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Instability in General Price Level caused by Financial Derivatives (Empirical Evidence from U.K.)

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AbstractFluctuation in general price levelis considered to have destabilizing effects for economies. In this study, the role derivatives in inflation volatility has been analyzed.UK, an important center for derivatives trading, has been taken as exemplar case. Student t EGARCH model has been applied on the monthly data of UK inflation (CPI of UK, collected from International Financial Statistics – IMF) from 1993M01 to 2016M09. Notional turnover of the exchange traded derivatives of UK capital markets (data collected from BIS Statistics Explorer) has been incorporated in the model as exogenous factor. Result suggests that exogenous factor, last period volatility, long term volatility, and GARCH effect are found significant; whereas leverage effect is found insignificant. Significance of GARCH effect and exogenous factor refers that fluctuation in general price level in UKis not only effected by its own previous period fluctuation but by the UKderivatives trade as well. Since both dependent and exogenous variables are log transformed therefore the relationship is interpreted in in terms of elasticity and It can be said that 1% increase in UK derivatives trade will increase UKprice fluctuation by 0.29%. It can be concluded that there is a role of derivatives trade in enhancing the price fluctuation in UK economy.

Keywords: Derivatives Trading,EGARCH Model,Financial Derivatives, Inflation, Price fluctuation

Introduction

Inflation is an important and heavily researched macroeconomic indicator in economics and finance. Fluctuation in general price level is a critical but neglected aspect of inflation phenomenon. Capistrán and Ramos-Francia (2009) have discussed three main tenants of inflation, average inflation level, tenacity of inflation, and inflation volatility. According to Banerjee (2013) fluctuation in general price level causes adverse economic impact but it has received less attention among economists. Commonly known “Friedman-Ball Hypothesis” provides theoretical bases to check causality running between inflation and inflation volatility. Banerjee (2013) has stated that volatile inflation impairs economic growth and stability, it leads to misallocation of resources, distorts prices, erodes savings, and deteriorates investment. Economies with volatile inflation face greater uncertainty.

Rationale of the Study

Fluctuation in inflation arises through exogenous shocks and tangles with the unanticipated components of inflation, but researchers have paid little attention towards exogenous factor while analyzing inflation volatility. Sarwat (2018) has stated that in the contemporary financial setup,financial and commodity derivatives haveappeared to be a chief cause of increasing price instability. There are very few studies addressing this issue. Although several studies have investigated impact of trading for specific commodity derivatives on the spot price of underlying asset, but overall impact of derivatives trade on price instability has hardly been studied. In this study, the role derivatives in price instability is analyzed empirically by using ARCH/GARCH type models with exogenous regressor.

Literature Review

Literature is fragmented on the determinants of price instability; Capistrán and Ramos (2009) studied the persistence of inflation 10 Latin American economies for the period 1980–2007. They found that only about a third of the total variation of inflation can be explained by a common factor and remaining variation is associated with idiosyncratic factors. Dua and Gaur (2010) pointed out a similar pattern in the variables determining inflation across developed and developing economies. Monetary variables (Papi& Lim, 1997;Moser, 1995), exchange rate (Altissimo, Benigno&Palenzuela, 2005; Papi& Lim, 1997; Moser, 1995), public sector deficit (Papi, & Lim, 1997), degree of price liberalization and central bank independence (Cottarelli, Griffiths &Moghadam, 1998), communication infrastructure and urbanization (Fielding, 2008), level of inflation (Davis &Kanago, 1998), and inertia (Baillie, Chung &Tieslau, 1996) are among the factors, which are reported as main determinants of price instability.

Davis and Kanago (1998) used panel data of inflation expectations of 44 countries for 20 years and investigated the relationship between the level and uncertainty of inflation. Their results suggest insignificant relationship between average inflation and average uncertainty across countries. Baillie, Chung and Tieslau (1996) have stated that the current inflation leads to additional volatility in future inflation. Okun (1971) reported a positive association between standard deviation and average value of inflation calculated from GDP deflator. Level of inflation and inertia are the two important factors, which motivated us to apply ARCH/GARCH type models to analysis the volatility of inflation.

ARCH model was proposed by Engle in 1982 and he was also the first one who used ARCH model to estimate price instability. He estimated the means and variances of inflation in the U.K. and found significant ARCH effect in UK's inflation measures. His findings suggest that variance in inflation increased substantially during the chaotic seventies in UK. A year later, Engle (1983) carried out a similar study for USA. He found that price instability in the seventies was slightly larger than in the sixties, but it was predictable. Since then several studies incorporated ARCH/GARCH type model to test price instability; for instance, Bollerslev (1986), Brunner and Hess (1993), Joyce (1995), and Kontonikas (2004). Among the recent studies, Fischer (2013), and Rizvi, Naqvi, Bordes and Mirza (2014) have also used ARCH/GARCH type model to gauge price instability.

There are several studies, which discusses the adverse impact of price instability not only on the economy but the society as well. Friedman (1977) was of the opinion that volatile inflation disturbs economic prosperity. Al-Marhubi, (1998) found that the high variability in general price level results in low average growth and causes negative effect on the productivity. His analyses are based on a cross-country sample of 78 countries using data from 1965 to 1994. Braun (2004) has shown that inflation variability can lead to higher corruption level and lower investment level. He analyzed panel data of 75 countries with country fixed effects and applied 2SLS estimation. His results indicate that one standard deviation increase in inflation variance from the median can cause 12 percent increase in standard deviation of corruption and reduces growth by 0.33 percentage points.

Assenmacher and Gerlach, (2008) have argued that in Switzerland, money growth is helpful in guarding against the inflation pressures and volatility. According to Rizvi et al. (2014), there are negative consequences of price instability on different financial and economic variables which eventually deteriorate the economic growth and welfare. Variability in prices alters the assets' returns and prompt portfolio adjustment for optimizing. Dibooglu&Kenc (2009) have argued that such portfolio adjustments are costly for economic growth and social welfare. Fischer (2013) has shown that the higher variability in prices causes reduction in fixed asset investment. Banerjee (2013) has empirically shown that inflation is substantially volatile in nature for developing countries than that of developed countries.

Research Methodology

Following Hypothetico-Deductive Approach,time series analyses have been performed in this study to explain the relationship between price instability and derivative trade. United States, being the pivot of financial derivatives, is taken as test case. EGARCH model from the ARCH family is employed for the analysis.

ARCH/GARCH Type Models

ARCH stands for Auto-Regressive Conditionally Heteroscedastic, introduced by Engle (1982). ARCH model is applied to estimate volatility in time series like stock returns, exchange rates, inflation etc. The important aspect of ARCH is that it captures time varying volatility and volatility clustering phenomenon. Non-linearity in variance is auto-correlated in various time series, on basis of which ARCH model works. Later on, Bollerslev (1986) and Taylor (1986) independently generalized Engle's model and called it GARCH.

In GARCH model, conditional variance is dependent upon its own previous lags along with lags of squared residuals. GARCH avoids overfitting, consequently, less likely to breach non-negativity constraints (Bollerslev, 1986). In comparison to ARCH, GARCH model is more parsimonious; it captures the effect of infinite number of past squared residuals on current volatility with only three parameters but it does not capture leverage effect. TARCH and EGARCH provide solution to the problem of leverage.

Research Design

There could be several ways from standard deviation to exponentially weighted moving average (EWMA) or ARMA to estimate price instability. Time series models like ARMA are not appropriate to explain nonlinearity, leptokurtosis, leverage effect, and volatility clustering. However, GARCH with its variants are the most commonly used volatility measure in the domain of finance. Although, ARCH/GARCH type models are primarily univariate in nature, but these models are flexible enough to incorporate exogenous variables as well. Exchange traded derivatives' turnover in UK markets is taken as exogenous factor in this model. There are certain financial and economic factors, which are generally thought to be important determinants of inflation, however, dynamic autoregressive process along with one exogenous factor i.e. derivatives trade to model price instability of UK is selected, so that the role of the exogenous variable in the volatility of inflation can be captured.

Model Specification

ARCH model uses conditional variance of the error to model volatility. ARCH (q) can be specified as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_1 u_{t-1}^2 + \cdots + \alpha_1 u_{t-q}^2 \qquad (1)$$

Where, σ_t^2 is the volatility of the variable, α_i is the constant and coefficient terms, and u_{t-i}^2 is the squared lags of error term from the mean equation.

ARCH is not parsimonious for increasing number of lags of the squared residual in the model. GARCH model allows the conditional variance to be dependent upon previous own lags along with lagged error terms. GARCH (p,q) model can be specified as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (2)$$

Where, β_j is the coefficient of the lagged variance σ_{t-j}^2. GARCH (1,1) model will be sufficient to capture the volatility clustering in the data,

Su (2010) has stated that GARCH (1, 1) only captures leptokurtosis (fat tails relative to the normal distribution), volatility clustering and some of the skewness, but not the asymmetry in behavior. Various researchers have found asymmetric response (leverage effect) in financial time series. Leverage effect refers to a phenomenon where a negative shock is likely to cause more volatility than by a positive shock of the same magnitude (Chris, 2008). Conventional GARCH (1,1) model does not capture this asymmetry. TARCH or GJR GARCH introduced by Glosten, Jagannathan and Runkle (1993), and Exponential GARCH (EGARCH) introduced by Nelson (1991), are the two GARCH variants that can capture asymmetry. EGARCH is being used in the study because of two reasons. First, it does not artificially impose non-negativity constraints and second, it takes natural log of volatility, which converts volatility into relative terms (percentage change). Log is also applied to the exogenous variable i.e. monthly turnover of the notional amount of exchange traded derivatives in UK markets. EGARCH (1,1) can be specified as follows:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \qquad (3)$$

This model has one additional term of exogenous variable for UK derivatives trade. lagged values have been incorporated in the model after taking natural log of derivatives trade. Having log of lag values has several advantages to the analysis; firstly, the data will be transformed from absolute values to relative values, which are generally stationary in nature, secondly the lag element allows us to analysis feedback mechanism of derivatives trade on UK inflation and finally it is in synchronization with response variable as it is also log term, which makes interpretation of results in terms of elasticity. Thus, the model with more generalized description is as follows:

$$\ln(GARCH_t) = \omega + \beta \ln(GARCH_{t-1}) + \gamma \frac{Residuals_{\ t-1}}{\sqrt{GARCH_{t-1}}} + \alpha \frac{|Residuals_{\ t-1}|}{\sqrt{GARCH_{t-1}}} \delta \ln(USDER_{t-1}) \qquad (4)$$

Here, $GARCH_t$ term is denoting current year volatility of inflation in terms of variance, which is dependent on lagged volatility of inflation and lagged values of exchange traded derivatives in UK markets. Term with γ coefficient is exhibiting leverage effect whereas α coefficient term is capturing ARCH effect. Dependent variable has log form in the model, thus the model will show the relative changes of volatility rather than absolute changes.

Financial time series data hardly exhibit normal distribution, because of which Gaussian GARCH models are not suited to fit market returns or macroeconomic indicators. Bollerslev (1987) showed that the conditional distribution of market volatility is t distributed. Thus, student t EGARCH is used. Lambert and Laurent (2001) extended Student-t EGARCH to skewed Student-t distributions. Su (2010) have also used student t EGARCH. According to him, model based on the Student-t distribution usually produces the larger log-likelihood value as compared to the Gaussian distribution. Rizvi et al. (2014) have applied EGARCH to price instability in Asian perspective.

Data Set

ARCH/GARCH type models are usually applied on high frequency data (i.e. daily data) because it carries more volatility, but researchers have also applied these models on the data with monthly or even quarterly frequencies as well (Banerjee, 2013). Monthly frequency is being used because of non-availability of higher frequency data. Monthly data on CPI of UK are collected from International Financial Statistics (IMF) for the sample period of 1993M01 to 2016M09 have 2010 as base year. Monthly data of daily average of notional amount of turnover of exchange traded derivatives, which include futures and options, are collected from BIS Statistics Explorer for the same sample period. From the dataset of UK CPI, inflation series are generated as the logarithmic difference of index between two consecutive time periods. Similarly, for the growth of derivatives trade, natural log of the ratio of current and previous month trade is calculated. All in all, there are 285 data points. All the analyses are performed through EViews 9.

Checking Data for Statistical Assumptions

In time series analysis, stationarity of the data is the most important and desired feature. For ARCH/GARCH type models, two additional assumptions are also crucial, i.e. volatility clustering and presence of ARCH effect.

Stationarity

There are several unit root tests for stationarity including Dickey–Fuller (DF) test, Augmented Dickey–Fuller (ADF), and Phillips–Perron (PP) etc. Phillips–Perron test is applied here because it uses nonparametric statistical methods to take care of the serial correlation in the error terms without adding lagged difference terms. Stationarity test has been applied to both dependent and exogenous variables. Results of unit root test on UK inflation are presented in table 1.

Table 1. Unit root test for UK Inflation

Null Hypothesis: UKINF has a unit root#		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-7.673485	0
Test critical values:	1% level	-3.850203	
	5% level	-3.392553	
	10% level	-3.101259	

Exogenous: Constant, Linear Trend,
Bandwidth: 26 (Newey-West automatic) using Bartlett kernel
*MacKinnon (1996) one-sided p-values.

Table 2. Phillips-Perron Test Equation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
UKINF(-1)	-0.53467	0.04933	-10.8397	0
C	0.001311	0.00041	3.17433414	0.0017

TREND(1993M01)	-2.09E-06	2.10E-06	-0.99524	0.3205

Here, null hypothesis can be reject as p value of the UKINF is less than 5%, means that there is no unit root and the time series of UK inflation is stationary. Trend is insignificant in the Philips-Parron equation. In this model, the decision about the number of lags to be included in each cross section is based on Bayesian information criterion (BIC) also known as Schwarz information criterion (SIC). Now the same test is applied on the log of derivatives trade in UK markets, Results are presented in table 3 and table 4.

Table 3. Unit root test for the log of derivatives trade in UK markets

Null Hypothesis: LN_UKDER has a unit root#		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-5.348567	0.0001
Test critical values:	1% level	-4.001342	
	5% level	-3.863382	
	10% level	-3.253646	

Exogenous: Constant, Linear Trend, *MacKinnon (1996) one-sided p-values.
Bandwidth: 10 (Newey-West automatic) using Bartlett kernel

Table 4. Phillips-Perron Test Equation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN_UKDER(-1)	-0.16544	0.04123	-4.01261	0
C	2.160438	0.48046	4.49660	0
TREND(1993M01)	0.00212	0.00045	4.70067	0

The growth in derivatives trade is also stationary as revealed by p value or t statistics values. Presence of stationarity in both the variables confirms the fact the data series are free of long memory process and both the variables have stable mean and variance. Thus, the data is fulfilling the primary condition for time series analysis.

Volatility Clustering

Volatility clustering is a precondition for ARCH/GARCH type models. It refers to a particular behavior of volatility in time series where periods of low volatility follow periods of low volatility and periods of high volatility follow period of high volatility. In other words, volatility appears in bunches. Volatility clustering can either be checked graphically or through statistical test. For graphical checking, first simple mean regression has to be run with constant and plot the residuals. Figure 1 is showing the graph of residuals from the mean of UK inflation.

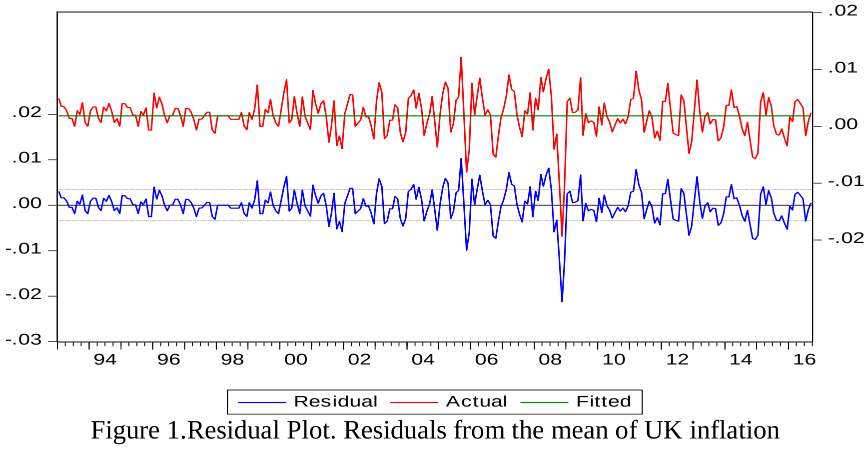

Figure 1.Residual Plot. Residuals from the mean of UK inflation

In figure 1, prolong periods of low and high volatility can be observed, which are evidencing volatility clustering. The conclusion can be counterchecked by the statistical method of correlogram. In the table of correlograms, assumption is checked up to 36 lags. P values for all lags are significant depicting presence of non-linear relationship among lags as it can be noted in table 5.

Table 5. Correlogram statistics for UK inflation (see Annexure A)

ARCH Effect

This is another very important assumption for ARCH/GARCH type models. ARCH effect is said to have present if data series is exhibiting autocorrelation in the squared residuals. This test is also known as heteroscedasticity test. In the test, the square of residuals is regressed on a constant and its lag values. This ARCH-LM test was proposed by Engel (1982). In this method, mean regression is run to acquire residuals then auto regression is performed on squared residuals. Results of test are presented in table 6.

Table 6. Heteroskedasticity Test: ARCH

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.28E-06	1.78E-06	3.52809	0.0005
RESID^2(-1)	0.434252	0.054531	7.96339	0
F-statistic	77.54018	Prob. F(1,282)		0
Obs*R-squared	62.69325	Prob. Chi-Square(1)		0

Here, the null hypothesis is: there is no ARCH effect. Results are significant as exhibited by p value, which is less than 5%. It means that ARCH effect is present in the data and UK inflation is conditionally heteroscedastic. In ARCH/GARCH type model, normality is rejected in favor of thick tail. Jarque–Bera test has been applied on the UK inflation data and found it to be significant. In Jarque–Bera test, null hypothesis is that the data is normally distributed (skewness = 0, Excess kurtosis = 0). Thus, the normality assumption is rejected in this case.

Results and Findings

After checking the preliminary statistical assumptions, EGARCH (1,1) model has been applied to check the impact of exchange traded derivatives on price instability in UK. Results generated through EViews 9 are presented in table 7.

Table.7. EGARCH (1,1), Impact of exchange traded derivatives on price instability in UK

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001851	0.000148	12.51927	0
Variance Equation				
C(2)	-12.99068	4.208088	-3.087074	0.002
C(3)	0.67929	0.136198	4.987525	0
C(4)	-0.007395	0.089418	-0.082705	0.9341
C(5)	0.471661	0.1656	2.84819	0.0044
C(6)	0.286843	0.165588	2.629119	0.0086
T-DIST. DOF	61.31578	230.4846	0.26603	0.7902
R-squared	-0.000001	Mean dependent var		0.001854
Adjusted R-squared	-0.000001	S.D. dependent var		0.003437
S.E. of regression	0.003437	Akaike info criterion		-8.84203
Sum squared resid	0.003343	Schwarz criterion		-8.75209

Log likelihood	1262.567	Hannan-Quinn criter.	-8.80597
Durbin-Watson stat	1.039737		

The result, presented in table 7, has three parts, mean equation, variance equation and summary statistics for model. Middle part of the results is the most important and relevant to study, with, where five parameters with their coefficient values and significance level are presented. Out of these five terms, four are significant at 5% level. The first one is constant term of variance equation, which is denoted by C(2), it indicates the last period volatility and it is significant. Second term C(3) indicates impact of long term volatility, which is also significant. C(4) term indicates the leverage effect, for which this term should be negative and significant. Here, C(4) is negative but insignificant; thus it can be concluded that UK inflation does not carry leverage effect. The next term C(5) is GARCH effect, which is significant. It means that volatility of UK inflation is effected by its own previous period volatility as well.

For this study, the most important term is C(6) indicating exogenous factor. Notional amount of the turnover of UK exchange traded derivatives is the exogenous factor in the model, which is significant at 5% level and has positive sign. It refers that the derivatives trade is contributing to the volatility of UK inflation. Since both dependent and exogenous variable are log transformed therefore the relationship is interpreted in in terms of elasticity. It can be said that 1% increase in UK derivatives trade will enhance UKprice instability by 0.29%.

As far as summary statistics are concerned, for ARCH/GARCH type models R square or adjusted R square is meaningless as it is valid only for mean equation while ARCH/GARCH type models deal with variance equation. Thus, negative value of very small magnitude does not undermine the explanatory power of the model. Another summary statistics of the model is log likelihood value, which is most of the time negative but in this model it is positive. Likelihood values are basically the product of the density of the observations in data, density generally takes very small values and resultantly its natural log becomes negative. But, this is not true for every distribution. As it has already been discussed and proved the time series, having fat tail, is not normal. Thus, the positive value of log likelihood is not problematic for the analysis. Finally, there are some information criteria in the summary part like Akaike information criterion (AIC), Schwarz information criterion, and Hannan–Quinn information criterion. These measures are employed to gauge the quality of the model in comparison to other models in terms of a tradeoff between parsimony of model and goodness of fit. Since only one model is being used in this study, therefore these measures do not play any role in the results.

Diagnostics of the Model

ARCH Effect

Post model analyses are very important for ARCH/GARCH types models. There are three assumptions to assure in post model analysis; whether the ARCH effect is still present in the model or not, residuals of the model have normal distribution, and no serial correlation exists in the residuals of the model. Results of model diagnostics summarized in table 8 and table 9.

Table 8. Post Model ARCH LM Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.9972	0.105233	9.476123	0
WGT_RESID^2(-1)	0.002185	0.0597	0.036601	0.9708
F-statistic	0.00134	Prob. F(1,281)		0.9708
Obs*R-squared	0.001349	Prob. Chi-Square(1)		0.9707

Null hypothesis in ARCH LM test is that there is no ARCH effect. Since the result is not significant, therefore null hypothesis cannot be rejected. Thus it can be concluded that ARCH effect is no more present in this model, which is very much desirable.

Test for Normal Distribution

Jarque-Bera statistics has been applied to check the normality assumption in residuals of model. Null hypothesis refers normality of data, as joint hypothesis of zero skewness and zero excess kurkosis (kurkosis =3) is tested. The p-value of the JB test is 0.905, which is not significant, means that null hypothesis cannot be rejected. Thus, it can be concluded the residuals of the model are normally distributed.

Test for Serial Correlation

Serial correlation assumption is tested through autocorrelation and partial autocorrelation functions of the squared residuals with Ljung-Box Q-statistics and corresponding p values. In EViews, there are 36 lags by default. Null hypothesis of the test is that there is no serial correlation. Results are given in table 9.

Table 9. Post model Correlogram Statistics (See Annexure B)

All the presented p values are insignificant, means that null hypothesis cannot be rejected. Thus, it can be concluded that there is no serial correlation among the residuals of the model. Finally, it can be concluded that all the three diagnostic statistics are suggesting the appropriateness of the model.

Conclusion

Price instability causes adverse economic impact by impairing growth and investment. The role of exogenous shocks in aggravating price instability is an under-researched area. Taking United States as a typical case, this study analyzes empirically the impact of derivatives trade on price instability by using EGARCH model with exogenous variable. Monthly data of UK inflation and exchange traded derivatives in UK capital market from 1993M01 to 2016M09 is the sample period. In the EGARCH model, log values of daily average of notional amount of turnover of exchange traded derivatives, which includes futures and options, are employed as exogenous variable. Thus, the model is demonstrating elasticity of UKprice instability over exchange traded derivatives.

The results suggest that the effect of derivatives trade on price instability in UK economy is significant. The sign of the coefficient of derivatives trade is positive, which refers that the increase in UK exchange traded derivatives has aggravated the volatility of inflation. As per this model, 1% increase in UK derivatives trade is enhancing UKprice instability by 0.29%. Thus, it can be concluded that derivatives are playing adverse role in UK economy by destabilizing the pricing mechanism. It is also evident from the results of the model that UKinflation does not carry leverage effect. The crucial finding of derivatives being catalyst for price instability can further be substantiated by employing same model to other regions of the world like Europe and Japan, where derivatives trade has accelerated rapidly in the last two decades. The trade volume of OTC derivatives can also be incorporated to make these analyses more robust.

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Annexure A

Lags	AC	PAC	Q-Stat	Prob.	Lags	AC	PAC	Q-Stat	Prob.
1	0.463	0.463	61.688	0	19	0.036	0.01	78.766	0
2	0.127	-0.11	66.377	0	20	0.07	0.064	80.286	0
3	0.049	0.045	67.083	0	21	0.014	-0.059	80.345	0
4	0.031	0.002	67.36	0	22	-0.033	-0.004	80.677	0
5	0.102	0.112	70.428	0	23	-0.027	-0.015	80.91	0

6	0.091	-0.007	72.853	0	24	0.005	0.033	80.917	0
7	0.101	0.075	75.864	0	25	0.073	0.059	82.591	0
8	0.071	-0.011	77.353	0	26	0.067	-0.003	84.003	0
9	0.001	-0.037	77.353	0	27	0.023	-0.018	84.172	0
10	-0.014	-0.006	77.413	0	28	0.07	0.095	85.712	0
11	0.009	0.02	77.435	0	29	0.019	-0.06	85.826	0
12	0.018	-0.009	77.531	0	30	0.028	0.051	86.069	0
13	0.013	-0.005	77.578	0	31	0.075	0.035	87.895	0
14	-0.022	-0.036	77.73	0	32	0.023	-0.048	88.074	0
15	-0.015	0.017	77.797	0	33	0.029	0.027	88.352	0
16	-0.01	-0.011	77.83	0	34	0.035	0.022	88.753	0
17	-0.041	-0.039	78.333	0	35	0.104	0.104	92.258	0
18	0.012	0.059	78.377	0	36	0.158	0.063	100.5	0

Annexure B

Lags	AC	PAC	Q-Stat	Prob.	Lags	AC	PAC	Q-Stat	Prob.
1	0.002	0.002	0.0014	0.971	19	-0.003	-0.015	10.708	0.933
2	0.039	0.039	0.4304	0.806	20	-0.002	0.02	10.708	0.953
3	-0.018	-0.018	0.5249	0.913	21	0.036	0.02	11.101	0.961
4	-0.057	-0.058	1.4535	0.835	22	-0.024	-0.037	11.283	0.97
5	0.074	0.076	3.0599	0.691	23	-0.044	-0.035	11.874	0.972
6	0.008	0.012	3.0776	0.799	24	-0.033	-0.03	12.223	0.977
7	0.043	0.035	3.6273	0.822	25	0.052	0.071	13.07	0.976
8	0.03	0.029	3.8908	0.867	26	-0.035	-0.025	13.449	0.98
9	-0.025	-0.019	4.0688	0.907	27	0.06	0.048	14.585	0.975
10	0.052	0.047	4.8645	0.9	28	0.016	0.027	14.669	0.982
11	0.104	0.112	8.1134	0.703	29	-0.08	-0.062	16.693	0.967
12	0.003	-0.005	8.1157	0.776	30	0.003	-0.005	16.696	0.976
13	-0.009	-0.023	8.1385	0.834	31	0.01	0.031	16.73	0.983
14	0.006	0.018	8.1487	0.881	32	-0.027	-0.05	16.967	0.986
15	-0.076	-0.073	9.8707	0.828	33	0.102	0.096	20.317	0.959
16	0.029	0.013	10.128	0.86	34	-0.033	-0.007	20.674	0.965
17	-0.01	-0.01	10.161	0.897	35	0.056	0.042	21.694	0.962
18	-0.042	-0.059	10.705	0.906	36	0.073	0.08	23.461	0.947