asymtotoc bound=0.04)

Notes

a. Q(K) is the Ljung Box statistic identifying the presence of first order autocorrelation in the returns. null hypothesis: no autocorrelation. Distributed as chi-square (K).(Ljung and Box(1978))

b. Q2 (K) is the Ljung Box statistic identifying the presence of first order autocorrelation in the squared returns. null hypothesis: no autocorrelation, distributed as chi-square (K).

c. ARCH LM statistic is the Lagrange Multiplier test statistic for the presence of ARCH . Null hypothesis: no heteroscedasticity, distributed as a chi-square (K). Critical value at 1 per cent level of significance is 6.63 at 1 degree of freedom. Values for other higher lag are also significant.

d. ACF is auto-correlation function for returns and squared returns resp.

e. GJR-GARCH (1,1): c=0.096;$\alpha 0$ = 0.183;$\alpha 1$ =0.065;$\beta 1$=0.86[Log-likelihood=-5789;AIC=-5.71;SBIC=-5.55

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$$y_t = \theta_i f(\{X_{t/S}{}^{H}\}, \lambda) + X'_t \beta + \varepsilon_t \tag{4.2}$$

Where:

y is a dependent variable of low frequency.

X_t^H are a set of regressors sample at a Higher frequency

λ,β,θ are the parameters to be estimated.

MIDAS uses three different methods to achive a middle ground:

(i) Exponential or PDL/Almon method which uses exponential weights of lags of polynomial 2.In our case it is 3.(refer Table 4.1).

(ii) Beta method :This method uses beta weightages and are extremely flexible. This methodis most suitable for all practical, non-linear models. We place restriction on slow decay(growth) on the weightages parameters i.e. zero weights at high frequency endpoints.

(iii) U-MIDAS method is suitable for parabolic shape weightages.

We conduct the MIDAS regression for two segregate volatility segment and determine which method of weighte is suitable under each senario.Also, we compare our findings with the Least square based regression. The results are tabulated in **Table : 4.1** for comparative assessment.

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	Volatility Regime	Least Square	MIDAS : Methods Used		
			Beta	PDL/Almon	U-MIDAS
Constant		***(1)***	***(2)***	***(3)***	***(4)***
	Regular♀	0.012***(0.112)	-1.05***(0.019 2)	-1.106(4.72)	------------
	Extreme	10.8***(1.01)	------------	40.68(0.98)	52.17(0.121)
RV	Regular	0.67**(0.79)	------------	------------	------------
	Extreme	0.21*(0.105)	------------	------------	------------
RV(-1)	Regular	0.12(0.005)	0.3**(0.17)	-1.10(4.72)	-0.64**(0.24)
	Extreme	0.176*(0.11)	------------	-0.29(0.66)	------------
DEPU	Regular	-0.044**(0.005)	------------	------------	------------
	Extreme	-0.24**(0.105)	------------	------------	------------
DEPU(-1)	Regular	-.0034(0.18)	-0.26**(0.076)	-0.24**(0.07 9)	------------
	Extreme	--0.016(0.11)	------------	------------	NS-5 lags
# Obs	Regular:358 2(***92.8%***)				
	Extreme:32(***0.8%***)				

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	N/A:207				
Total	3821	3582/32	3582/32	3582/32	3582/32
Log-likelihood ratio		-202.67/-203.17	-5100.42/-----	-783.09--439	-----/-42.055
AIC		-2.47/-3.61	-3.04/-----	10.16/9.68	------/-4.613

Table 4.1: **Impact of EPU on Index returns under (MIDAS) differential regime criteria.** *MIDAS based differential regime regression represents the mixed frequency (data) regression. The period of the analysis is from 9th Feb/2004 to 5th December/2017 inclusive.LR test is the linearity test. Robust standard errors are into parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels (S.L.) resp.Note:dEPU is the change in EPU and RV(-1) is the one period lag inindex daily returns. Regular = measure of volatility given by RV ± 1 σGJR-GARCH(1,1)is used as the benchmark for the regular volatility of NSE(see Sinha., B(2006)). NS = Not Significant (here upto5 lags). [Author's computation]*

5.0 Empirical Explanation

We empirically determined the relationship between economic policy uncertainties and equity market volatility in an emerging market like India. To avoid any loss of information due to the difference in frequency of the data. The Relative volatility data were daily (low frequency) and the policy uncertainty was monthly (High frequency). Taking advantage of MIDAS regression so that there is no loss of information we arrived at the output as tabulated in Table # 4.1.

From the table we can infer that comparing amongst the three methods, beta issuitable under regular volatility regime. This is based on the Akaike Information Criterion (AIC). The result indicates that on average Relative variance of the previous day has a significant impact on the volatility. Also, the difference in Economic policy uncertainty has an, on average, a negative impact on volatility. Nonetheless, it is difficult to infer that what does the lag in the economic policy uncertainties indicated. One conjecture could be that it takes about 30 days, on average, for a more (less) than expected change in policy indicators.

However, during extreme volatile scenario the Economic policy uncertainties, on an average, doesn't show a significant impact on the volatility. The lag volatility and other factors (white noise) have some statistical significance.

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This finding is important. It is often perceived, especially in the press that due to some macroeconomic policy change or budgetary implications related to the whole economy the market showed high volatility. We found that it is not an empirically justifiable argument. Other factors like political events, change in corporate Law or other market-specific events may have a greater impact.

Also, during the high volatility phase, past volatility has a significant impact (presence of volatility clustering) but no empirical evidence to suggest Economic policy uncertainties has a causal impact on volatility.

6.0 Conclusion

We studied the impact of economic policy uncertainty (EPU) on stock markets in India over the long period 2004-2017 using both linear and MIDAS differential regime models. Our findings suggest that an increase in policy-related uncertainty increases the representative stock volatility significantly during the high volatility phase. However, as expected, the relationship between stock market returns and EPU is not linear and the effect of EPU on stock returns is stronger and persistent during regular volatility periods, but not so during the extreme phase. This paper emphasis that, in India, economic policy stability impacts the stock market (equity prices) with a lag and also under the extreme scenario.

7.0 References

1. Andreou E, Ghysels E, Kourtellos A (2010). “Regression Models With Mixed Sampling Frequencies.” *Journal of Econometrics*, **158**, 246–261. DOI:10.1016/j.jeconom.2010.01.004.

2. Andreou E, Ghysels E, Kourtellos A (2010). “Regression Models With Mixed Sampling Frequencies.” *Journal of Econometrics*, **158**, 246–261. doi:10.1016/j.jeconom.2010.01.004.

3. Antonakakis, N., Chatziantoniou, I., Filis, G. (2013). "Dynamic Co-movements between Stock Market Returns and Policy Uncertainty”, *Economics Letters*, 120 (1), 87-92.

4. ArouriM,Estay C,Rault(2016),”Economic policy uncertainty and stock markets: Long-run evidence from the US”, Finance Research Letters , DOI: 10.1016/j.frl.2016.04.011

5. Bai J, Ghysels E, Wright J (2013). “State Space Models and MIDAS Regressions.” *Econometric Reviews*, **32**(7), 779–813. DOI:10.1080/07474938.2012.690675.

Electronic copy available at: https://ssrn.com/abstract=4037135

6. Bai J, Ghysels E, Wright J (2013). “State Space Models and MIDAS Regressions.” *Econometric Reviews*, **32**(7), 779–813. doi:10.1080/07474938.2012.690675.

7. Baker, S.R., Bloom, N., Davis, S.J., (2014). “Measuring economic policy uncertainty. Unpublished working paper”. Stanford University and University of Chicago.

8. Bloom, N. (2009). “The Impact of Uncertainty Shocks”, *Econometrica* 77(3),623-685.

9. Brogaard J. and Detzel A. (2014), "The asset pricing implications of government economic policy uncertainty". *University of Washington mimeo.*

10. Fernandez-Villaverde, J., Guerron-Quintana, P., Kuester, K., Rubio-Ramirez, J., (2014). “Fiscal volatility shocks and economic activity”. *NBER Working Paper*

11. Ghysels E, Kvedaras V, Zemlys V (2016). *Mixed Frequency Data Sampling Regression Models: The R Package MIDASr*. R package version 0.6, URL https://CRAN.R-project.org/package=MIDASr.

12. Ghysels E, Sinko A, Valkanov R (2006). “MIDAS Regressions: Further Results and New Directions.” *Econometric Reviews*, **26**, 53–90. doi:10.1080/07474930600972467.

13. Gulen, H.and M. Ion, (2013). “Policy Uncertainty and Corporate Investment”, Working paper, Purdue University.

14. Heber G, Lunde A, Shephard N, Sheppard K (2009). “Oxford-Man Institute’s Realized Library.” Oxford-Man Institute, University of Oxford. Library Version 0.2.

15. Julio, B., Yook, Y.,(2012). "Corporate financial policy under political uncertainty: international evidence from national elections", *Journal of Finance* 67,45–83.

16. Kang W. and Ratti R.A. (2013), "Oil shocks, policy uncertainty, and stock market return", *Journal of Intentional Financial Markets, Institutions and Money* 26, 305–318.

17. Kvedaras V, Račkauskas A (2010). "Regression Models with Variables of Different Frequencies: The Case of a Fixed Frequency Ratio." *Oxford Bulletin of Economics and Statistics*, **72**(5), 600–620. doi:10.1111/j.1468-0084.2010.00585.x.

18. Liu L. and T. Zhang (2015). “Economic policy uncertainty and stock market volatility”, *Finance Research Letters* 15, 99-105.

Electronic copy available at: https://ssrn.com/abstract=4037135

19. Pastor, L., and Veronesi P.,(2013). “Political uncertainty and risk premia*”, Journal of Financial Economics*, 110, 520–545

20. Pastor, L., Veronesi, P. (2012). “Uncertainty about government policy and stock prices”. *Journal of Finance* 67, 1219–1264.

21. Rodriguez A, Puggioni G (2010). “Mixed Frequency Models: Bayesian Approaches to Estimation and Prediction.” *International Journal of Forecasting*, **26**, 293–311. doi:10.1016/j.ijforecast.2010.01.009.

22. Sinha.B(2006),”Modelling Stock Market Volatility in Emerging Market:Evidence from India”,ssrn #954189.

23. Wohlrabe K (2009). *Forecasting with Mixed-Frequency Time Series Models*.Ph.D. thesis,Ludwig-Maximilians-Universität München.

24. Glosten L, R Jagannathan and D Runkle. (1993), On the Relation Between the Expected Value and Volatility of the Nominal Excess Return on Stocks. Journalof Finance. 48(5): 1779-1801.

25. Ljung, G and G. Box,(1978) “On a Measure of Lack of Fit in Time Series Models,” Biometrika, Vol 66, 1978, pp 67-72.

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