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Monetary Stability and Stock Returns: A Bivariate Generalized Autoregressive Conditional Heteroscedasticity Modelling Study

Ning Zeng

International Business School, Jinan University

206 Qianshan Lu, Zhuhai, Guangdong, 519070, China

Tel: 86-756-850-5921   E-mail: tningzeng@jnu.edu.cn

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Abstract

This paper employs a constant conditional correlation bivariate EGARCH-in-mean model to investigate interactions among the rate of inflation, stock returns and their respective volatilities. This approach is capable of accommodating all the possible causalities among the four variables simultaneously, and therefore could deliver contemporary evidence of the nexus between monetary stability and stock market. The postwar dataset of the US inflation and stock returns is divided into pre- and post- Volcker period and the estimation results show some significant changes of inflation-stock return relation, as well as indirect links between two volatilities. The core findings in this study suggest that promoting monetary stability contributes to more mutual interactions among the four variables, in particular, common stock is a more effective hedge against inflation, and the level of inflation rate is central to explaining the relation between the two volatilities.

Keywords: Monetary stability, Stock returns, Inflation, Bivariate EGARCH

1. Introduction

This paper uses a constant conditional correlation (ccc) bivariate exponential generalized autoregressive conditional heteroskedasticity (EGARCH) approach to model dynamics of US inflation, stock returns and their respective volatilities simultaneously. This has the advantage of simplifying the estimation and inference procedures, casting light on the interaction of the level of the rate of inflation and stock returns as well as the two volatilities without positivity constraints, and so providing empirical evidence on the relation between monetary stability and stock market.

As the primary goal of monetary policy is price stability, central banks use policy instruments such as adjusting interest rates to maintain monetary stability – generally defined in terms of low and stable inflation (for example, Borio and Lowe 2002, Granville and Mallick 2009) – and thereby ultimately to promote a prosperous and sustainable economy. But the rate of inflation responds slowly to monetary policy actions (Friedman, 1972), while the same monetary policy actions have direct and immediate effects on financial markets. So that monetary policy is transmitted through changes in asset prices and returns, and eventually influences economic activities (Bernanke and Kuttner, 2005).

Financial system stability has therefore become a key concern for central banks. For example, it is the second core objective of the Bank of England[1] and also one of the Fed's duties[2]. In particularly, the level and variability of returns on investment in debt and equity stock could consequently affect "capital investment, consumption, and other business cycle variables" (Schwert, 1989 p. 1115) as well as a large number of households, companies and financial intermediaries, and hence may have important implications for economic conditions (Officer 1973, Bernanke and Kuttner 2005). As Brealey and Vila (1998) mentioned, a rise in equity prices may "expand the availability of credit, and enable firms and households to increase their purchases of capital goods"; a substantial fall in equity prices may reduce "personal consumption and corporate investments" and "the loans that supported the earlier capital acquisitions [proving] ill-judged", and "thereby affect inflation outlook" (pp. 11-12). Thus a key issue has arisen regarding the relationship between stock market movements and monetary stability.

According to the Fisher equation[3] encapsulating the simple relation between inflation rates and asset returns under the assumption that real returns are determined by real factors and unrelated to inflation, assets ought to be effective hedges against inflation which erodes purchasing power, implying a strong correlation between trends in inflation rates and asset returns. Fama and Schwert (1977) examined the empirical relationships between inflation and returns on various assets including common stocks, treasury bills, long-term US government bonds and real estate. What they describe as "the most anomalous result" (p. 115) is that common stock returns are negatively related to inflation. This puzzling relation between stock returns (both nominal and real) and inflation (both expected and unexpected components) has been documented in earlier work by Linter (1975), Jaffe and Mandelker (1976), Nelson (1976) and Bodie (1976), and has been supported by overwhelming evidence in the literature (among others Graham 1996, Barnes et al. 1999, and Gallagher and Taylor 2002).

A number of scholars have been trying to explain this anomalous inflation-stock return link in several ways. Modigliani and Cohn (1979) suggested that investors discount real stock cash flows with nominal rates due to money illusion and hence undervalue the stock market as

[1] See http://www.bankofengland.co.uk.
[2] See The Federal Reserve System Purposes & Functions (p. 1).
[3] See Fisher (1896, 1907 and 1930).

inflation rises. Feldstein (1980) indicated that this inverse relation between stock returns and inflation results from the high effective tax rate on corporate income by historic-cost depreciation and the tax on artificial capital gains by inflation, which both reduce the real net yield.

Other explanations emphasize that monetary factor plays an important role. For instance, Fama (1981) hypothesized the negative stock return–inflation relation is "proxying for positive relations between stock returns and real variables" and "induced by negative relations between inflation and real activity which in turn are explained by a combination of money demand theory and the quantity theory of money"[4](p. 545). Geske and Roll (1983) added, in reinforcement of Fama's "proxy hypothesis", that the negative stock return–inflation relation signals changes in fiscal and monetary policy. And yet they argued that when stock prices drop government will tend to run a budget deficit, and expected inflation will rise due to the anticipated monetization of the deficit. So that stock prices will be negatively related to changes in inflation expectations under the association between stock returns and interest rates, which eventually cause changes in actual inflation. While Kaul (1987) pointed out that "money demand and counter-cyclical monetary supply effects" (p. 253) cause the inverse correlation between stock returns and inflation, and, more importantly, that this inverse correlation varies over time[5].

Subsequent studies on the inflation-stock return relation have produced more extensive results. For example, Boudoukh and Richardson (1993) reported a positive inflation-stock return link in the long run as Fisher (1907, p. 283) concluded that "the adjustment of (money) interest to long price-movements is more perfect than to short price-movement". Moreover, Ram and Spencer (1983) found that there is a unidirectional causality running from inflation to stock returns, which is in line with Mundell's hypothesis – an increase in inflation will reduce asset returns. By contrast, Lee (1992) claimed that there is no causality between stock returns and inflation using a multivariate VAR approach with interest rates in the system. Ioannidis et al. (2005) applied an autoregressive distributed lag approach to cointegration (ARDL) and found a bidirectional negative long-run causal relation between stock returns and inflation in Greece. Hristu-Varsakelis and Kyrtsou (2008) proposed a nonlinear version of the Granger (1969) causality test, and detected a positive effect of stock returns on inflation, and a negative effect of inflation on stock returns proxied by the US monthly CPI and the Dow Jones Index during 1960:01-2002:07.

Other empirical studies on interactions among inflation, stock returns and their volatilities bear fruitful results as well. Schwert (1989) investigated the relation of stock market volatility with volatility of macroeconomic data including inflation, money growth and industrial production. If stock market is efficient, it will reflect all relevant information (Fama et al 1969, Fama 1970, 1991, Schwert 1981, 1989). Yet Schwert (1989) found two types of volatilities are not closely linked[6], except for strong evidence that stock return volatility could

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[4] See also Marshall (1992).

[5] See also Kaul (1990), Graham (1996), and Kolluri and Wahab (2008). Hess and Lee (1999) proved that the inflation-stock return relation depends on different source of inflation, that is, supply shocks cause negative relationships while demand shocks cause positive relationships.

[6] Schwert (1989) found some week evidence on the link between output volatility and volatilities of financial variables.

affect output volatility, and he concluded that macroeconomic uncertainty does a poor job in explaining stock market volatilities – a conclusion supported by many other empirical studies, for example, Davis and Kutan (2003), Berben (2007).

However Najand and Rahman (1992) showed evidence that stock return volatility relates positively to inflation volatility, which is partly responsible for the negative relation between their level values. By reexamining the proxy hypothesis, Cochran and DeFina (1993) revealed significant negative impacts of inflation uncertainty on stock returns. In recent studies, Arnold and Vrugt (2006) demonstrated – through measurements based on the Survey of Professional Forecasters – that stock volatility is strongly linked to macroeconomic uncertainty. Saryal (2007) evidenced that higher inflation rates lead to a greater stock market volatility based on Turkey and Canada data.

A common feature of these studies is the fact that they focus *separately* on these various relations: inflation-stock return, inflation-stock return volatility, inflation uncertainty-stock return or both volatilities. It is worth noting the complexity that inflation rates, stock returns and their respective volatilities interact among each other. For example, inflation uncertainty can cause high/low inflation[7] and then may affect stock return volatility indirectly, which easily leads to conjecture that inflation and stock returns volatility could influence each other indirectly via their level values, and this relation might be time-varying as well.

Perhaps a more promising approach is to construct a model to accommodate all the possible relations simultaneously. Hence this paper hereby employs a ccc bivariate GARCH type approach, commonly applied in modelling multivariate financial time series as well as macroeconomic variables[8], to examine the relations among inflation rates, stock returns and their volatilities. In particular, a bivariate autoregressive fractionally integrated moving average (ARFIMA)- EGARCH-in-mean model allowing inflation and stock returns to affect both volatilities largely relaxes parameter constrains, significantly simplifies estimation and inference procedures, and shall be capable of modelling the interaction among inflation, stock returns and their volatilities. The US monthly inflation and stock returns are divided into two subsamples – pre- and post-Volcker – to reflect the view held by various authors that there is a significant shift in macroeconomic behaviour before and after Paul Volcker took office as Chairman of the Fed in 1979. This shift concerns a reduction in inflation and its volatility[9], which could influence interactions among inflation, stock return and their volatilities[10]. If this bivariate model will be well estimated for both subperiods, it should yield useful insights about the relation between monetary stability and the stock market.

By splitting the dataset of US monthly inflation and stock returns into pre- and post-Volcker episodes, this study reveals some significant changes in the inflation-stock return relation and indirect links between the two volatilities. Findings suggest that promoting monetary stability contributes to more mutual interactions among inflation, stock returns and their volatilities. Particularly, in a more stable monetary environment, common stock is a more effective hedge

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[7] See Cukierman and Meltzer (1986), Ungar and Zilberfarb (1993), Holland (1995).

[8] See for example Braun et al. (1995), Lee (1998), Elder (2004), Wei (2008), Karonasos et al. (2006), Conrad et al. (2010.2011), Karanasos and Zeng (2013), Zeng (2013), and many others.

[9] For example, Kaul (1990), B. Friedman and Kuttner (1996), Gertler (1996), Sargent (1999), Clarida et al. (2000), and Lindsey et al (2005).

[10] Kaul (1990) showed the change of inflation-stock return link during pre- and post-Volcker period.

against inflation; meanwhile the level of inflation rate is central to explaining the relation between the two volatilities.

Section 2 outlines the ccc bivariate ARFIMA-EGARCH(*p*, *q*)-in-mean model. Then section 3 describes the data and presents the estimation results. Section 4 discusses these results and section 5 offers some concluding remarks.

2. The Model

To assess the linkage between inflation and stock returns, one of the most general and convenient approaches is to conduct a simple vector autoregression (VAR) model, accommodating long-memory feature and heteroskedasticity in both series which have been observed in the empirical literature (for example, Ding et al. 1993, Hamilton 2010). Specifically, a neglect of conditional heteroskedasticity will result in considerable size distortion in the least squares causality test if the conditional variances are correlated (Vilasuso, 2001). In these regards, this study accordingly develops a system of equations to simultaneously estimate the conditional means, variances, and covariances of inflation and stock return.

Let π_t and s_t denote the dynamics of inflation and stock returns respectively, a bivariate(B) ARFIMA(*n*, *d*, *0*)- GARCH(*p*, *q*)-in-mean model is written as[11]

$$\Phi(L)P^d(x_t-\mu_0)=\Delta(L)h_t^{1/2}+\varepsilon_t \tag{1}$$

where $\varepsilon_t=\hat{H}_t^{1/2}z_t$, $\hat{H}_t=diag(h_t)$, $z_t\sim iid(0,C)$[12], and C is a 2×2 fixed correlation matrix with units on the diagonal. $x_t=\begin{bmatrix}\pi_t\\ s_t\end{bmatrix}$, $\mu_0=\begin{bmatrix}\mu_\pi\\ \mu_s\end{bmatrix}$, $h_t=\begin{bmatrix}h_{\pi t}\\ h_{st}\end{bmatrix}$, $\varepsilon_t=\begin{bmatrix}\varepsilon_{\pi t}\\ \varepsilon_{st}\end{bmatrix}$, $z_t=\begin{bmatrix}z_{\pi t}\\ z_{st}\end{bmatrix}$, $\Phi=\begin{bmatrix}\phi_{\pi\pi} & \phi_{\pi s}\\ \phi_{s\pi} & \phi_{ss}\end{bmatrix}$, $\Delta=\begin{bmatrix}\delta_{\pi\pi} & \delta_{\pi s}\\ \delta_{s\pi} & \delta_{ss}\end{bmatrix}$, $\Phi(L)=I-\sum_{i=1}^{n}\Phi_iL^i$, I is a 2×2 identity matrix.

P^d is a 2×2 diagonal matrix with elements $(1-L)^{d_\pi}$ and $(1-L)^{d_s}$, with d_π and d_s lying between zero and unity and measuring the long memory of inflation and stock returns respectively. According to Baillie et al. (1996), the general properties of I(*d*) is as follows. When *d*=0, the series is an I(0) process with short-run behavior, in which the effects of shocks occur at an exponential rate of decay, that is, the series quickly regains its equilibrium. In the case of an I(1) process for given shocks, when *d*=1, the series does not revert to its mean and the persistence of shocks is infinite. Between the distinctive I(0) and I(1), there is an I(*d*) process with long-run dependence, when 0<*d*<1, in which persistence dies out hyperbolically. In this case, the series takes a considerable time to reach mean reversion after shocks. Specifically, when *d*=0.45, there is a typical feature of long memory, which signifies that the

[11] ARFIMA is developed by Granger (1980) and Granger and Joyeux (1980), GARCH is proposed by Bollerslev (1986) and ARCH-in-mean is introduced by Engle et al.(1987).
[12] *iid* is an abbreviation for independently and identically distributed.

series is very persistent.

Here, x_t is the column vector of inflation and stock return, μ_0 denotes the intercepts and h_t is the variances. Φ is the coefficient matrix of the vector autoregressive signifying the mutual effects between inflation and stock return, and in this regard Fisher (1930, pp. 407-38) reported early "no direct and consistent connection of any real significance between P' [rate of price change per annum] and i' without lagging (and even a negative correlation coefficient r for some subperiods, notably -0.459 for Great Britain from 1820 to 1864)". Δ captures the in-mean effects implying how the level rates of the two variables are affected by their volatilities. ε_t is the innovations assumed to be serially uncorrelated, normally distributed[13] with mean vector 0, variance h_t and covariance $h_{\pi s,t}$ conditional on information set up to time *t*-1, while h_t is formed following the ccc GARCH process (Bollerslev, 1990)[14]

$$h_t = \omega_0 + A(L)\varepsilon_t^2 + B(L)h_t + \Gamma(L)x_{t-1} \tag{2}$$

$$h_{\pi s,t} = \rho\sqrt{h_{\pi t}}\sqrt{h_{st}},\ -1 \le \rho \le 1 \tag{3}$$

where $\omega_0 = \begin{bmatrix} \omega_\pi \\ \omega_s \end{bmatrix}$, $A = \begin{bmatrix} \alpha_{\pi\pi} & \alpha_{\pi s} \\ \alpha_{s\pi} & \alpha_{ss} \end{bmatrix}$, $B = \begin{bmatrix} \beta_{\pi\pi} & \beta_{\pi s} \\ \beta_{s\pi} & \beta_{ss} \end{bmatrix}$, $\Gamma = \begin{bmatrix} \gamma_{\pi\pi} & \gamma_{\pi s} \\ \gamma_{s\pi} & \gamma_{ss} \end{bmatrix}$. Γ captures the impacts of the level rates of both variables on their volatilities[15].

In equation 2, elements of ω_0, A, B and Γ should be positive to ensure a positive h_t, which do not account for negative effects and may not be adequate to reflect the interactions among the four variables as discussed above. To address this issue, this study employs a bivariate process of Braun et al. (1995) assuming that each variance follows a univariate EGARCH of Daniel Nelson (1991),

$$\ln h_t = \omega_0 + \alpha(L)g(z_t) + \beta(L)\ln h_t + \Gamma(L)x_{t-1} \tag{4}$$

$$g(z_t) = \theta_1 z_t + \theta_2\left[|z_t| - E|z_t|\right] \tag{5}$$

where $g = \begin{bmatrix} g_\pi \\ g_s \end{bmatrix}$, $\theta_1 = \begin{bmatrix} \theta_{1\pi} \\ \theta_{1s} \end{bmatrix}$ and $\theta_2 = \begin{bmatrix} \theta_{2\pi} \\ \theta_{2s} \end{bmatrix}$. h_t in equation 4 will be almost surely covariance stationary if $\theta_{1\pi}/\theta_{1s}$ and $\theta_{2\pi}/\theta_{2s}$ do not both equal zero, and positive definite for all *t* allowing Γ to

[13] Maximum likelihood estimates will be consistent and asymptotically normal (Weiss 1986, Bollerslev and Wooldridge 1992, Ling and LI 2001, Ngatchou-Wandji 2008). In addition, the MLE computing saves estimation time considerably under the normality assumption.
[14] The assumption of CCC "allows for obvious between period comparisons" (Bollerslev, 1990 p. 498), which is particularly useful for examining pre and post Volcker period in this study.
[15] See Baillie et al. (1996).

reflect positive/negative influences of inflation and stock returns on their variances. The parameter θ_1 captures the leverage effects when $\theta_1 < 0$ and $\ln h_t$ responds symmetrically to z_t when $\theta_1 = 0$. Note, $E|z_{\pi/st}| = \sqrt{\frac{2}{\pi}}$ under the assumption of that ε_t is normally distributed[16] and the MLE is computed by the following logarithm likelihood function[17]

$$L(\mu, d, \Phi, \Delta, \theta, \omega, \alpha, \beta, \gamma) = -\frac{NT}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{T}(\log\det \widehat{H}_t + \log\det C + \varepsilon_t^{'}\widehat{H}_t^{-1/2}C^{-1}\widehat{H}_t^{-1/2}\varepsilon_t) \tag{6}$$

3. Empirical Results

3.1 The Data

I estimate inflation and stock returns by taking the natural log difference of CPI and Standard & Poor's 500 index (S&P 500), that is $\pi_t = 100 \times (\log CPI_t - \log CPI_{t-1})$ and $s_t = 100 \times (\log SP_t - \log SP_{t-1})$ respectively. Note s_t is a continuously compounded single period stock return. The postwar period (1961:01-2009:12) time series monthly data of CPI is not seasonally adjusted given the results of the seasonality test shown in Appendix 1, compiled from the BLS, and S&P is a value weighted index[18] obtained from Thomson Reuters Datastream, which researchers have used to develop relevant theories and provide empirical evidence[19]. The two variables compose the bivariate VAR of x in equation 1 split into pre-Volcker (1961:01-1979:09) and post-Volcker (1979:10-2009:12) periods[20] for looking at changes of interactions among inflation, stock returns and their volatilities.

It is worth mentioning that some studies decompose inflation into its expected and unexpected components, which nevertheless has been limited in existing methods. For example, the survey-based expectations represent different inflation expectation from economists, consumers and etc. with insufficient ranges and frequencies (Mankiw et al. 2004 and Zeng 2010). As for empirical approaches applied in the literature, such as Fama (1975), he noted that the expected real return is constant through time if the bill market is efficient, and then derived that expected inflation is the difference between the nominal return on a short-term treasury bill and the constant expected real return on it. The choice of nominal inflation in this study is due to the difficulties of measuring unbiased inflation expectations as discussed above, and is also supported by empirical studies showing that using nominal inflation yields similar results (Fama and Schwert 1977, Fama 1981, Graham 1996).

Figure 1 plots the dynamics of inflation and stock returns, and their conditional standard

[16] $\pi \approx 3.141592653...$

[17] N in equation 6 is the number of variables in VAR, which is equal to 2 in this study.

[18] See *S&P 500 Fact Sheet*.

[19] See Fisher (1930), Fama and Schwert (1977), Fama (1981), Kaul (1987), Lee (1992) and many others.

[20] Kaul (1990) classified the period of 1961:01-1979:09 as "money supply control" monetary regime (p. 319). The sample of 1960:01-1979:09 has been estimated as well, and the results are the same.

deviations for the pre- and post-Volcker periods in panel A and B respectively. At first glance, panel A shows some apparent trade-offs between inflation rates and stock returns during the pre-Volcker period[21], specifically throughout 1970s, while this phenomenon fades away since early 1980s[22]. Panel B tells the familiar story. Over the sample, the volatilities of the rate of inflation and the stock return do not seem to be related[23].

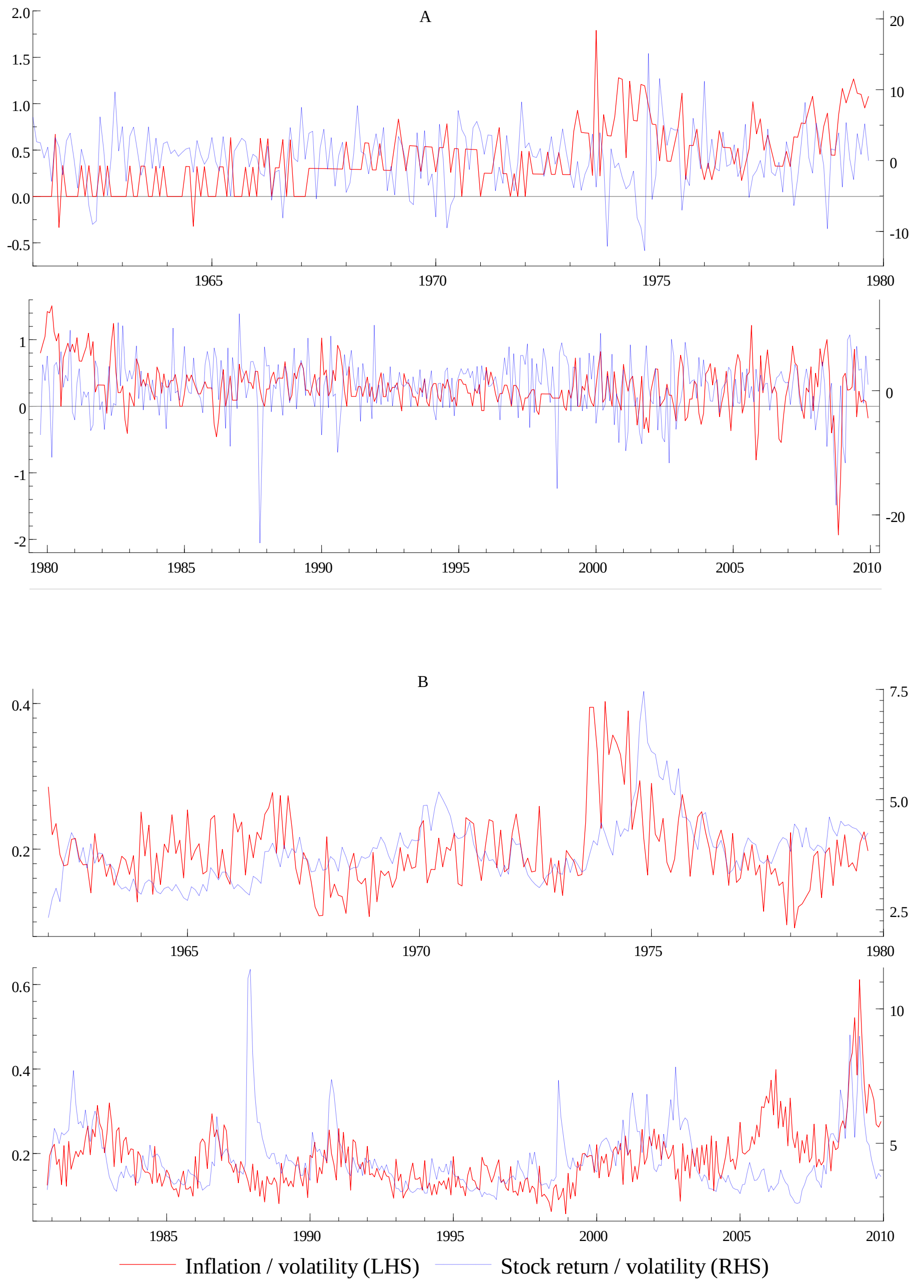

Figure 1. US inflation and stock returns

Sources: BLS, Thomson Reuters Datastream.

Notes: LHS and RHS stand for left and right hand scale respectively.

[21] Empirical evidence has been provided by Fama and Schwert (1977), Graham 1996, Barnes et al. 1999, Gallagher and Taylor (2002) and many others.

[22] See Kolluri and Wahab (2008) for empirical evidence.

[23] See Schwert (1989) for empirical evidence.

As presented in table 1, average rates of inflation in the post-Volcker period have been substantially reduced. The average conditional standard deviations are 0.198 and 0.187 for the former and latter subsample respectively, showing that inflation is less volatile than during the pre-Volcker period despite the unconditional values being higher. The post-Volcker period has seen an increase in both stock returns and volatility (the latter reflecting the stock market crashes of 1987 and 2008 (Carlson 2006, Authers and Mackenzie 2008)[24]). In addition, the rates of inflation and stock returns exhibit strong heteroskedasticity except for the stock returns in the latter sample. However, White Heteroskedasticity tests for VAR provide significant statistics of 111.506 and 163.210 at 1% level for former and latter sample respectively, indicating the presence of heteroskedasticity in both subsamples. Also the Chow's Breakpoint Test indicates that the date of 1979:10 is the structural break for both inflation and stock return series.

Table 1. Data descriptive statistics

<table>
<tr><th></th><th>Mean</th><th>Std. Dev</th><th>ARCH_LM</th><th colspan="2">Chow's Breakpoint Test</th></tr>
<tr><td></td><td colspan="3">1961:01-1979:09 (Obs. 225)</td><td colspan="2">Date: 1979:10</td></tr>
<tr><td>π</td><td>0.408</td><td>0.344
(0.198)</td><td>53.113
[0.000]</td><td></td><td>F-statistic</td></tr>
<tr><td>s</td><td>0.281</td><td>4.078</td><td>7.465
[0.001]</td><td rowspan="3">π</td><td rowspan="3">1.907
[0.168]</td></tr>
<tr><td>x</td><td>-</td><td>-</td><td>111.506
[0.000]</td></tr>
<tr><td></td><td colspan="3">1979:10-2009:12 (Obs.363)</td></tr>
<tr><td>π</td><td>0.293</td><td>0.358
(0.187)</td><td>84.360
[0.000]</td><td rowspan="3">s</td><td rowspan="3">0.270
[0.604]</td></tr>
<tr><td>s</td><td>0.638</td><td>4.518</td><td>2.582
[0.077]</td></tr>
<tr><td>x</td><td>-</td><td>-</td><td>163.210
[0.000]</td></tr>
</table>

Notes: Obs. and Std. Dev denote the number of observations and standard deviations respectively. The numbers in parentheses are average conditional standard deviations and in brackets are *p*-values. For x, the test for heteroskedasticity is White Heteroskedasticity with cross terms.

To better capture the stability of the series, several unit root tests are applied to detect the short/long memory. The PP (Phillips-Perron, 1988) test is for I(1) against I(0). On the contrary, the KPSS (Kwiatkowski et al., 1992) test is for I(0) against I(1). Unlike the two threshold tests, the HML (Harris et al., 2008) test is for the null hypothesis of short memory against long memory alternatives, that is the test of I(0) against I(d). As reported in table 2, the PP test rejects the null at 1% level for both inflation rates and stock returns, implying the each series does not have a unit root. The KPSS fails to reject that stock returns are stationary at 5% level and inflation at 5% level for pre-Volcker period; however, the stationarity of inflation rates at 2% level for post-Volcker period is rejected. Finally, the HML test fails to reject that stock returns are stationary at 10% level; whereas it rejects the stationarity of

[24] See also *Preliminary Observations on the October 1987 Crash* (United States General Accounting Office 1988), and Soros (2009).

inflation rates at 1% level, which should follow a I(d) process. All the unit root tests together with descriptive statistics for data suggest that the postwar US inflation and stock returns can be described properly in a bivariate ARFIMA-GARCH type model of equation 1, 4 and 5.

Table 2. Unit root tests

Sample	PP H_0: I(1) $Z(t_{\hat{\alpha}})$	KPSS H_0: I(0) η_μ	HML H_0: I(0) $\hat{S}_k$
		π	
1961:01-1979:09	-4.911	0.717*	4.235
1979:10-2009:12	-6.970	0.515**	4.251
		s	
1961:01-1979:09	-14.312	0.094***	-0.309***
1979:10-2009:12	-17.369	0.246***	0.847***

Notes: $Z(t_{\hat{\alpha}})$ and η_μ are Phillips-Perron adjusted statistic, LM statistic respectively, using Parzen Kernel estimation method with Newey-West Bandwidth and drift. $\hat{s}_k$ is HML statistic with c=1 and L=0.66. The statistics are all significant at 1% level except for those with asterisks.
* Significant at 1% level
***Significant at 10% level.

3.2 Estimates

The BARFIMA(*n*, *d*, *0*)-EGARCH(1, 1)-in-mean model is estimated by maximizing the log-likelihood function of equation 6, and the preferred specification is selected by the Akaike information criterion (AIC). The estimations show that the asymmetric coefficient, cross term of A and B, that is $\theta_1, \alpha_{\pi s}, \alpha_{s\pi}, \beta_{\pi s}, \beta_{s\pi}$, are insignificant (as shown in Appendix 2), suggesting that the two variances respond symmetrically to their shocks and may not affect each other directly. Thus equation 4 restricts $\theta_1, \alpha_{\pi s}, \alpha_{s\pi}, \beta_{\pi s}, \beta_{s\pi}$ to zero, and modelled two univariate EGARCH process with robustness of results across alternative time periods, lagged level rates of inflation, stock returns and their respective volatilities.

The best-fit results all reported in table 3. According to the Box-Pierce (Box and Pierce, 1970) Q statistics at lag 12 for the levels and squares of the standardized residuals, there is no statistically significant evidence of mispecification of the estimated model. The estimated values of *d* for inflation are 0.48 for pre-Volcker and 0.32 for post-Volcker period. They present small standard errors, and thus are significantly different from 0 and 1. The clear implication is that the inflation rate of each subsample is a long memory process, and its degree switches as monetary policy changes.

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Table 3. Bivariate ARFIMA(n, d, 0)- GARCH(1, 1)-in-mean estimates for inflation rates and stock returns

	Sample			
	1961:01-1979:09		1979:10-2009:12	
	π	s	π	s
d	0.485 (0.066)	-	0.298 (0.053)	-
ϕ	$0.074^{(6)}$ (0.037)	$-0.160^{(3)}$ (0.100)	$0.031^{(1)}$ (0.028)	$-0.050^{(2)}$ (0.087)
δ	$0.010^{(3)}$ (0.267)	$-0.816^{(2)}$ (0.880)	$0.340^{(1)}$ (0.152)	$-0.296^{(1)}$ (0.324)
	$0.122^{(3)}$ (0.171)	$0.622^{(2)}$ (0.531)	$-0.113^{(1)}$ (0.079)	$0.347^{(1)}$ (0.200)
α	0.645 (0.389)	0.204 (0.110)	0.336 (0.101)	0.235 (0.094)
β	-	0.735 (0.087)	0.900 (0.038)	0.814 (0.152)
γ	$0.091^{(5)}$ (0.025)	$0.025^{(7)}$ (0.017)	$0.023^{(1)}$ (0.012)	$0.026^{(1)}$ (0.016)
	$0.034^{(5)}$ (0.018)	$-0.005^{(7)}$ (0.018)	$-0.022^{(1)}$ (0.015)	$-0.036^{(1)}$ (0.024)
Q(12)	7.109 [0.850]	8.994 [0.703]	26.689 [0.004]	3.529 [0.991]
$Q^2(12)$	9.277 [0.679]	8.615 [0.735]	10.115 [0.606]	3.738 [0.988]
ρ	-0.203 [0.013]		-0.071 [0.296]	
AIC	-882.509		-1517.52	
Log (L)	-860.509		-1496.52	

Notes: Standard errors and t probabilities are given respectively in parentheses and brackets. Q (12) and Q^2 (12) are the Box Pierce tests based on residuals and squared residuals. ϕ only reports the most significant cross AR term. AIC is Akaike information criterion and Log (L) is log likelihood. For δ and γ, the first and second rows report the coefficient of inflation and stock return respectively. The superscript denotes the number of lagged terms. In formulation, θ_2 is set to be 1, and therefore only α is reported.

Results also provide statistical evidence on the interaction among inflation, stock returns and their volatilities. In the first subperiod, inflation and stock returns affect each other, with positive sign from stock return to inflation and negative sign from inflation to stock return supporting Hristu-Varsakelis and Kyrtsou's (2008) findings. While in the post-Volcker period, there remains only a positive effect of stock returns on inflation. On the other hand, the two volatilities perform poorly in explaining each other as well as their level values, although an indirect relation between inflation and stock return exists in the latter subperiod. By contrast, both inflation and stock return have a strong impact on their volatilities. Inflation leads to more stock return volatility for both subperiods, which is consistent with the finding of Saryal

(2007). In addition, stock return exhibits two opposite effects on inflation uncertainty, positive in the former and negative in the latter period.

Moreover, all the conditional parameters are significant at 5% level except for $\alpha_{s\pi}$ for pre-Volcker period which is significant at 10% level, demonstrating that heteroskedasticity in VAR is well described by GARCH approach. According to the Box-Pierce (Box and Pierce, 1970) Q statistics at lag 12 for the levels and squares of the standardized residuals, there is no statistically significant evidence of mispecification of the estimated model. Particularly, the Wald tests in table 4 emphasize the significant specifications of the effects of volatilities on the level of the rates in the mean and that of level rates on volatilities in the variance.

Table 4. Wald tests for restrictions on parameters of volatilities and level rates effects

	Sample			
	1961:01-1979:09		1979:10-2009:12	
	π	s	π	s
δ	$0.010^{(3)}$ (0.267)	$-0.816^{(2)}$ (0.880)	$0.340^{(1)}$ (0.152)	$-0.296^{(1)}$ (0.324)
	$0.122^{(3)}$ (0.171)	$0.622^{(2)}$ (0.531)	$-0.113^{(1)}$ (0.079)	$0.347^{(1)}$ (0.200)
γ	$0.091^{(5)}$ (0.025)	$0.025^{(7)}$ (0.017)	$0.023^{(1)}$ (0.012)	$0.026^{(1)}$ (0.016)
	$0.034^{(5)}$ (0.018)	$-0.005^{(7)}$ (0.018)	$-0.022^{(1)}$ (0.015)	$-0.036^{(1)}$ (0.024)
	$\delta = 0$ and $\gamma = 0$			
W	34.574 [0.000]		35.478 [0.000]	

Notes: Standard errors and *t* probabilities are given respectively in parentheses. W is Wald test ~ $\chi^2(8)$.

4. Discussion

The results presented in table 5 and 6 summarize the effects between monetary stability and stock market performances. Notably, there are several shifts and different types of interactions among inflation, stock returns and their volatilities in the pre- and post-Volcker periods.

First, my results suggest a bidirectional relationship between inflation and stock returns in the former, while the negative effect of inflation on stock returns appears insignificant in the latter episode. Over the post-Volcker period, monetary stability is well maintained, as inflation is less persistent, and inflation rates and volatility have been moderated and relatively stable. When prices are stable and believed likely to remain so, the prices of goods, services, materials and labor will not be distorted by inflation. Thus the risk of erosion of asset value resulting from inflation is minimized, which is reflected by the estimated ccc, i.e. ρ – a stronger correlation in former period and it is weaker in the latter. In fact, there is an

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insignificant positive effect of inflation on stock returns[25], implying that a rise in price level may increase stock returns. Clearly promoting monetary stability might lead two variables to move together, and so that common stock could be a better hedge against inflation.

Table 5. Direct and indirect effects

Dependent Variables \ Independent variables	π	s	h_π	h_s
π		+	/	/
		+	+	−
s	−		/	/
	/		/	+
h_π	+	+		/
	+	−		$h_s \xrightarrow{+} s \xrightarrow{-} h_\pi$
h_s	+	−	/	
	+	−	$h_\pi \xrightarrow{+} \pi \xrightarrow{+} h_s$	

Notes:+ (-) indicates positive (negative) effect. / stands for no effects. The upper and lower rows report the results of pre- and post-Volcker period respectively.

Another significant shift is that the effect of stock returns on inflation volatility has turned from positive into negative in post-Volcker episode. For example, the Fed made several attempts to curb the inflation of the 1970s, a policy effort which was accompanied by two recessions – in 1980:01 to 1980:07 and in 1981:07 to 1982:11 (as defined by the NBER). This then induces policymakers to reduce inflation uncertainty in the future to maintain monetary stability.

Finally, the stock market tends to be more efficient (Fama et al., 1969; Fama, 1970, 1991; Schwert 1981, 1989) and the monetary factor seems to be more effective in post-Volcker period, since inflation sets up a bidirectional channel through which the two volatilities influence each other indirectly. During this subperiod, inflation volatility has a positive impact on the level of the rate of inflation (Cukierman and Meltzer, 1986). These authors suggested that there exists an incentive for monetary authorities to create an inflation surprise in order to stimulate output growth and therefore the increase in the level of inflation rate. At the same time, the inflation level positively affects stock returns' volatility (Saryal, 2007). Conversely, stock return volatilities negatively influence inflation, which affects positively its uncertainty (Friedman, 1977; Holland, 1995). As a result, a rise in inflation indirectly increases stock return, and stock return volatility indirectly decreases inflation volatility via

[25] See Appendix 3.

the rate of inflation.

Table 6. Key statistics and links in pre and post-Volcker era

	pre-Volcker	post-Volcker
d	0.485	0.298
ρ	-0.203	-0.071
$\pi \rightleftarrows s$	-0.160$^{(3)}$	-0.050$^{(2)}$
	0.074$^{(6)}$	0.031$^{(1)}$
$h_\pi \to h_s$	/	$h_\pi \xrightarrow{+} \pi \xrightarrow{+} h_s$
$h_s \to h_\pi$	/	$h_s \xrightarrow{+} s \xrightarrow{-} h_\pi$
$h_\pi \to s$	-0.816$^{(2)}$	-0.296$^{(1)}$
$h_s \to \pi$	0.122$^{(3)}$	-0.113$^{(0)}$
$\pi \to h_s$	0.025$^{(7)}$	0.026$^{(1)}$
$s \to h_\pi$	0.034$^{(5)}$	-0.022$^{(1)}$

Notes: The bold numbers indicate significant values.

5. Conclusion

This paper has employed a ccc BEGARCH approach to model simultaneously the dynamics of US inflation, stock returns and their volatilities during the pre- and post-Volcker periods. No sign restrictions were imposed, and it has thereby cast significant light on the relationship between monetary stability and the stock market.

The empirical results support previous findings: (i) a bidirectional relation between inflation and stock returns, which is time-varying; (ii) no direct links between inflation uncertainty and stock return volatility; and (iii) a positive effect of inflation on volatilities of inflation rates and stock returns. Meanwhile by dividing the dataset into two subperiods characterized monetary instability and monetary stability, this paper has demonstrated some significant shifts among the interactions between both variables: (i) the bidirectional inflation-stock returns relation in the former has changed to a unidirectional one since the negative effect of inflation on stock returns appears insignificant in the latter episode, showing common stock could be a more effective hedge against inflation; (ii) the positive effect of stock returns on inflation volatility has turned negative in the post-Volcker episode. (iii) the two volatilities help to explain each other indirectly through the channel of inflation rates in the latter period, implying that lower and more stable inflation – the primary goal of monetary policy – is also conducive to a more effective stock market. As Greenspan (2009) noted, fears of short-term deflation and long-term inflation drove the stock market swings seen in the crisis that began in 2008, and this threatens a sustained economic recovery.

Findings in this study strongly suggest that promoting monetary stability has indeed contributed to a more efficient stock market, which in turn has proved sensitive to monetary policy actions. Further research could extend this bivariate framework to investigate a broader range of financial and macroeconomic variables such as to interpret bond market, the housing market, and to consider output and unemployment as well as their variabilities, in search of anchors for both monetary and financial stability.

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References

Arnold, I. J. M. Vrugt, E. B. (2006). Stock Market Volatility and Macroeconomic Uncertainty Evidence from Survey Data. NRG Working Paper no. 06-08

Authers, J. Mackenzie, M. (2008). Shares crash dashes hopes for bear market rally. *Financial Times.* Nov 22 2008

Baillie, R. T. Chung, C. F., & Tieslau, M. A. (1996). Analysing inflation by the fractionally integrated ARFIMA-GARCH model. *Journal of Applied Econometrics. 11*(1). 23-40.http://dx.doi.org/10.1002/(sici)1099-1255(199601)11:1<23::aid-jae374>3.0.co;2-m

Barnes, M. J.H.Boyd, & B.D.Smith. (1999). Inflation and Asset Returns. *European Economic Review. 43*. 737-754.http://dx.doi.org/10.1016/S0014-2921(98)00090-7

Berben, R. (2007). Does stock market uncertainty impair the use of monetary indicators in the euro area? *Applied Economics. 39*. 13-23.http://dx.doi.org/10.1080/00036840600903436

Bernanke, B. Kuttner, K. (2005). What Explains the Stock Market's Reaction to Federal Reserve Policy? *Journal of Finance. 60*(3). 1221-1257. http://dx.doi.org/10.1111/j.1540-6261.2005.00760.x

Bodie, Z. (1976). Common Stocks as a Hedge against Inflation. *Journal of Finance. 31*(2). 459-470. http://dx.doi.org/10.1111/j.1540-6261.1976.tb01899.x

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics. 31*. 307-327.http://dx.doi.org/10.1016/0304-4076(86)90063-1

Bollerslev, T. (1990). Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model. *Review of Economics & Statistics. 72*(3). 498-505.http://dx.doi.org/10.2307/2109358

Bollerslev, T. Wooldridge, J. M. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric Reviews. 11*(2). 143-172 http://dx.doi.org/10.1080/07474939208800229

Borio, C. Lowe, P. (2002). Asset Prices, Financial and Monetary Stability: Exploring the

Nexus BIS Working Paper No. 114

Boudoukh, J. Richardson, M. (1993). Stock Returns and Inflation - a Long-Horizon Perspective. *American Economic Review. 83*(5). 1346-1355.<Go to ISI>://WOS:A1993ML61400018

Box, G. E. P. Pierce, D. A. (1970). Distribution of the residual autocorrelation in autoregressive integrated moving average time series models. *Journal of the American Statistical Association, 65*. 1509-1526. http://dx.doi.org/10.1080/01621459.1970.10481180

Braun, P. A. Nelson, D. B., & Sunier, A. M. (1995). Good-News, Bad-News, Volatility, and Betas. *Journal of Finance. 50*(5). 1575-1603. http://dx.doi.org/10.2307/2329327

Brealey, R. Vila, A. (1998). Equity Prices and Financial Stability. *Bank of England Financial Stability Review. 1998*(5). 10-18

Carlson, M. (2006). A Brief History of the 1987 Stock Market Crash with a Discussion of the Federal Reserve Response. Finance and Economics Discussion Series 2007-13

Clarida, R. Gal í J., & Gertler, M. (2000). Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory. *The Quarterly Journal of Economics. 115*(1). 147-180. http://dx.doi.org/10.3386/w6442

Cochran, S. J. DeFina, R. H. (1993). Inflation's Negative Effects on Real Stock Prices: New Evidence and a Test of the Proxy Effect Hypothesis. *Applied Economics. 25*(2). 263-274. http://dx.doi.org/10.1080/00036849300000032

Conrad, C. Karanasos, M., & Zeng, N. (2010). The link between macroeconomic performance and variability in the UK. *Economics Letters. 106*(3). 154-157. http://dx.doi.org/10.1016/j.econlet.2009.11.002

Conrad, C. Karanasos, M., & Zeng, N. (2011). Multivariate fractionally integrated APARCH modeling of stock market volatility: A multi-country study. *Journal of Empirical Finance. 18*(1). 147-159. http://dx.doi.org/10.1016/j.jempfin.2010.05.001

Cukierman, A. Meltzer, A. H. (1986). A Theory of Ambiguity, Credibility, and Inflation under Discretion and Asymmetric Information. *Econometrica. 54*(5). 1099-1128. http://dx.doi.org/10.2307/1912324

Davis, N. Kutan, A. M. (2003). Inflation and output as predictors of stock returns and volatility: international evidence. *Applied Financial Economics. 13*(9). 693-700. http://dx.doi.org/10.1080/09603100210139429

Du, D. (2006). Monetary policy, stock returns and inflation. *Journal of Economics and Business. 58*(1). 36-54. http://dx.doi.org/10.1016/j.jeconbus.2005.06.003

Elder, J. (2004). Another Perspective on the Effects of Inflation Uncertainty *Journal of Money, Credit and Banking. 36*(5). 911-928. http://dx.doi.org/10.2139/ssrn.262182

Engle, R. Lilien, D., & Robins, R. (1987). Estimating Time Varying Risk Premia in the Term

Structure: The Arch-M Model. *Econometrica*. *55*(2). 391-407. http://dx.doi.org/10.2307/1913242

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance*. *25*(2). 383-417. http://dx.doi.org/10.1111/j.1540-6261.1970.tb00518.x

Fama, E. F. (1975). Short-Term Interest Rates as Predictors of Inflation. *American Economic Review*. *65*(3). 269-282. http://dx.doi.org/10.2307/252556

Fama, E. F. (1981). Stock Returns, Real Activity, Inflation, and Money. *American Economic Review*. *71*(4). 545-565.<Go to ISI>://WOS:A1981ME69900002

Fama, E. F. (1991). Efficient Capital Markets: II. *Journal of Finance*. *46*(5). 1575-1617. http://dx.doi.org/10.1111/j.1540-6261.1991.tb04636.x

Fama, E. F. Fisher, L. Jensen, M. C., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review*. *10*(1). 1-21. http://dx.doi.org/10.2307/2525569

Fama, E. F. Schwert, G. (1977). Asset returns and inflation. *Journal of Financial Economics*. *5*(2). 115-146. http://dx.doi.org/10.1016/0304-405X(77)90014-9

Feldstein, M. (1980). Inflation and the Stock Market. *American Economic Review*. *70*(5). 839-847.<Go to ISI>://WOS:A1980KT75900001

Fisher, I. (1896). *Appreciation and Interest*. (Vol. 1). New York: Macmillan for the American Economic Association.

Fisher, I. (1907). *The Rate of Interest*. (Vol. 3). New York: Macmillan.

Fisher, I. (1930). *The Theory of Interest*. New York: Macmillan.

Friedman, B. Kuttner, K. (1996). A Price Target for U.S. Monetary Policy? Lessons from the Experience with Money Growth Targets. *Brookings Papers on Economic Activity*. *1996*(1). 77-125. http://dx.doi.org/10.2307/2534647

Friedman, M. (1972). Have Monetary Policies Failed? *American Economic Review*. *62*(1/2). 11-18. http://www.jstor.org/stable/1821518

Friedman, M. (1977). Nobel Lecture:Inflation and Unemployment. *Journal of Political Economy*, *85*. 451-472.http://dx.doi.org/10.1086/260579

Gertler, M. (1996). Comments on A Price Target for U.S. Monetary Policy? Lessons from the Experience with Money Growth Targets. *Brookings Papers on Economic Activity*. *1996*(1). 126-134. http://dx.doi.org/10.2307/2534647

Geske, R. Roll, R. (1983). The Fiscal and Monetary Linkage Between Stock Returns and Inflation. *Journal of Finance*. *38*(1). 1-33. http://dx.doi.org/10.2307/2327635

Graham, F. C. (1996). Inflation, Real Stock Returns, and Monetary Policy. *Applied Financial Economics*. *6*(1). 29-35. http:/dx.doi.org/10.1080/096031096334448

Granger, C. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods *Econometrica*. *37*(3). 424-438. http://dx.doi.org/10.2307/1912791

Granger, C. (1980). Long Memory Relationships and the Aggregation of Dynamic Models. *Journal of Econometrics*, *14*. 227-238. http://dx.doi.org/10.1016/0304-4076(80)90092-5

Granger, C. Joyeux, R. (1980). An Introduction to Long-Memory Time Series Models and Fractional Differencing. *Journal of Time Series Analysis 1*. 15-29. http://dx.doi.org/10.1111/j.1467-9892.1980.tb00297.x

Granville, B. S. Mallick. (2009). Monetary and Financial Stability in the Euro Area: Pro-cyclicality versus Trade-off *Journal of International Financial Markets, Institutions and Money. 19*(4). 662-674. http://dx.doi.org/10.1016/j.intfin.2008.11.002

Greenspan, A. (2009). Inflation is the big threat to a sustained recovery. *Financial Times*. June 26 2009

Hamilton, J. D. (2010). Macroeconomics and ARCH. In T. Bollerslev, J. R. Russell and M. Watson (Ed.), *Festschrift in Honor of Robert F. Engle* (pp. 79-96). Oxford: Oxford University Press.

Harris, D. McCabe, B. P. M., & Leybourne, S. J. (2008). Testing for Long Memory *Econometric Theory. 24*. 143-175. http://dx.doi.org/10.1017/S0266466608080080

Hess, P. Lee, B. S. (1999). Stock Returns and Inflation with Supply and Demand Disturbances. *The Review of Financial Studies. 12*(5). 1203-1218. http://dx.doi.org/10.1093/rfs/12.5.1203

Holland, S. (1995). Inflation and Uncertainty: Tests for Temporal Ordering. *Journal of Money, Credit and Banking. 27*(3). 827-837. http://dx.doi.org/10.2307/2077753

Hristu-Varsakelis, D. Kyrtsou, C. (2008). Evidence for Nonlinear Asymmetric Causality in US Inflation, Metal, and Stock Returns. *Discrete Dynamics in Nature and Society* Research Article 138547

Jaffe, J. Mandelke, G. (1976). The 'Fisher Effect' for Risky Assets: An Empirical Investigation. *Journal of Finance. 31*(2). 447-458. http://dx.doi.org/10.2307/2326616

Karanasos, M. Sekioua, S. H., & Zeng, N. (2006). On the order of integration of monthly US ex-ante and ex-post real interest rates: New evidence from over a century of data. *Economics Letters. 90*(2). 163-169. http://dx.doi.org/10.1016/j.econlet.2005.07.021

Karanasos, M. Zeng, N. (2013). Conditional heteroskedasticity in macroeconomics data: UK inflation, output growth and their uncertainties. In N. Hashimzade & M. Thornton (Eds.), *Handbook of Research Methods and Applications in Empirical Macroeconomics*. London: Edward Elgar Pub.

Kaul, G. (1987). Stock Returns and Inflation : The Role of the Monetary Sector. *Journal of Financial Economics. 18*(2). 253-276. http://dx.doi.org/10.1016/0304-405X(87)90041-9

Kaul, G. (1990). Monetary Regimes and the Relation Between Stock Returns and Inflationary Expectations. *The Journal of Financial and Quantitative Analysis. 25*(3). 307-321. http://dx.doi.org/10.2307/2330698

Kolluri, B. Wahab, M. (2008). Stock Returns and Expected Inflation: Evidence from an Asymmetric Test Specification. *Review of Quantitative Finance and Accounting. 30*(4). 371-395. http://dx.doi.org/10.1007/s11156-007-0060-9

Kwiatkowski, D. Phillips, P. Schmidt, P., & Shin, Y. (1992). Testing the Null Hypothesis of Stationary against the Alternative of a Unit Root. *Journal of Econometrics. 54*. 159-178. http://dx.doi.org/10.1016/0304-4076(92)90104-Y

Lee, B. S. (1992). Causal Relations Among Stock Returns, Interest Rates, Real Activity, and Inflation. *Journal of Finance. 47*(4). 1591-1603. http://www.jstor.org/stable/2328955

Lee, J. (1999). The inflation and output variability tradeoff: evidence from a Garch model. *Economics Letters. 62*. 63-67. http://dx.doi.org/10.1016/S0165-1765(98)00212-2

Lindsey, D. E. Orphanides, A., & Rasche, R. H. (2005). The Reform of October 1979: How It Happened and Why. *Federal Reserve Bank of St. Louis Review. 87*(2). 187-236

Ling, S. Li, W. K. (2001). Asymptotic Inference For Nonstationary Fractionally Integrated Autoregressive Moving-Average Models. *Econometric Theory. 17*(4). 738-764. http://dx.doi.org/10.1017/S0266466601174049

Lo, A. W. (1991). Long-Term Memory in Stock Market Prices. *Econometrica. 59*(5). 1279-1313. http://dx.doi.org/10.2307/2938368

Mankiw, N. G. Reis, R., & Wolfers, J. (2004). Disagreement about Inflation Expectations. *NBER Macroeconomics Annual 2003. 18*. 209-270. http://www.jstor.org/stable/3585256

Modigliani, F. R. A. Cohn. (1979). Inflation, rational valuation and the market. *Financial Analysts Journal. 35*(2). 24-44. http://dx.doi.org/10.2469/faj.v35.n2.24

Mundell, R. (1963). Inflation and Real Interest. *The Journal of Political Economy. 71*(3). 280-283. http://dx.doi.org/10.1086/258771

Najand, M. Rahman, H. (1992). Stock Market Volatility and Macroeconomic Variables: International Evidence. *Journal of Multinational Finance Management. 1*(3). 51-66. http://dx.doi.org/10.1300/J284v01n03_03

Nelson, C. R. (1976). Inflation and Rates of Return on Common Stocks. *Journal of Finance. 31*(2). 471-483. http://dx.doi.org/10.1111/j.1540-6261.1976.tb01900.x

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica. 59*(2). 347-370. http://dx.doi.org/10.2307/2938260

Ngatchou-Wandji, J. (2008). Estimation in a class of nonlinear heteroscedastic time series models. *Electronic Journal of Statistics. 2008*(2). 40-62. http://dx.doi.org/10.1214/07-EJS157

Officer, R. R. (1973). The Variability of the Market Factor of the New York Stock Exchange.

The Journal of Business. 46(3). 434-453. http://dx.doi.org/10.1086/295551

Perron, P. (1990). Testing for a Unit Root in a Time Series with a Changing Mean. *Journal of Business and Economic Statistics 8*. 153-162. http://dx.doi.org/10.1080/07350015.1990.10509786

Phillips, P. Perron, P. (1988). Testing for a Unit Root in Time Series Regression. *Biometrika. 75*(2). 335-346. http://dx.doi.org/10.1093/biomet/75.2.335

Ram, R. Spencer, D. E. (1983). Stock Returns, Real Activity, Inflation, and Money: Comment. *American Economic Review. 73*(3). 463-470

Sargent, T. J. (1999). *The Conquest of American Inflation*. Princeton: Princeton University Press.

Saryal, F. S. (2007). Does Inflation Have an Impact on Conditional Stock Market Volatility?: Evidence from Turkey and Canada. *International Research Journal of Finance and Economics* (11). 123-133

Schwert, G. (1989). Why Does Stock Volatility Change Over Time? *Journal of Finance. 44*. 1115-1153. http://dx.doi.org/10.2307/2328636

Soros, G. (2009). *The Crash of 2008 and What it Means.* New York: PublicAffairs.

Ungar, M. Zilberfarb, B. (1993). Inflation and Its Unpredictability--Theory and Empirical Evidence. *Journal of Money, Credit and Banking. 25*(4). 709-720. http://dx.doi.org/10.2307/2077800

Vilasuso, J. (2001). Causality tests and conditional heteroskedasticity: Monte Carlo evidence *Journal of Econometrics. 101*(1). 25-35. http://dx.doi.org/10.1016/S0304-4076(00)00072-5

Wei, C. (2008). Multivariate GARCH modeling analysis of unexpected U.S. D, Yen and Euro-dollar to Reminibi volatility spillover to stock markets. *Economics Bulletin. 3*(64). 1-15

Weiss, A. A. (1986). Asymptotic Theory for ARCH Models: Estimation and Testing. *Econometric Theory. 2*. 107-131. http://dx.doi.org/10.1017/S0266466600011397

Zeng, N. (2013). *The Usefulness of Econometric Models with Stochastic Volatility and Long Memory: Applications for Macroeconomic and Financial Time Series*. Hertford: M-Y Books.

Appendix

Appendix 1. F-tests for the presence of seasonality assuming stability

Sample	H_0: Stability F-value	H_0: Stability Probability (Nonparametric)	Moving Seasonality F-value	Seasonality presence
1961:01-1979:09	3.113#	0.002	1.585**	Probably No
1979:10-2009:02	12.831#	0.000	4.407**	Probably No

Notes:
#Seasonality present at the 0.1 per cent level.
**Moving seasonality present at the one percent level.

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Appendix 2. Estimates of $\theta_1, \alpha_{\pi s}, \alpha_{s\pi}, \beta_{\pi s}, \beta_{s\pi}$

	Sample			
	1961:01-1979:09		1979:10-2009:02	
	π	s	π	s
θ_1	-	-	0.123 (0.178)	-3.768 (4.946)
α	0.176 (0.419)	-0.081 (0.349)	0.140 (0.256)	-0.095 (0.128)
β	-0.463 (0.617)	0.239 (0.545)	-0.153 (0.261)	0.007 (0.099)

Notes: Standard errors are given in parentheses. Note, for α and β , the values reported are cross coefficients.

Appendix 3. Bivariate ARFIMA(*n*, *d*, *0*)- GARCH(1, 1)-in-mean estimates for inflation and stock return post-Volcker period with $\phi_{s\pi}^{(9)}$

	Sample 1979:10-2009:02	
	π	s
d	0.319 (0.054)	-
ϕ	$0.029^{(1)}$ (0.026)	$0.034^{(9)}$ (0.080)
δ	$0.239^{(0)}$ (0.176)	$-0.262^{(0)}$ (0.412)
	$-0.081^{(0)}$ (0.092)	$0.274^{(0)}$ (0.266)
α	0.333 (0.106)	0.219 (0.086)
β	0.908 (0.035)	0.864 (0.083)
γ	$0.022^{(1)}$ (0.013)	$0.022^{(1)}$ (0.014)
	$-0.024^{(1)}$ (0.015)	$-0.026^{(1)}$ (0.021)
Q(12)	34.604 [0.001]	3.233 [0.994]
$Q^2(12)$	10.378 [0.583]	2.723 [0.997]
ρ	-0.075 [0.246]	
AIC	-1471.51	
Log (*L*)	-1449.51	

*Notes :*As in table 3.