Vol. 2, No. 05; 2018

ISSN: 2456-7760

INVESTIGATING THE IMPACT OF PAST PERIOD INFLATION VOLATILITY ON CURRENT PERIOD INFLATION VOLATILITY AND CREDIT RISK USING VECTOR ERROR CORRECTION MODEL

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Abstract

This research investigated the relationship between pajjst period inflation volatility and current period inflation volatility and also the impact of inflation volatility on credit risk using the vector error correction model. The study relied on secondary data for the analysis, which covered all the thirty three banks that operated in Ghana from the year 1990 to 2010. The GARCH model was adopted in modelling inflation volatility. The study established that current period inflation volatility is influenced by past period inflation volatility significantly and also credit risk is influenced by the volatility of inflation significantly.

Keywords: inflation volatility, credit risk, GARCH Model, vector error correction model

INTRODUCTION

The risky banking environment in developing economies has been exacerbated by the high and volatile inflation rates of such economies. The relationship between inflation and economic development is certainly an important issue. In recent years, policy discussions have included increasing references to inflation levels and inflation stability as crucial elements to improve economic performance in emergent countries, such as Ghana. Credit risk management is an important activity in banks because credit is a major revenue earner for banks. It is therefore imperative to do a research on inflation and its relationship with credit risk especially in a developing economy. The general objective of this research is to investigate the extent to which past period inflation volatility impacts current period inflation volatility and the effect of the volatility of the macro economy due to inflation on credit risk, using data on Ghana, a country noted for its high and volatile inflation rates.

A research on the impact of inflation is important because according to Mensah (2005), writing on Ghana, investors always factor macroeconomic variables such as inflation into their investment decisions and that the high degree of uncertainty associated with Ghana's unstable macroeconomic environment has negatively affected financial intermediation. Long-term savings is virtually non-existent in Ghana, constraining the availability of long-term capital. Also according to McKay and Sowa (2008), high and variable inflation is typically seen as a symptom or indicator of macroeconomic instability. Saunders and Cornett (2008) identify macroeconomic or systematic risks, such as increased inflation and inflation volatility among others which can directly or indirectly impact on financial institution's level of interest rate, credit, and liquidity

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risk exposure. This research would help deepen the understanding of the effect of inflation volatility on inflation and also on credit risk. Researchers have tried to conceptualise and measure volatility in applied economics and finance using the GARCH model. Kontonikas (2004) and Nor (2009), have proved that on the theory side, there is a positive relationship between the level of inflation and inflation uncertainty.

A research on inflation volatility and its impact on credit risking emerging economies have received limited attention in the extant literature. This study attempts to supplement existing literature by bringing new evidence from Sub-Saharan Africa (SSA) using data on Ghana. This is achieved through the use of secondary data (annual financial reports of commercial banks and macroeconomic data) from the year 1990 to 2010. The GARCH model was adopted in modeling inflation volatility. Analysis was carried out using unbalanced panel data.

In determining the impact of inflation volatility on credit risk, the vector error correction model (VECM) was employed to estimate the long run relationship between the variables. VEC models are employed because many economic time series appear to be 'first-difference stationary,' with their levels exhibiting unit root or no stationary behaviour An error correction model is a <u>dynamical system</u> with the characteristics that the deviation of the current state from its long-run relationship will be fed into its short-run dynamics. Error Correction Models (ECMs) are a category of multiple time series models that directly estimate the speed at which a dependent variable returns to equilibrium after a change in an independent variable. ECMs are a theoretically-driven approach useful for estimating both short-term and long-term effects of one time series on another. If a set of variables are found to have one or more co integrating vectors then a suitable estimation technique is a VECM (Vector Error Correction Model) which adjusts to both short run changes in variables and deviations from equilibrium. The model can lead to a better understanding of nature of any non-stationary among the different component series and can also improve longer term forecasting over an unconstrained model.

Credit risk is measured by the ratio of Loan Loss Provision to total bank asset (LLP/bank assets, CR1) and the ratio of net interest income to total bank asset (NII/bank assets, CR2), while the consumer price index is used as a proxy for inflation. Other independent variables used in this study are: management efficiency, which is the ratio of expenditure to income, financial sector development which is defined in two ways as M2+/GDP and bank assets/GDP, and competition using Herchman-Herfindal Index, the discount rate, and the Treasury bill rate.

Empirical work on inflation volatility goes back to early studies by Okun (1971), Logue and Willett (1976), Friedman (1977), Taylor (1981), Cukierman and Meltzer (1986) and Froyen and Waud (1987) who emphasise the positive association between inflation volatility and the level of inflation. Since then, there have been a number of studies providing additional explanations of inflation volatility. Friedman (1977) postulates that by creating political pressure to reduce inflation, high inflation results in future inflation uncertainty because policy makers may fear the resultant recessionary effects and therefore be reluctant to lower inflation. Ball (1992) formalises the view of Friedman by indicating that inflation uncertainty tends to be higher during periods of high inflation. Ball's model proposes that for low levels of inflation observed in the economy,

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policy makers aim to keep inflation at these levels that give rise to low inflation uncertainty in the eyes of economic agents. However, for the high levels of inflation, the public is uncertain for how long it will take the policy makers to dis-inflate the economy. In this case, uncertainty regarding future monetary policy would be greater and as a result inflation would be able to cause inflation uncertainty. Dagha (2007) refers to volatility as the frequency on movement on upside or downside. It is considered a measure of risk, and investors as well as businesses want premium for investing in risky assets. According to Berry (2010), volatility clustering models attempt to capture the volatility of the financial markets, which are sometimes low, sometimes high, over a given period of time. But within each state (and over a short time period), there is a strong chance that a day of high volatility will be followed by another day of high volatility. Therefore, we may estimate volatility conditionally to the observation of previous days. Moradi (2006), also observes that the central focus of theoretical and empirical studies is whether a rise in the level of inflation raises uncertainty about future inflation. The idea behind this relationship is that high inflation creates uncertainty about future monetary policy and makes monetary policy less stable. In the opinion of Rother (2004), among the harmful effects of inflation, the negative consequences of inflation volatility are of particular concern. These include higher risk premium, hedging costs and unforeseen redistribution of wealth. He again proposes that a lack of price stability exerts harmful effects on the economy not only through changes in the pricelevel but also through increased price level uncertainty. Thus, inflation volatility can impede growth even if inflation on average remains restrained.

METHODS

GARCH (1, 1) Model for Measuring Inflation Volatility

To determine the impact of inflation volatility on credit risk, we need to, first, determine the relationship between past inflation volatility and current period inflation volatility, which is measured using the GARCH model. Before GARCH model can be used we need to estimate the mean equation as indicated in Table 1. It can be seen that Treasury bill rate significantly influences inflation (CPI) at the 5% significance level. The residual of inflation in Figure 1 helps to determine if the GARCH model can be used. It can be seen from Figure 1 that, there is a prolonged period of high volatility from one period to another and also there exists a prolonged period of low volatility and periods of low volatility tend to be followed by periods of low volatility. This suggests that residual or error term is conditionally heteroskedastic and can be represented by GARCH model.

A monthly inflation data was used to run a regression mean equation using OLS method. After that, monthly residuals were obtained which were then averaged to arrive at annual inflation volatility. This inflation volatility was then used in modeling the GARCH. It can be seen that Treasury bill rate at first difference significantly influences inflation (CPI) at the 5% significance level. Residual derived from mean equation is used in making variance equation in Table 1. From the variance equation it can be seen that GARCH (-1) significantly influences inflation volatility

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at the 5% significance level. This means that previous year residual variance or volatility of inflation influences current period volatility of inflation. The RESID (-1)² which is previous year's squared residual or previous year's inflation information about volatility also known as ARCH significantly influences current period inflation volatility. It means that inflation volatility is influenced by its own ARCH and GARCH factor or shock. This suggests that inflation volatility are internal causes or shocks caused by own family. In effect the current and past volatility of inflation can be used to predict future inflation volatility. This outcome supports the findings of Berry (2010), Nor (2009), Kontonikas (2004) and Cukierman and Meltzer (1986).Also, Credit Risk one (DCR1), Credit Risk Two (DCR2) and Financial Sector Development one (DFSD 1) are significant at the 5% significance level. This means that inflation volatility is also influenced by external shocks such as Credit Risk and Financial Sector Development.

Table 1: GARCH Model for Measuring Inflation Volatility

Dependent Variable: DCPI Method: ML - ARCH (Marquardt) - Normal distribution Sample (adjusted): 1990M02 2010M12 Included observations: 263 after adjustments Failure to improve Likelihood after 96 iterations Resample variance: back cast (parameter = 0.7)

| GARCH = α + $\beta 1(4)$ *RESID(-1)^2 | $+ \beta 2^* \text{GARCH}(-1) + \beta 3^* \text{DCR1} +$ | ╀ |
|--|--|---|
| β 4*DCR2 + β 5*DFSD1 + β 6*DFSD2 | | |
| | | |

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|--------------------|-------------|-----------------------------|-------------|-----------|
| С | 0.099915 | 0.610412 | 0.163685 | 0.8764 |
| DTBILL | 0.823254 | 0.06595 | 12.48297 | 0.0000 |
| | Variance Eq | uation | | |
| С | 28.45757 | 11.66381 | 2.439817 | 0.0147 |
| RESID(-1)^2 | 0.347054 | 0.103884 | 3.340779 | 0.008** |
| GARCH(-1) | 0.502744 | 0.099057 | 5.075288 | 0.000** |
| DCR1 | 9.595584 | 3.475259 | 2.761113 | 0.005** |
| DCR2 | 27.88398 | 6.973232 | 3.998717 | 0.001** |
| DFSD1 | -6581.16 | 3291.353 | -1.99953 | 0.045** |
| DFSD2 | 0.007665 | 0.377016 | 0.02033 | 0.9838 |
| R-squared | 0.306464 | Mean depe | endent var | -0.100760 |
| Adjusted R-squared | 0.303807 | 7 S.D. dependent var 14.088 | | |
| S.E. of regression | 11.75554 | Akaike info | o criterion | 7.714757 |
| Sum squared resid | 36068.30 | Schwarz ci | riterion | 7.836998 |

International Journal of Economics, Business and Management Research Vol. 2, No. 05; 2018 ISSN: 2456-7760 Log likelihood -1005.490 Hannan-Quinn criter. 7.763882 Durbin-Watson stat 2.803436 All probability value with two asterisk ** are significant at 5% significance level 40 -30



Serial correlation and Heteroskedasticity tests in Tables 2 and 3 test the presence of serial correlation and arch effect. The tests are significant meaning that the error term are not serially correlated and hence no arch effect. This means that GARCH model is appropriate model. This model was chosen because of its lowest Akanke information Criterion. Figure 2 tests the normality of data used in modelling GARCH. The normality is significant, meaning that the data are not normally distributed. However, many researchers suggest that when the model is not normal, it can still be an appropriate model to use.

Table 2: Correlogram Of Residual Squared (Garch Model)

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| | Partial | | | | | |
|-----------------|-------------|----|--------|--------|--------|--------|
| Autocorrelation | Correlation | | AC | PAC | Q-Stat | Prob* |
| | . . | 1 | -0.063 | -0.063 | 1.0449 | 0.3070 |
| . * | . * | 2 | 0.11 | 0.107 | 4.2845 | 0.1170 |
| * . | * . | 3 | -0.105 | -0.093 | 7.2273 | 0.0650 |
| . . | . . | 4 | -0.019 | -0.041 | 7.3195 | 0.1200 |
| * . | * . | 5 | -0.102 | -0.086 | 10.109 | 0.0720 |
| . . | . . | 6 | 0.044 | 0.032 | 10.634 | 0.1000 |
| . . | . . | 7 | -0.057 | -0.042 | 11.527 | 0.1170 |
| . . | * . | 8 | -0.044 | -0.078 | 12.055 | 0.1490 |
| . . | . . | 9 | 0.035 | 0.041 | 12.392 | 0.1920 |
| * . | * . | 10 | -0.118 | -0.122 | 16.207 | 0.0940 |
| * . | * . | 11 | -0.067 | -0.100 | 17.452 | 0.0950 |
| * . | * . | 12 | -0.073 | -0.071 | 18.919 | 0.0910 |
| . . | . . | 13 | 0.032 | 0.012 | 19.208 | 0.1170 |
| * . | * . | 14 | -0.07 | -0.078 | 20.584 | 0.1130 |
| . . | * . | 15 | -0.003 | -0.075 | 20.586 | 0.1510 |
| . . | . . | 16 | -0.013 | -0.016 | 20.637 | 0.1930 |
| . . | . . | 17 | -0.015 | -0.047 | 20.697 | 0.2400 |
| * . | * . | 18 | -0.078 | -0.125 | 22.433 | 0.2130 |
| . * | . . | 19 | 0.076 | 0.036 | 24.08 | 0.1930 |
| * . | * . | 20 | -0.077 | -0.089 | 25.777 | 0.1730 |

All probability value with two asterisk ** are significant at 5% significance level

Table 3: Heteroskedasticity Test: ARCH

| F-statistic | 1.027153 | Prob. F(1,260) | 0.3118 |
|---|----------|---------------------|--------|
| Obs*R-squared | 1.030982 | Prob. Chi-Square(1) | 0.3099 |
| All probability value with two asterisk ** are significant at 5% significance level | | | |

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Figure2: Normality Test

Vector Error Correction Model (VECM) for Credit Risk 1

In order to determine the relationship between inflation volatility and credit risk the vector error correction model was employed. Given the evidence in favour of at least one co integrating vector, the study proceeded to estimate the VECM to examine the causal associations between the variables. The result of the VECM estimation is reported in Table 4. Table 4 shows the VECM for Credit Risk 1(CR1) with significant error correction term in the Credit Risk 1 equation. The sign and magnitude of the error correction coefficient indicates the direction and speed of adjustment towards the long-run equilibrium path. It should be negative and significant, which is the case here. The negative sign implies that, in the absence of variation in the independent variables, the model's deviation from the long run relation is corrected by increase in the dependant variable. Highly significant error correction term is an evidence of the presence of a stable long-term relationship (Bannerjee, Dolado & Mestre, 1998). The estimated coefficient of the ECM (-1) is -0.001453 [p-value= 0.040] suggesting that in the absence of changes in other variables, deviation of the model from the long-term path is balanced by 0.145 per cent increase in Credit Risk 1per year. This means that deviation from the long run relationship takes almost a year to be corrected. The results also show that Credit risk lag one and two and inflation volatility lag one significantly influence credit risk1. This suggests that the two previous year's credit risk and previous year inflation volatility actually have effect on credit risk.

The fundamental regression statistics show that R^2 (36%) is moderate implying that overall goodness of fit of the VEC model is satisfactory. The Durbin Watson Statistic (1.55397) shows that there is no autocorrelation in the residuals. The F-statistic of 4.132432with its corresponding p-value [0.007] suggests that inflation volatility, competition, management, discount rate and financial sector development jointly influence Credit Risk 1(CR1). The diagnostic test statistics reported in Table 5indicates that the model passed serial correlation

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and heteroscedasticity test at the 5% significance level but failed normality test. However, again many researchers suggest that when the model is not normal, it can still be an appropriate model to use.

Dependent Variable: D(CREDIT RISK 1) Method: Panel Least Squares Sample (adjusted): 1990 2010 Periods included: 21 Cross-sections included: 32 Total panel (balanced) observations: 608

| | Coefficient | Std. Error | t-Statistic | Prob. |
|--|-------------|--------------------|-------------|---------|
| ECM(-1) | -0.001453 | 0.000709 | -2.049924 | 0.040** |
| Δ CREDIT RISK 1 _{t-1} | -0.504124 | 0.037875 | -13.31017 | 0.000** |
| ΔCREDIT RISK 1 _{t-2} | -0.437856 | 0.037081 | -11.80802 | 0.000** |
| Δ INFLATION VOLATILTIY _{t-1} | -0.172444 | 0.078565 | -2.194936 | 0.028** |
| Δ INFLATION VOLATILTIY _{t-2} | -0.038958 | 0.032253 | -1.207893 | 0.2277 |
| $\Delta COMPETITION_{t-1}$ | -0.012265 | 0.026429 | -0.464081 | 0.6428 |
| $\Delta COMPETITION_{t-2}$ | 0.013403 | 0.025818 | 0.520187 | 0.6032 |
| Δ MANAGEMENT _{t-1} | -0.007454 | 0.004779 | -1.559697 | 0.1195 |
| Δ MANAGEMENT _{t-2} | -0.008024 | 0.004141 | -1.937777 | 0.0532 |
| $\Delta DISCOUNT RATE_{t-1}$ | 0.179281 | 0.092207 | 1.944336 | 0.0524 |
| ΔDISCOUNT RATE _{t-2} | 0.069314 | 0.088554 | 0.782737 | 0.4342 |
| Δ FIN. SEC. DEVT 1 _{t-1} | 73.17012 | 125.2917 | 0.583998 | 0.5595 |
| Δ FIN. SEC. DEVT 1 _{t-2} | 78.40119 | 105.5127 | 0.743056 | 0.4578 |
| Δ FIN. SEC. DEVT 2 _{t-1} | 0.511072 | 0.407761 | 1.253361 | 0.2107 |
| Δ FIN. SEC. DEVT 2 _{t-2} | 0.501322 | 0.409014 | 1.225685 | 0.2209 |
| R-squared | 0.360527 | Mean deper | ndent var | 6.08427 |
| Adjusted R-squared | 0.342514 | S.D. dependent var | | 7.22960 |
| S.E. of regression | 6.836814 | Akaike info | o criterion | 6.72529 |
| Sum squared resid | 7151.529 | Schwarz criterion | | 6.85982 |
| Log likelihood | -531.0228 | Hannan-Qu | inn criter. | 6.77992 |
| F-statistic | 4.132432 | Durbin-Wa | tson stat | 1.55397 |
| Prob(F-statistic) | 0.0007** | | | |

Table 4: VECM Estimation for Credit Risk One

** means significant at 5% level

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| Table 5: VECM Model Diagnostic Tests | | |
|--|-----------------------------|--|
| Serial Correlation | F(2, 208)=0.780126[0.4598] | |
| Heteroskedasticity | F(12, 315)=0.193894[0.9986] | |
| Normality X^2 (2)=115565.0[0.0000] | | |
| Vector Error Correction Model (VECM) for Credit Risk 2 | | |

Again given the evidence in favour of at least one co integrating vector, the study can proceed to estimate the VECM to examine the causal associations between the variables. The result of the VECM estimation is reported in Table 6.The Table shows the VECM for Credit Risk 2 (CR2) with significant error correction term in the credit risk 2 equation. Again as stated above, the sign and magnitude of the error correction coefficient indicate the direction and speed of adjustment towards the long-run equilibrium path. It should be negative and significant, which is the case here too. The negative sign implies that, in the absence of variation in the independent variables, the model's deviation from the long run relation is corrected by increase in the dependant variable. Highly significant error correction term is an evidence of the presence of a stable long-term relationship (Bannerjee, Dolado & Mestre. 1998). The estimated coefficient of the ECM (-1) is --0.009746 [p-value= 0.001] suggesting that in the absence of changes in other variables, deviation of the model from the long-term path is balanced by 0.9746 per cent increase in Credit Risk 2 per year.

This means that deviation from the long run relationship takes almost a year to be corrected. The results also show that Credit risk 2 lags one and two, inflation volatility lag one, competition lag one and financial sector development 2 (FSD2) lags one and two significantly influence credit risk 2. This means that the two previous year's credit risk and previous year inflation volatility actually have effect on credit risk. The fundamental regression statistics show that R^2 (44.5%) is moderate implying that overall goodness of fit of the VEC model is satisfactory. The Durbin Watson Statistic (1.00413) shows that there is no autocorrelation in the residuals. The F-statistic of 2.261137 with it corresponding p-value [0.040] suggests that inflation volatility, Competition, management, discount rate and financial sector development jointly influence Credit Risk two (CR2). The diagnostic test statistics reported in Table 7 indicates that the model passes serial correlation and heteroscedasticity test at the 5% but fail normality test. Again as indicated above, many researchers suggest that when the model is not normal, it can still be an appropriate model to use.

Dependent Variable: D(CREDIT RISK 2) Method: Panel Least Squares Sample (adjusted): 1990 2010 Periods included: 21

Cross-sections included: 32

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Total panel (balanced) observations: 608

| | Coefficient | Std. Error | t-Statistic | Prob. |
|--|-------------|-----------------------|-------------|---------|
| ECM(-1) | -0.009746 | 0.002979 | -3.271112 | 0.001** |
| Δ CREDIT RISK 1 t-1 | -0.773572 | 0.043081 | -17.95613 | 0.000** |
| ΔCREDIT RISK 1 t-2 | -0.414951 | 0.043127 | -9.621586 | 0.000** |
| Δ INFLATION VOLATILTIY _{t-1} | -0.086126 | 0.029753 | -2.894699 | 0.004** |
| Δ INFLATION VOLATILTIY _{t-2} | -0.022442 | 0.012179 | -1.842607 | 0.0666 |
| $\Delta COMPETITION_{t-1}$ | -0.010202 | 0.010004 | -1.019774 | 0.3083 |
| $\Delta COMPETITION_{t-2}$ | -0.023805 | 0.009786 | -2.43249 | 0.015** |
| Δ MANAGEMENT _{t-1} | 0.000135 | 0.001814 | 0.074436 | 0.9407 |
| Δ MANAGEMENT _{t-2} | 0.000737 | 0.001552 | 0.475064 | 0.6345 |
| $\Delta DISCOUNT RATE_{t-1}$ | 0.048094 | 0.035119 | 1.369472 | 0.1715 |
| $\Delta DISCOUNT RATE_{t-2}$ | -0.044769 | 0.033942 | -1.318996 | 0.1878 |
| Δ FIN. SEC. DEVT 1 _{t-1} | 68.67727 | 47.56733 | 1.443791 | 0.1494 |
| Δ FIN. SEC. DEVT 1 _{t-2} | -25.54105 | 40.01429 | -0.638298 | 0.5236 |
| Δ FIN. SEC. DEVT 2 _{t-1} | 0.461989 | 0.154995 | 2.980664 | 0.003** |
| Δ FIN. SEC. DEVT 2 _{t-2} | 0.341943 | 0.156561 | 2.184094 | 0.024** |
| R-squared | 0.445458 | Mean depend | ent var | 7.89205 |
| Adjusted R-squared | 0.429838 | S.D. dependent var | | 2.19257 |
| S.E. of regression | 2.142185 | Akaike info criterion | | 4.40429 |
| Sum squared resid | 702.1105 | Schwarz criterion | | 4.53883 |
| Log likelihood | -345.3435 | Hannan-Quin | n criter. | 4.45893 |
| F-statistic | 2.261137 | Durbin-Watso | on stat | 1.00413 |
| Prob(F-statistic) | 0.0404** | | | |

Table 6: VECM Estimation for Credit Risk Two

** means significant at 5% level

Table 7: VECM Model Diagnostic Tests

| Serial Correlation | F(2,197)=0.780126[0.4598] |
|--------------------|-----------------------------|
| Heteroskedasticity | F(12,183)=0.193894[0.9986] |
| Normality | $X^{2}(2)=105565.0[0.0000]$ |

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Implication of Findings

In order to evaluate and investigate the impact of past inflation volatility on current inflation and credit risk respectively, a panel and time series data analyses for thirty-three banks in Ghana was employed. This paper applied recent developments in non-stationary panel and time series data analyses to explore the long-run relationship between inflation volatility and inflation and inflation volatility and credit risk respectively for all banks in Ghana. The use of co integration vector error-correction provides a more realistic dynamic representation of the relationship by incorporating an important feedback relationship that may exist between variables. The results of the panel unit root tests suggest that all of the series are non-stationary integrated variables. Further, evidence from co integration implies that there is causality between variables considered in the study.

The results suggest that past values of inflation are sufficient to determine the current value of inflation. In other words, when given the value of inflation at time t-1, as well as the disturbance period at that same time, volatility in inflation can be determined. The relationship is such that, there exists a positive relationship between inflation at time, t and inflation at time, t-1. Hence, the model suggests that inflation at time, t would consistently be higher than previous inflation levels for the industry since an increase in inflation at time, t-1 points to an increase at time, t as well.

However inflation volatility is influenced by other factors too as indicated above. These are Credit Risk 1(DCR1), Credit Risk 2 (DCR2) and Financial Sector Development 1(FSD 1) and the coefficients are positive in all cases. This means that inflation volatility is also influenced by external shocks such as Credit Risk and Financial Sector Development. The VECM results show that CR1 and CR2 are both influenced by last year's inflation volatility only. That is last year's inflation volatility exacerbates current year credit risk. However CR1 and CR2 are both influenced by the two previous years' credit risk. Also, CR2 is influenced by other factors such as previous year's competition and two previous years' Financial Sector Development.

It can therefore be concluded that credit risk is influenced by the volatility of inflation significantly, confirming the results of the work done by Yigit (2002) on both developed and developing countries that inflation uncertainty has significant effect on credit markets.

There are several implications for practice and policy that can be gleaned from the results of the research. Evidence suggests that there is a strong chance that a period of high volatility will be followed by another period of high volatility. Therefore as suggested by Dagha (2007) which confirms the earlier works of Kontonikas (2004) and Cukierman and Meltzer (1986) that there is a positive relationship between past inflation and uncertainty about future inflation, we may estimate volatility conditionally to the observation of previous years. With this result, policy makers should be able to predict the direction of future inflation. An inflation rate fully anticipated by the bank's management implies that banks can appropriately adjust interest rates in order to increase their revenues faster than their costs and thus acquire higher profits.

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However, in a volatile macro economy, if anticipated changes do not take place, or changes take place in opposite direction, banks can experience heavy losses. Yigit's (2002) tests on both developed and developing countries show that inflation uncertainty has significant bearing on credit markets either directly or indirectly regardless of the depth of financial markets. Therefore, the removal of inflation uncertainty will decrease the risk around these contracts and will ensure efficiency and growth of investment in a country. According to Ocran (2007), high inflation renders the cost of loan able funds prohibitive and also the high interest rates that are associated with high inflation prevents productive sectors of the economy from accessing finance for growth and development. Confirming the harmful effects of inflation, Boyd and Champ (2006) reiterate that inflation exacerbates so-called frictions in credit markets. Flaming, McDonald and Schumacher (2009), therefore, suggest that macroeconomic policies that promote low inflation and stable output growth do boost credit expansion.

Theoretically, inflation can have positive and negative effects on an economy. However, economists believe that the negative effects far outweigh the positive effects. Inflation erodes the income of fixed income earners and it causes locally produced goods and services to become very expensive relative to foreign goods and services. Local goods and services then become less competitive in foreign markets. This reduces the volume and value of a country's exports. High and volatile inflation and interest rates make the risk profile of a country so high that it is difficult for that country to attract external funding; which means that the country does not become an attractive destination for business and financial services.

Again confidence in the economic environment may wane especially due to the unpredictability of the future. Under uncertainty, the businesses may choose to adopt a wait-and-see strategy as it may be risky to take a firm decision on business strategies. A highly volatile rate of inflation has the potential to harm economic performance. The irreversibility of investment exacerbates the effect of uncertainty on investment decision and so dampening the desire of investors to undertake long term ventures. Economic analysts may not be able to predict correctly the future and so investors become unsure of what the future holds for their investments and so become sceptical about starting an investment or increasing their investment outlays.

Uncertainty about future prices is likely to result in higher risk and unanticipated distortions in the distribution of wealth leading to higher economic costs that can depress economic growth. For the banks, this calls for higher lending rate and low borrowing rates, leading to high interest rate spread. Higher inflation can decrease the real rate of return on assets. Lower real rates of return discourage savings but encourage borrowing due to the fact that the money is worth more at present than in the future. However, new borrowers entering the market are likely to default on their loans. To compensate for future increase in inflation, savers must ask for higher interest on their deposits. The inflation premium that is attracted is supposed to protect the investor against loss of purchasing power due to anticipated inflation... It leads to inefficient allocation of economic resources.

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During periods of increased uncertainty, policies tend to be discretionary due to the lack of commitment mechanisms. Policy makers tend to act opportunistically using short term measures in response to the uncertainties; discretionary policies can increase volatility. In addition, as discretionary measures are usually not reversed automatically with a changing economic environment, further discretionary acts are necessary to revert to the long-term equilibrium.

Portfolio holding is also affected by inflation as investors prefer investing in fixed assets to liquid assets especially those with fixed interest rates. Lenders may not be willing to lend money for long periods if the purchasing power of that money will fall below the original value at the time of repayment. To minimise this problem, banks resort to high IRS (demanding inflationary premium) and short term lending which might not be suitable for projects with long term gestation periods.

An increase in inflation volatility leads to a reduction in a country sovereign debt rating. This puts the economy in a bad light to foreign investors and therefore central bank should be targeting inflation stability as a macro-policy strategy. A high inflation raises inflation volatility and leads to a rise in short term interest rate. This signals a change in credit risk. If markets were efficient, then we would expect to see an immediate change in the credit spread following a rate shock. This could have an adverse effect on the financial sector and the economy at large.

References

- Ball, L. P. (1992), Why Does High Inflation Raise Inflation Uncertainty? *Journal of Monetary Economics*, 29, p. 371-388.
- Bannered, A., Dolado, J., & Mestre, R. (1998). Error-Correction Mechanism Tests for Co integration in Single-Equation Framework. Journal of Time Series Analysis. Wad ham College and Institute of Economics and Statistics, University of Oxford, Universidad Carlos III de Madrid and Research Department, Bank of Spain.
- Berry, R. (2010). Modelling Univariate Volatility, J. P. Morgan Investment Analysis and Consulting.
- Cukierman, A., & Meltzer, A. (1986). A Theory of Ambiguity, Credibility, and Inflation Under Discretion and Asymmetric Information, *Econometrical*, 54, 1099-1128.
- Dagha, J. (2007). Derivatives: Forwards, Futures and Options; The Best Way to Mitigate Volatility. Submission for Crisil Young Thought Leader. Bangalore: Alliance Business School.
- Friedman, M. (1977), "Nobel lecture: Inflation and unemployment", *Journal of Political Economy*, 85, June, 451–472.

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ISSN: 2456-7760

- Froyen, R. & R. Waud (1987), An examination of aggregate price uncertainty in four countries and some implications for real output, *International Economic Review*, 28(2), 353–372.
- Kontonikas, A. (2004). Inflation and Inflation Uncertainty in the United Kingdom, Evidence from GARCH modelling. *Economic Modelling, Elsevier,* 21(3), 525-543.
- Logue, D. E., & Willett, T. D. (1976): A Note on the Relationship between the Rate and the Variability of Inflation. *Economica*, 43, 151-58.
- Moradi, M. A. (2006). A GARCH Model of Inflation and Inflation Uncertainty in Iran. Scientific Information Database, *SID The Economic Research*, Spring 2006; 6(121-145.
- Mensah, S.(2005). Challenges and Opportunities Facing the Financial Services Industry in a Stable Macroeconomic Environment. Key Note Address, 8th National Banking Conference of the Chartered Institute of Bankers (Ghana).
- McKay, A. & Sowa, N.K. (2008). Does Inflation in Ghana Hit the Poor Harder? The Economy of Ghana, Analytical Perspectives on Stability, Growth & Poverty, James Currey &Woeli Publishing Services.
- Nor, A. H. S. M. (2009) Pusat Penguin Economic, Faculty Economides Perniagaan UKM, Bangi 43600 SELANGOR. Modelling and Forecasting on the Malaysian Inflation Rates: An Application of GARCH Models.
- Okun, A (1971). The Mirage of Steady Anticipated Inflation. Brookings Papers on Economic Activity (2): 485-98.
- Rother, P. C (2004). Fiscal Policy and Inflation Volatility; European Central Bank, Working Paper Series, No. 317.
- Saunders, A., & Cornett, M. M. (2008). Financial Institutions Management (6th ed), McGraw-Hill/Irwin, pp 183-184.
- Taylor, J. (1981). On the Relation Between the Variability of Inflation and the Average Inflation Rate. Carnegie-Rochester Conference Series on Public Policy, Spring, 57-86.
- Yigit T. M. (2002). Effects of Inflation Uncertainty on Credit Markets: A Disequilibrium Approach.