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Essays on Dynamics of Financial Markets

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ESSAYS ON DYNAMICS OF FINANCIAL MARKETS

by

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Abstract

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In this study, the effects of different macroeconomic news on stock markets and different stock market co-movements are investigated. Impacts of good and bad macroeconomic news announcement surprises on the mean and conditional volatility of U.S. daily equity and Treasury bond market returns during economic recessions and expansions are examined. By jointly modeling returns and volatilities using a generalized autoregressive conditional heteroskedasticity (GARCH) models, it is found that surprise in unemployment news has no impact on stock returns during business cycles. On the other hand, the results indicate a significantly positive relation between the short term (long term) bond prices and unemployment surprises during business cycles (expansions), indicating that U.S. government bonds is a complete hedge against unexpected unemployment. However, positive inflation surprises affect all considered market returns negatively during expansions. The price movements in stock markets can be explained by expected future interest rates when an inflation surprise is arrived.

Hence, both news surprises have more impact on volatility during economic recessions than expansions. Another way to see the dynamics of stock markets is to search the effect of different country equity market effects on each other. The second essay investigates it by linear and nonlinear Granger causality tests for US, UK and Japan stock markets, implying an arbitrage opportunity between stock markets. The third study examines the dynamic relationship between the monthly inflation, inflation uncertainty and stock for G3 countries. Using a GARCH model to generate a measure of inflation uncertainty, the empirical evidence indicates that higher inflation rates lead to greater inflation uncertainty for all countries as predicted by Friedman (1997). However, in all countries, except Japan, inflation uncertainty does not significantly either rise or fall average inflation. In contrast to linear linkages, there is a strong bi-directional non-linear causal relationship between inflation and its uncertainty for all countries. The similar findings are found for the inflation uncertainty and stock returns. Inflation uncertainty does not linear Granger-cause stock returns, except Japan. However, there is a bi-directional nonlinear Granger causality for all countries.

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This dissertation is dedicated to my mother. Without her sacrifice none of this would have been possible. I send her my deepest gratitude. My only wish is health to all of us.

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Chapter 1

Introduction

The financial markets are affected by many different factors. Well known factor is mostly firm based news. On the other hand, stock and bond markets are also priced by the announcements of macroeconomic news surprises. Chapter 2 focuses on the impacts of good and bad macroeconomic news announcements on the mean and conditional volatility of the U.S. stock and Treasury bond market returns during economic recessions and expansions. By jointly modeling returns and volatilities, we find that surprise in unemployment news has no impact on stock returns during business cycles. These findings are in contradiction to Boyd et al. (2005) who find that increase in unemployment rate is good news for stocks during economic expansions, and bad news during contractions. Furthermore, we find that stock market becomes more risky to an unemployment news shock. On the other hand, the results indicate a significantly positive relation between the short term (long term) bond prices and unemployment surprises during business cycles (expansions), indicating that U.S. government bonds is a complete hedge against unexpected unemployment. Inflation surprises affect all market returns negatively during good state of the economy, which is well supported in the literature. Hence, both news surprises have more impact on volatility during economic recessions than expansions.

Interactions among stock markets, increasing with globalization process, encourage economists to assess whether any relationships exist. Chapter 3 focuses on the dynamic relationship between the Dow Jones Industrial Average index of the US and Japan, France, and the UK stock markets by using the non-linear

Granger causality test . The empirical evidence indicates that there is a strong bi-directional non-linear causality relationship between the US and the others while the US stock market statistically significant Granger causes the stock markets examined, but Japan and France do not linear Granger causes the US stock market with the exception of UK.

Highlighting the importance of testing for non-linear linkages in addition to linear linkages, the results of Hiemstra and Jones (1994) non-linear test suggest that Japan, France, and the UK non-linear Granger causes the US, and vice-versa. Under the light of that linear Granger causality tests generally have low power against non-linear relationships, the overall statistical analysis of this paper clearly supports a non-linear modeling of the relationship between the US and the other countries we examined. The efficient market hypothesis implies that price changes in equities and bonds reflect the arrival and processing of relevant new information. By using daily for four stock market prices we find a significant bi-directional non-linear Granger causality relationship in four cases, implying a degree of market inefficiency in the sense that lagged information from one stock market price can be used to forecast changes in another stock market price. The contribution of that paper is to show with the evidence that the general believe of the US stock market is not effected by the other equity markets is not true. Following the efficient market hypothesis, there should not be any nonlinear relationships between those markets. Having a nonlinear relation shows that information does not processed and that information can be used to forecast changes in the other stock market. Chapter 4 focuses on the dynamic relationship between the monthly inflation, inflation uncertainty and stock returns in Japan, US and the UK by employing the linear and non-linear Granger causality tests for the 1957-2006 period for US and 1984-2006 period for UK and Japan. Using a generalized autoregressive conditional heteroskedasticity (GARCH) model to generate a measure of inflation uncertainty, the empirical evidence indicates that higher inflation rates lead to greater inflation uncertainty for all countries as predicted by Friedman (1997). However, in all countries, except Japan, inflation uncertainty does not significantly either rise or fall average inflation. In contrast to linear linkages, there is a strong bi-directional non-linear causal relationship between inflation and its uncertainty for all countries. The similar findings are found for the inflation uncertainty and stock returns. Inflation uncertainty does not linear Granger-cause stock returns, except Japan. However, there is a bi-directional nonlinear Granger causalities for all countries.

Chapter 2

Do Good and Bad Economic News Affect The Stock Market Differently From The Bond Market?

2.1 Introduction

Macroeconomic conditions are known to affect risk factors and thereby influence asset returns within a given economy. Fama and French (1992 and 1995) suggests that fundamental risk factors that captured by macroeconomic variables significantly impact asset pricing. They find that within a given economy, unexpected macroeconomic surprises affect stock return levels and volatilities. Therefore, in the past decade, the impact of macroeconomic news announcements on financial markets has received considerable attention in the literature. Recent studies have examined not only macroeconomic news but also differentiating the good and bad economic news on the stock markets (Boyd et al., 2005, Verenossi, 1999). The general opinion is that asset prices and volatilities in the exchange rate markets (Andersen and Bollerslev, 1998), bond markets (Balduzzi et al., 2001) and stock markets (Becker et al.,1995; Jones et al.,2005; Veronesi, 1999, Christiansen, 2000; Li and Engle, 1998, Adams et al.,1999; Fleeming and Remolona, 1998) are affected by macroeconomic news announcements.[1]

In this study, jointly modeling returns and volatilities, we investigate how the good and bad news component of unemployment and inflation announcement surprises affect the behavior of daily equity and Treasury bond market returns

[1] Besides the stock and bond markets, there are some other markets that the researchers study on to examine the effect of macroeconomic news. Kim and Kim (2003) examine the currency option markets, Ederington and Lee (1996), Fornari and Mele (2001), Heuson and Su (2003) and Vähämaa,Watska, and Äijö (2005) examine the bond options markets, while the equity options markets are studied by Graham, Nikkinen, and Sahlström (2003), Nofsinger and Prucyk (2003) and Nikkinen and Sahlström (2004).

during the business cycles in U.S from January 1981 to December 2005.[2] We consider the asymmetric volatility in the conditional variance of returns, and use exponential generalized autoregressive conditional heteroscadasticity (EGARCH). To determine effect of news surprises on different markets, we consider large and small caps; and long and short term bonds.

The motivation for studying the transmission of macroeconomic shocks to financial markets is twofold. First, Boyd et al. (2005) employs only the announcement of unemployment rate news on stock and bond returns, but we model returns and volatility simultaneously believing the conditional volatility is an important factor on mean returns. In addition, we analyze the impact of unemployment rate and inflation announcements on stock and bond returns separately in recession and expansion periods to search the effect of different macroeconomic variables.

Macroeconomic variables are candidates for systematic risk factors and macroeconomic innovations can generate global impact on firms' fundamentals, such as their cash flows, risk adjusted discount factors and/or investment

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[2] Moreover, Andersen and Bollerslev (1997), based on foreign exchange data, categorize PPI announcements as "important" but CPI announcement as "less important", and both Balduzzi et.al (1997) and Fleming and Remolona (1997) find both markets are more sensitive to PPI than CPI surprises. Adams et. al. (2004) find that the response to PPI news more significant than the CPI news in stock markets and large stocks respond significantly to PPI news. The sample of Jones et.al. (1998) runs from October 9, 1979 to December 31, 1993, and they find strong evidence that releases of employment data have an effect on bond cash market volatility. Ederington and Lee (1993) point to the public announcements as a major source of price volatility in the T-bond market.

opportunities. Therefore, we consider monthly pre-announced unemployment rate and producer price index (hereafter PPI) as the main macroeconomic data that we find newsworthy to study in examining the equity and bond market price movements. Some studies use regression models to obtain an unexpected part of the announcement as a surprise (Boyd et al., 2005). However, Pearce and Roley (1985), who find that the unexpected component of the announcements, the surprise, moves stock prices by using survey data on market participants' expectations of these announcements, conclude that the surveys are more accurate, in the sense of having lower mean squared errors, than the forecasts from standard autoregressive time series models. Moreover, Gürkaynak and Wolfers (2006) also introduced the concept of using derivative data to measure market expectations.

Economic news affect the financial markets on the announcement days. However, the same news might have different effects on the financial markets during different economic states. This idea is first tested by Blanchard (1981) who shows in equilibrium, the same news might be good or bad for financial assets, depending on the state of the economy. Therefore, state of the economy may be the main reason that cause different impact of the same news on the markets (Veronesi, 1999; Orphanides, 1992; and McQueen and Roley, 1993). For instance, rising unemployment is a bad signal for an economy because it is generally a bad signal for economic growth and also for most investors' growth expectations. However, it might have an inverse effect: rising unemployment may have an impact on interest rate expectations, depending on the state of the economy. For example, the impact on interest rates might be negligible in recessions, assuming interest rates are very low. In that case, rising unemployment may be a bad news for equity prices. However, in expansion period, rising unemployment more than anticipated may lead to a downward pressure of future interest rates. On the other hand, the growth expectations might be revised and increased due to a lower interest rate, and finally the net impact of growth expectations might turn out as positive, if not indeterminate. Therefore, stock market might increase at the final point. These two results are totally different outcomes from each other. Therefore, we can conclude that announcement shocks affect market differently depending on the state of the economy and it is important to consider the economic states in determining the effects of the news on financial markets. We consider official business cycle turning points to distinguish between economic recession and expansion periods.

Boyd et al. (2005) present evidence about the impact of unemployment news on stock price index depending on the business cycles. They find that during contractions, stock price responds negatively to news of rising unemployment and during expansions, stock prices respond positively to an increase in unemployment. In the latter case, according to their argument, the effect on the stock prices of a downward revision of interest rate is stronger than the effect of a downward revision of growth expectations. Veronesi (1999) shows that bad news in good times and good news in bad times would generally be associated with increased uncertainty and hence with an increase in the equity risk premium.[3] Funke and Matsuda (2002) use daily US and Germany stock market data to examine the effect of 27 different types of macroeconomic news for both US and Germany, and analyze each news with non-standardized surprise effect following McQueen and Roley (1993) for distinguishing between three states of economy (a boom period, a recession period and a normal period) using EGARCH model in the conditional volatility. They find that in a boom (recession) period, bad (good) news on GDP growth and unemployment or lower (higher) than expected interest rates may be good news for stock prices. Flannery and Protopapadakis (2002) use seventeen announcements to investigate announcements effects in the stock market volatility. Balduzzi et al. (2001) and Beber and Brandt (2005) examine many announcements in the bond market without considering their effect on bond market volatility. Christiansen (2000) and Li and Engle (1998), measure the effect of news on bond and bond futures, respectively, by introducing a dummy variable for announcements. Andersen et al.(2002) use a high frequency exchange rate of US versus different currencies and stocks; and find that the market reacts to news in an asymmetric fashion: bad news has greater impact than good news. Balduzzi et al.(2001) uses intraday data to investigate the effects of 17 news releases measured by the surprise in the announced quantity and they find that both trading volume and volatility increase immediately after the announcements and persist for up to 60 minutes after the announcements. They examine the price changes of

[3] Nelson (1990) and Glosten et.al. (1993) demonstrate that bad news has a bigger impact on subsequent volatility than good news. Ng and Kroner (1998) show bad news about large firms can cause volatility in both small-firm returns and large-firm returns.

treasury bills and bonds but they do consider how the conditional volatility has changed with the announcements. David et al.(2003) examines the effects of unanticipated macroeconomic news on two interest rate futures using intraday data. They define the surprises on the potential effects on debt markets (negative and positive) and by their size (large, medium or small); and sign the surprises as positive, negative, or no surprise. Li and Hu (1998) show that small cap stocks are less sensitive to macroeconomic news than large cap stocks. Boyd et al. (2001) presents evidence that the impact of unemployment news is asymmetric, where stock prices respond negatively to a rise in unemployment during recession but positively during expansion. Li and Engle (1998), find that, in Treasury bond futures markets, positive shocks depress volatility on successive days whereas negative shocks increase volatility. They suggest that asymmetric effects of negative and positive shocks from scheduled news call for further exploration.

In this study, we find some evidence for asymmetric effect of macroeconomic news. Jointly modeling returns and volatilities, first we find that on average, surprises in unemployment news has no impact on level of stock returns during business cycles. In another words, we cannot explain the stock returns by expected future interest rates, therefore the stock and bond returns do not move in the same direction to an unemployment news announcement surprise, but they move in the same direction to an unexpected inflation increase. Secondly, we find that stock markets become more risky to a news announcement of surprise of rising unemployment. Moreover, there is asymmetric impact on stock volatilities between recession and expansion. News surprises have more impact on volatility during economic recession than economic expansion. Thirdly, U.S. government bonds is a complete hedge against unexpected unemployment.

The rest of the paper is organized as follows: section two discusses the data and methodology. The third section presents the regression models and empirical results, and the last section concludes the remarks of the study.

2.2 Data and Methodology

2.2.1 Data

2.2.1.1 Announcements Data

Our primary data contains announcements of unemployment rate, producer price index (henceforth PPI), stock prices and bond yields. The unemployment rate and the PPI are the most two important economic information viewed as newsworthy. Unemployment rate release has a long and accurately dated time series. The announcements are generally made before the stock market opens, specifically at 9.00 AM before March 1982 and at 8.30 A.M after April 1982. The monthly unemployment announcements used in this paper cover the period from January 2, 1981 to December 30, 2005. There are 296 announcements during that period.

The PPI measures the change in the selling prices received by domestic producers for all finished goods. The price changes at the wholesale level as captured by the PPI numbers, are often passed through to the consumer price index in a later date. Therefore, investors can anticipate inflationary consequences in the coming months by following the PPI news. The PPI data is published by the Bureau of Labor Statistics. The monthly PPI announcements used in this paper cover the period from January 2, 1981 to December 30, 2005. There are 297 PPI announcement days.

2.2.1.2 Business Cycles Data

The business cycles data is taken from National Bureau of Economic Research (NBER). The data set covers the period from January 2, 1981 to December 30, 2005 with 6239 observed days. Expansion and contractions are based on NBER's dating of business cycle turning points. There are three recessionary periods in which our data is considered. There are 666 contraction and 5573 expansion business cycle days, respectively.

2.2.1.3 Daily Returns on Stock Data

We use daily returns from January 2, 1981 to December 30, 2005 on the S&P 500 and the Russell 2000 price index. They represent large and small stocks separately. The data are from http://finance.yahoo.com/. Daily stock returns are calculated as the log difference of the daily closing stock prices in the S&P 500 stock Index and R2000 Index. There are there are 6239 observations used in this study. We dropped October 19, 1987 data from our data set to eliminate the outlier effect. It does not affect our results since there is no any announcement on that day.

2.2.1.4 Bond Data

Data for historical yields on the 1-year and 10-year Treasury bond yields with constant maturity are from the Federal Reserve Board. The daily changes of yields are used to construct the 1-year and 10-year government bond returns. The yield on the 10-year Treasury bond with constant maturity is interpolated by the U.S. Treasury from the daily yield curve. Such a yield can be found even if there is no outstanding security that has exactly 10 years remaining to maturity. The returns for the 10-year government bond are constructed from a duration model. For 10-year government bond, we computed daily returns from daily yield changes, using the approximate relation between the change in price and yield:

$$\frac{dp}{p} = -D\frac{dy}{1+y} \tag{2.1}$$

The duration of the 10-year government bond is taken to be the duration of the bond closest to 10 years in maturity in the Center for Research in Security Prices (CRSP) Fixed Term Indexes monthly file. For the 1-year government bond, the following formula is used for the bond equivalent yield:

$$r_{bey} = \frac{10{,}000 - p}{p} \times \frac{365}{n} \tag{2.2}$$

2.2.1.5 Expectations and Survey Data

The data on economic announcements and expectations are from Money Market Service (MMS). The MMS data are the most commonly used data in the studies of economic announcements. Money Market Services (MMS), a San Francisco-based company, which has conducted telephone surveys normally one week or less before any news release since late 1977. Pearce and Roley (1985) find MMS forecasts unbiased and efficient.

2.2.2 Methodology

2.2.2.1 Data Creation

In order to estimate the effect of each announcements on the return of stock market mean and conditional volatility, we look the surprise effect of announcements. We define surprise size of the announcements, S, as in Balduzzi et al. (2001). Let F_i denote the median of the MMS forecast survey and A_i the released value of announcement i. We measure the surprise in announcements i as:

$$E_t = A_t - F_t(A_t) \tag{2.3}$$

This surprise E_t divided by their standard deviation across all observations to facilitate interpretation. So the standardized surprise measure is:

$$S_i = \frac{E_i}{\sigma_i} \tag{2.4}$$

When we examine the conditional variance of stock returns by regressing the conditional variance of the return on surprises, the regression coefficient is the change in return for a one standard deviation change in surprise. Since the σ_i is constant across all observations for a given announcement i, this adjustment does not affect either the significance of the estimates or fit of regression (Balduzzi et al., 2001). The standardized surprise allows us to compare the size of regression coefficients across different announcements.

The main aim of this paper is to examine the conditional variance of stock prices changes during the business cycles. To examine those effects, we use the interaction dummies for each specific situation. In our data set there are 5573 business expansion and 666 business contraction days. On the days that the unemployment rate is announced and negative surprise (good news) is experienced, 12 of these days are subject to business contraction and 132 days are subject to business expansion. In positive surprise days (bad news), there are 12 business recession and 194 business expansion days are interacted. The numbers are slightly different for PPI announcement days. For negative surprise in PPI announcement days, there are 14 recession and 138 expansion interacted days where in positive surprise days there are 8 recession and 92 expansion interacted days.

Totally there are 299 announcement days but out of 299 days, the stock market was closed for 3 days. Finally, we considered just 296 announcement days for UR and 297 days for PPI.

[See Table 1]

[See Table 2]

2.2.2.2 Good and bad economic news

We use Boyd et. al (2005) surprise definitions where good economic news means "actual announcement is less than expected" and bad economic news means "actual announcement is greater than expected". This study works on unemployment rate and PPI news announcements, therefore an increase in any of these announcements is considered as bad news for the economy. [4] To be more precise:

Good Economic News = (Actual Ann. - Expected Ann.) < 0

Bad Economic News = (Actual Ann. - Expected Ann.) > 0

Actual announcements refer to unemployment rate and PPI values and expected announcement refers to the value of survey data.

2.2.2.3 Summary of Data

[4] Some researchers define bad news as news that lowers the returns, and good news as news that uppers the returns. We do not use that definition. (Li and Engle, 1998; Kim and Verrecchia, 1991a) McQueen and Roley (1993) it is not straightforward to interpret whether the unexpected positive news is good for the stock market. For example, a news announcement of unexpectedly low unemployment is good for the economy, but may influence the stock market negatively due to the fear of a future rise in the interest rate. Consequently, the state of the economy (recession/expansion) causes these reactions to unexpected news to vary with time.

Table 1 summarizes the number of observations, means and standard deviations of the standardized surprise sizes for unemployment and inflation news announcements during business recession and expansion periods. There are 296 announcements days and out of 296 days, US economy was in recession in 32 days and in expansion in 264 days; and in recession for 30 and in expansion for 267 days when unemployment rate and inflation rate are announced, respectively. Table 2 summarizes the average daily returns on announcement and non-announcement days of unemployment and inflation news considering the business cycles. In table 2, Panel A shows that stock and bond market returns are on average higher in announcement days than non-announcement days for both type of announcements. In table 2, Panel B shows that, on announcement days, both markets have higher returns in expansion than in recession. Small caps have higher returns than large caps in expansion. During contraction, both caps have negative returns and have very close return values to each other. On non-announcement days returns of small and large caps are close to each other. Bond market follows a different summary statistics. On average, the returns for bonds are approximately zero. On the announcement days, long term bonds have higher returns in recession than in expansion when the unemployment-related news announced, but short term bonds have higher returns.

In Table 3, we partition data for both good and bad unemployment and inflation news surprises. During contraction, average stock return is -0.16% on good news and 0.04% on bad news from the labor market. Bad news from the labor market has a positive effect on both equity markets during expansion (approximately 0.21%). On the other hand, bad news affect equity returns negatively during expansion, which shows that twodifferent macroeconomic news might affect the financial markets differently. Table 3, Panel C and D summarizes the statistics of bond market returns to a good and bad news during business cycles. Unfortunately, most of the returns for bond market are very close to zero. These first summary statistics show that the bad news has a positive effect on large caps in both cycles. Bad and good economic news have little effect on bond prices in any cycles.

2.2.2.4 Regression Design

Most earlier analyses used standard OLS regression techniques to search the impact of news on stock and bond market returns. However, an appropriate estimation procedure has to take into account two potential characteristics of the stock market return data: volatility clustering and the possibility of asymmetries in stock market data. Volatility clustering implies that large changes in returns are followed by larger changes. Asymmetries refer to the fact that negative innovations to stock returns tend to increase volatility more than positive innovations of the same magnitude. Various specifications of generalized autoregressive conditional heteroskedasticity (GARCH) models take these features into account. In standard GARCH(1,1) model the mean equation is a function of exogenous variables (X) with an error term

$$y_t = X_t b + u \tag{2.5}$$

The specification of the conditional variance is consistent with a forecast of this period's variance σ^2_t on the basis of a long term average, the forecast of the variance from the last period and the information about volatility in the previous period:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 u_{t-1}^2 \tag{2.6}$$

This standard model is symmetric in that negative and positive shocks have the same effect on volatility. In contrast to linear GARCH models, nonlinear models allow for an asymmetric reaction of volatility to good and bad innovations. One of the most popular models in this class is the exponential GARCH (EGARCH) model, first proposed by Nelson (1991). The specification for the conditional variance can be represented as:

$$\log \sigma_t^2 = \beta_0 + \beta_1 \left| \frac{u_{t-1}}{\sigma_{t-1}} \right| + \beta_2 \frac{u_{t-1}}{\sigma_{t-1}} + \beta_3 \log \sigma_{t-1}^2 \tag{2.7}$$

where β_0, β_1, β_2, and β_3 are constant parameters. The EGARCH model is asymmetric because the level of $\frac{u_{t-1}}{\sigma_{t-1}}$ is included with a coefficient β_2. Since this coefficient is typically negative, positive return shocks generate less volatility than negative return shocks, all else being equal. The model assumes that the leverage effect is exponential as the left hand side is the logarithm of the conditional variance. The impact is asymmetric if $\beta_2 \neq 0$. The advantage of EGARCH model is that it always satisfies the positive conditional variance constraint.

2.3 Regressions and Results

2.3.1 Estimation Models

In this section, we investigate the response of the stock price index and bond price to the unemployment and inflation news arrivals. It is believed that the stock and bond market reactions to news announcements may depend on the state of the economy. Therefore, we consider the surprise size effects on stock and bond market returns during business expansion and recession days on the mean and the conditional variance matrix of the unexpected stock and bond returns. We start estimating a mean model for return:

$$\mathrm{Re}\,turn_t = \alpha_0 + \alpha_1 .br.surprise_t^a + \alpha_2 .be.surprise_t^a + u_t \qquad (2.8)$$

where $\mathrm{Re}\,turn_t$ denotes the change in the logarithm of the stock price index from the market close of business day or percentage change of the bond price on day t. br and be denote the business recession and expansion days as binary dummies, respectively. *surpsize* denotes the standardized surprise size of the considered news announcement, which is the standardized unanticipated component of each announcement. a denotes the announcement news as the unemployment rate or the PPI news.

Following Boyd et al. (2005), we create the mean return equation as in Equation (2.7). In addition to mean equation, we model the conditional variance to capture the effect of volatility on the mean equation, as given in Equation (2.8). We apply EGARCH (1,1) by expanding the general model with surprise size effects during business cycles as:

$$\log \sigma_t^2 = \beta_0 + \beta_1 \left| \frac{u_{t-1}}{\sigma_{t-1}} \right| + \beta_2 \frac{u_{t-1}}{\sigma_{t-1}} + \beta_3 \log \sigma_{t-1}^2 + \beta_4 .br.surprise_t^a + \beta_5 .be.surprise_t^a + \upsilon_t \tag{2.9}$$

where υ_t is a white noise and β_0, β_1, β_2, β_3, β_4, and β_5 are constant parameters. We expect a negative sign for β_2 for an asymmetric shock. Otherwise, we use standard GARCH with surprise size considering business cycles given as:

$$\sigma_t^2 = \beta_0 + \beta_1 \sigma_{t-1}^2 + \beta_2 u_{t-1}^2 + \beta_3 br.surprise_t^a + \beta_4 be.surprise_t^a + \upsilon_t \qquad (2.10)$$

We use equation (2.10) for modeling bond market explained in detailed in the next section.

2.3.2 Estimation Results

The impact of unemployment and inflation news may vary between boom and recession periods. In a boom period, good (bad) economic news may be bad (good) news for stock and bond prices. Conceptually, "three primitive factors" determine stock prices: the risk-free rate of interest, the expected rate of growth of corporate earnings and dividends, that is, growth expectations, and the equity risk premium (Boyd et al., 2005). Macroeconomic news that conveys information on one or more of these three primitive factors may thus be expected to have an impact on stock and bond prices. For example, for S&P 500 and the R2000 index, a higher than expected unemployment rate (bad economic news) has a positive impact on prices during a boom period and a negative impact during a recession period (Boyd et al, 2005). In a boom period, higher than expected unemployment announcement may reduce expectations of higher future interest rates, and thus overall effect on stock prices may be positive. In a recession period, higher than expected unemployment announcement may have little effect on interest rates, in a particular when interest rates are already low. Thus, in a recession, higher than expected unemployment only reduces growth expectations and thus leads to lower stock prices. Therefore, if unemployment news has an effect on stock prices, that must be because it conveys information about one or more of these primitives.

2.3.2.1 Stock market responses to the unemployment rate news announcements

In Table 4, Panel A shows the results for S&P 500 and Russell 2000 price index returns and summarizes the results of estimation for equations (7) and (8) simultaneously. The coefficients α_1 and α_2 are not statistically significant which lead us to conclude that stock returns do not rise/fall with a labor market announcement surprise during different economic states. This result is contrary to Boyd et al. (2005) findings that increase in unemployment is good news for stock market during economic expansions, and bad news during economic recessions. We do not find supportive empirical results for that hypothesis. It might be because of the length and type of the data they use. They follow a definition of Stock and Watson for business cycles instead of NBER announcements. They calculate the surprise size as a residual (shock) vector from an estimated regression, where we use a survey data.[5] We believe using the market survey medians is more reliable for the estimations even though it is for a shorter period

[5] Boyd et al. (2005) use the data from June 1972 to December 2000. They did not use forecasts made by Money Market Services International (MMS) to identify the surprise element of the unemployment rate announcement, since MMS forecasts have only been available since November 1977, whereas their data goes back to January 1962. They use their own time-series models to forecast the unemployment rate announcement and its unanticipated component.

of time. We conclude that their results are not robust. However, the results of conditional variance equations show both markets have different reactions to the unemployment news surprises. We find some evidence for asymmetric volatility and macroeconomic news effect on the market. First, the conditional volatility EGARCH model is appropriate for the stock market returns. For both indices, asymmetric volatility coefficients of the models, β_2, are negative and statistically significant. Focusing on the dummies in conditional covariance coefficients, the coefficients β_3 and β_4 are statistically significant. In addition, all estimated coefficients, which are statistically significant, show positive values indicating that they raise the conditional variance. This implies the release of this information may increase future uncertainty, and therefore investors need more compensation for the increased risk. In other words, inferred from the empirically established link between trading volume and volatility, the positive coefficients refers that the increased volatility in response to macroeconomic news announcements arises from the increased volume of trade following the announcement (Kim and In, 2002). The results show that the impact of unemployment news surprise size on conditional volatility differs across states of the economy.

[See Table 4]

Analyzing the results in more detailed, in recession, the surprise size of unemployment news in conditional volatilities are significant for S&P 500 and

R2000. In Table 4, β_4 is statistically significant and greater than β_5 indicating that unemployment news has more impact on stock returns volatility in recession more than in expansion and creates an asymmetric impact on volatility between business cycles (0.1775 and 0.0369 for S&P 500, 0.1437 and 0.025 for R2000 in recession and expansion, respectively).For summary, both stock indicies become more risky under the possibility of bad news from the labor market.

2.3.2.2 Stock market responses to the PPI news announcements

In Table 4, Panel B summarizes the results of inflation news surprises on equity markets. Equity market returns result negatively with a bad inflation surprise in expansion. In our models, α_1 measures the stock price sensitivity to PPI news during contractions, and α_2 measures the sensitivity during expansions. Notice that since the α_1 is not statistically significant, PPI news does not have significant effect on stock prices in contractions. In expansions, α_2 is negative and statistically significant for both indexes, and PPI announcement shock has a negative and significant effect on stock prices. Moreover, the good news in PPI announcement shocks in good times increase the mean returns of S&P 500 and Rusell 2000 price indexes, and bad news decreases the mean returns. One explanation is that, in good times, the bad news about inflation effects the expectations for the future interest rates to increase. An increase in the nominal interest rates might decrease the returns in the stock market. There are different channels by which inflation surprises may affect on stock prices. A lot of studies have found that higher expected inflation depresses stock prices. Therefore, any positive inflation surprise (bad economic news) that causes to raise the agents' expectations for future inflation will affect the stock market in a negative way. One explanation for this phenomenon is that investors capitalize corporate earnings by using inflation-swelled nominal interest rates. Firms sell securities to switch to have higher interest rates in the future, pushing up the interest rates upward assuming the stock and bonds are substitutes. The empirical results of this study, given in Panel B in Table 5 support that bond price also decreases as a responses to a given positive inflation surprise in Panel B in Table 5, the bond prices decreases in expansion leading an increase in nominal interest rates. This result is consistent with the above explanation by which stock prices go down due to an increase in interest rates, therefore price of the bonds go down resulting an increase in nominal interest rates. Second possible channel occurs by the policy makers reaction to inflation news. As the inflation is higher than expected, the general believe is that the policy makers will use restrictive policies on economy which cause to firms have reduced cash flows and lower the stock prices. Similarly, positive inflation surprise causes to agents revise their expectations about future money demand on a higher level causing a higher interest rates, so it lowers the stock price assuming FED will maintain its previous monetary growth objectives. Bali and Tang (2007) finds that inflation related news decreases portfolio returns supporting our findings.

Panel B in Table 4 also gives the risk level of stock market during inflation-related news. The risk in stock markets during expansion periods decreases with good news about the inflation-related announcement shocks. More detail, small caps become more volatile with a good news in good times. Both markets become less risky in expansion. Risk-averse investors can invest on small caps during the announcement of inflation-related news in expansions.

2.3.2.3 Bond price responses to the unemployment rate news announcements

This section summarizes the results of bond market returns for a possible impact of an unemployment announcement news. Panel A, in Table 5, gives the result of mean and conditional volatility estimations for the 1 year and 10 year bond price changes. We use GARCH model to examine the effect of unemployment rate news surprises on conditional volatility. The mean equation coefficients α_1 and α_2 are positive and statistically significant for the short term bonds (0.2683 and 0.3276) and just α_2 significant for 10 year bond (1.4592). The mean return of 1-year bond falls in both business cycles, but it falls more in expansion to a bad news. The response of 10-year bond shows contradiction with the 1-year bond results. We can explain the decrease in returns to an unemployment surprise in bond markets with an expected future interest rates. As the unemployment increases, the future expected interest rates go up, while it decreases the price level of the bonds. Therefore, the returns on bonds falls. However, those result are consistent with Boyd et al. (2005) paper only for 10-year bond. Moreover, short term bonds becomes risky during recessions, but long term bond returns become risky during expansions. One explanation for that result is that long term U.S government bonds are more secure and they are complete hedge against unexpected unemployment. To summarize, the results of government bond price responses to the arrival of unemployment new is different from the stock prices.

2.3.2.4 Bond price responses to the PPI news announcements

In Table 5, Panel B summarizes the response of 1 and 10 year bond returns to the PPI news announcement surprises. The mean equation coefficients α_1 and α_2 are negative and statistically significant during recessions implying that bad economic news about the inflation decreases the bond returns. Long term bond returns are affected more than short term bond returns. Those results can be explained by expected future interest rates and positive inflation surprises allow the market to move in the same direction with the stock markets. Increase in inflation has a negative impact on volatility for the short term bonds in recession.

[See Table 5]

2.4 Conclusion

This study investigates the interaction between announcement shocks and volatility in stock and bond markets during business cycles, whether news announcement surprises affect market during business cycles or not, and how bad and good economic news' surprises effect financial markets. Therefore, we accommodate the E-GARCH model of Nelson (1991) and GARCH model in such a way that macroeconomic news announcement surprises in S&P 500 and Russell 2000, and Treasury bond markets are accounted for. We use daily returns on the 1 and 10 years Treasury bonds and S&P 500 and Russell 2000 price indices, for the period from January 1981 to December 2005. Macroeconomic announcement shocks have impact on volatility during the business cycles because those announcements are scheduled, such as timing is known before the announcements take place. Our study differs from Boyd et al. (2005), and Funke and Matsuda (2002) in the sense of surprise size creation, business cycles states, and modeling EGARCH with dummies in conditional volatility. Our results show that on average, stock returns neither rise nor fall when there is a labor market announcement during different economic states, which is not favoring Boyd et al. (2005) results. But the conditional volatility of stock market returns increases with a bad news during business cycles, regardless of the cycle phase. The impact of macroeconomic news in the second moment of large and small cap returns increases, which means both indexes become more risky under the possibility of bad news from the labor market than under the possibility of good news.

A similar pattern of the stock market reactions to unemployment news can not be followed in the bond price changes. Short and long term bond return rise when there is a bad unemployment announcement shock in expansions, but it does not respond significantly in recession periods. These phenomena can be explained with the expectations for the future interest rates. In expansion, bad news from the labor market will decrease the expectations for the future interest rates with a decrease in output. A decrease in expected future interest rate will cause an increase in bond prices, which may explain our findings for the bond market in expansion. On the other hand, in recession, the interest rates are already low, and any good news will change the expectation for output in a positive way for the future, letting an increase in the interest rate. Therefore, an increase in the expected future interest rates will decrease the bond prices. The conditional volatility of bond market increases with a bad unemployment-related news for 1 year bonds in expansion. Additionally, the short term bonds become riskier in recession, but long term bonds become riskier in expansion with a positive unemployment announcement shocks. We can conclude that long term U.S government bonds are more secure and they are complete hedge against unexpected unemployment. To summarize, the results of government bond price responses to the arrival of unemployment new is different from the stock prices. Our results are not consistent with Boyd et. al (2005) paper which finds unemployment news is effective on stock price index but not on bond prices.

Inflation shocks affect both of the market in a different way than the unemployment shocks. Bad news for the inflation is bad for the return of stock markets during a boom period. In other words, the bad news in inflation-related announcement shocks in expansion decrease the mean returns of S&P 500 and Russell 2000. The possible explanation is that in good times, the bad news about inflation effects the expectations for the future interest rates to increase. Increasing the interest rates might decrease the returns in the stock market believing that economy is in good condition and will stay in expansion. Therefore, any positive inflation surprise (bad economic news) that causes to raise the agents' expectations for future inflation will affect the stock market in a negative way. One explanation for this phenomenon is that investors capitalize corporate earnings by using inflation-swelled nominal interest rates. Firms sell securities to switch to have higher interest rates in the future, pushing up the interest rates upward assuming the stock and bonds are substitutes. On the other hand, both equity markets become less risky in good times. Bond returns decrease with bad economic news about the inflation during recession. Those results can be explained by expected future interest rates and positive inflation surprises allow the market to move in the same direction with the stock markets. Increase in inflation has a negative impact on volatility for the short term bonds in recession.

Tables of Chapter 2

Table 1. The news announcements statistics

This table gives the means and standard deviations of stock and bond returns during unemployment and inflation announcement dates and other dates for the period from January 1981 to December 2005. Unemployment (UR) and Producer Price Index (PPI) announcement dates are from Bureau of Labor Statistics (BLS), and S&P 500 and R2000 are from http://finance.yahoo.com. Bond returns are computed from bond yields as described in Data part 2. All numbers are in percentages.

	UR news announcements		**PPI news announcements**	
	# of obs.	*Surprise Mean (Std. Dev.)*	*# of obs.*	*Surprise Mean (Std. Dev.)*
Whole Sample	296	-0.0138 (0.2246)	297	-0.0074 (0.2193)
Contraction	32	-0.0003	30	-0.0004
Expansion	264	-0.01355	267	-0.0069
	Good Economic News (Actual UR < Predicted)		*Good Economic News (Actual PPI < Predicted)*	
	Num. of Obs.	*Mean (Std. Dev.)*	*Num. of Obs.*	*Mean (Std. Dev.)*
Contraction	12	-0.0022 (0.0618)	14	-0.002 (0.04)
Expansion	132	-0.0230 (0.1772)	138	-0.02 (0.16)
	Bad Economic News (Actual UR > Predicted)		*Bad Economic News (Actual PPI > Predicted)*	
	# of obs.	*Mean (Std. Dev.)*	*# of obs.*	*Mean (Std. Dev.)*
Contraction	12	0.0019 (0.05)	8	0 (0.033)
Expansion	94	-0.013 (0.209)	92	0.012 (0.14)

Table 2. Returns on UR and PPI announcement and nonannouncement days

This table gives the means and standard deviations of stock and bond returns during unemployment and inflation announcement dates and other dates for the period from January 1981 to December 2005. Unemployment and Producer Price Index (PPI) announcement dates are from Bureau of Labor Statistics (BLS), and S&P 500 and R2000 are from http://finance.yahoo.com. Bond returns are computed from bond yields as described in Data part 2. All numbers are in percentages.

		UR news ann.		**PPI news ann.**	
		Mean	Std. Dev	Mean	Std. Dev.
Panel A: All Days					
Ann. days	SP 500 Index	0.0461	1.1298	0.0945	1.1046
	R2000 Index	0.1123	1.0587	0.1177	0.9004
	1 y-gov. bond	0.0021	0.0177	0.0011	0.0115
	10 y-gov. bond	0.0029	0.0916	0.0059	0.0690
Nonann. days	SP 500 Index	0.0337	0.9925	0.0313	0.9938
	R2000 Index	0.0326	0.9579	0.0324	0.9659
	1 y-gov. bond	0.0000	0.0104	0.0000	0.0109
	10 y-gov. bond	0.0010	0.0612	0.0008	0.0627
Panel B: Only Annoucement Days					
Contraction	SP 500 Index	-0.1843	1.2635	0.0376	1.0098
	R2000 Index	-0.1694	1.1796	-0.0685	0.7543
	1 y-gov. bond	0.0086	0.0171	0.0007	0.0147
	10 y-gov. bond	0.0225	0.0555	-0.0012	0.0752
Expansion	SP 500 Index	0.0741	1.1119	0.1009	1.1164
	R2000 Index	0.1464	1.0404	0.1387	0.9142
	1 y-gov. bond	0.0013	.01764	0.0011	0.0112
	10 y-gov. bond	0.0005	.09492	0.0067	0.0684

Table 3. Returns on unemployment(UR) and producer price Index(PPI) announcement and nonannouncement days according to news types during recession and expansion periods

This table gives the means and standard deviations of stock and bond returns in unemployment and inflation announcement dates and other dates during economic recession and expansion periods according to type of the news from January 1981 to December 2005. Unemployment and Producer Price Index (PPI) announcement dates are from Bureau of Labor Statistics (BLS), S&P 500 and Russell 2000 price data are from http://finance.yahoo.com, and business cycle for expansions and contarctions are from National Bureau of Economic Research web page (http://www.nber.org/cycles.html). Bond returns are computed from bond yields as described in Data part 2. All numbers are in percentages. Good news is determined as the standardized suprise size if Actual news is less than predicted.

	UR news announcements		**PPI news announcements**	
	Good Economic News Mean (St. Dev.)	*Bad Economic News* Mean (St. Dev.)	*Good Economic News* Mean (St. Dev.)	*Bad Economic News* Mean (St. Dev.)
Panel A: S&P 500				
Contraction	-0.1641	0.0489	0.1584	0.3075
	(1.2129)	(1.4022)	1.0544	(1.0423)
Expansion	-0.0519	0.2140	0.1811	-0.0667
	(1.1617)	(1.0294)	(0.8768)	(1.3186)
Panel B: R2000				
Contraction	-0.1229	0.0357	0.1199	0.0008
	(0.9781)	(1.4578)	(0.7893)	(0.5102)
Expansion	0.0528	0.2367	0.2382	-0.0195
	(1.0496)	(1.0274)	(0.7344)	(1.0537)
Panel C: 1 year government bond				
Contraction	0.0004	0.0174	0.0013	0.0036
	(0.0114)	(0.0203)	(0.0114)	(0.0206)
Expansion	-0.0020	0.0063	0.0021	-0.0006
	(0.0172)	(0.0168)	(0.0116)	(0.0106)
Panel D: 10 year government bond				
Contraction	0.0060	0.0422	0.0075	0.0158
	(0.0405)	(0.0574)	(0.0627)	(0.0743)
Expansion	-0.0101	0.0101	0.0089	0.0025
	(0.0910	(0.1032)	(0.0665)	(0.0703)

Table 4. Change in the conditional variance of stock price returns in response to macroeconomic news announcements surprise with EGARCH model

This table summaries the mean and conditional volatility of stock returns with EGARCH model. *br* and *be* denotes for business recessions and expansions as a binary variable, respectively. $surprise^a$ is the standardized surprise component of the corresponding news announcement.

$$\mathrm{Re}turn_t = \alpha_0 + \alpha_1 .br.surprise_t^a + \alpha_2 .be.surprise_t^a + u_t$$

$$\log\sigma_t^2 = \beta_0 + \beta_1 \left|\frac{u_{t-1}}{\sigma_{t-1}}\right| + \beta_2 \frac{u_{t-1}}{\sigma_{t-1}} + \beta_3 \log\sigma_{t-1}^2 + \beta_4 .br.surprise_t^a + \beta_5 .be.surprise_t^a + \upsilon_t$$

	Panel A:		**Panel B:**	
	UR news announcements		*PPI news announcements*	
	S&P 500	**R_2000**	**S&P 500**	**R_2000**
Mean Equation Coefficients				
α_0	-0.0285***	0.0501***	0.0267***	0.0499***
α_1	0.0826	0.0420	0.0821	0.1185
α_2	0.0584	-0.0361	-0.1939***	-0.1874
Variance Equation Coefficients				
β_0	-0.074***	-0.174***	-0.085***	-0.1831***
β_1	0.0953***	-0.2102***	0.109***	0.2208***
β_2	-0.059***	-0.060***	-0.060***	-0.0609**
β_3	0.9874***	0.9692***	0.9855***	0.9675***
β_4	0.1775***	0.1437***	-0.1444	0.0034
β_5	0.0369**	0.0205	0.0705***	0.1350***

"*", "**", "***" indicate that the coefficient is significant at 10%, 5% and.1% respectively

Table 5. Change in the conditional variance of bond market in response to news announcements with GARCH model.

This table summaries the mean and conditional volatility of bond returns with GARCH model. *br* and *be* denotes for business recessions and expansions as a binary variable, respectively. $surprise^a$ is the standardized surprise component of the corresponding news announcement.

$$\mathrm{Re}turn_t = \alpha_0 + \alpha_1.br.surprise_t^a + \alpha_2.be.surprise_t^a + u_t$$
$$\sigma_t^2 = \beta_0 + \beta_1\sigma_{t-1}^2 + \beta_2 u_{t-1}^2 + \beta_3 br.surprise_t^a + \beta_4 be.surprise_t^a + \upsilon_t$$

	Panel A:		**Panel B:**	
	UR news announcements		*PPI news announcements*	
	1 y-bond	**10 y-bond**	**1 y-bond**	**10 y-bond**
Mean Equation Coefficients				
α_0	-0.0010	0.1396**	-0.0071	0.1049
α_1	0.2683**	0.7497	0.2112	0.9768
α_2	0.3276***	1.4592***	-0.1362**	-0.9390***
Variance Equation Coefficients				
β_0	0.0081**	0.2815***	0.0079***	0.2693**
β_1	0.940***	0.9499***	0.9409***	0.9498***
β_2	0537***	0.0432***	0.0533***	0.0435***
β_3	0.1244***	1.9820	-0.1145***	0.4239
β_4	-0.0034	0.9163**	0.0099	0.5580

"*", "**", "***" indicate that the coefficient is significant at 10%, 5% and.1% respectively

Chapter 3

Nonlinear Dynamic Linkages in the International Stock Markets

3.1 Introduction

The studies during the 1980s and 1990s detected that financial time series exhibit non-linear dependence (Hsieh 1989, Hsieh 1991). Sheinkman and LeBaron (1989) showed that it seems a substantial part of variation of the US weekly stock returns is coming from nonlinearities as opposed to randomness. Unfortunately, these findings were neglected and casual relationships relied on traditional linear Granger causality tests, even though these tests generally have low power against non-linear relationships (Baek and Brock, 1992)

Following Baek and Brock (1992) test, who proposed a non-parametric statistical method for uncovering non-linear causal relationships, Hiemstra and Jones (1994) modify the test and applying the methodology they report highly significant bi-directional non-linear causality between daily returns on the Dow Jones Industrial Average and the percentage changes in New York Stock Exchange (NYSE) trading volume over the 1915-1946 and 1947-1990 periods. Fujihara and Mougoue (1997) show that significant bi-directional non-linear causality between returns and trading volume for three petroleum futures contracts exist. Abhyankar (1998) finds a significant bi-directional non-linear causal relationship between the FTSE 100 index futures and cash markets.

Asimakopoulos et al. (2000) who investigate the non-linear relationship between currency futures returns finds unidirectional non-linear causality relationships in British Pound, Deutche Mark, The Japanese Yen, Swiss Frank and the US dollar. They also filter the residuals by GARCH(1,1) model and report insignificant and statistically weaker non-linear causality relationships.

The integration of world capital markets has increased over the last decade with the increase of easiness of capital flow across countries and financial integration, which is stimulated by the development and growth of derivative securities. Most of the studies found that the US is the most influential market (Eun and Shin 1989,Berument and Ince 2005, Berument et al. 2007, Ghosh et al. 1999, Wu and Su 1998). Fuerstenberg and Jeon (1989) investigated which factors move global markets and examined correlation between the New York, Tokyo, Frankfurt, and London market for the period 1986–88. Eun and Shim (1989) also find that substantial amount of interdependence exists among international stock markets. Historically, it's well known that the US market has always had an influence on other markets. The October 1987 crash triggered great interest in the interrelation of global stock markets. There is evidence of greater interdependence among international stock markets after the October 1987 crash and the breakdown of the Japanese 'bubble economy' at the end of 1989. Especially, the Japanese market started to play a more active role in the global stock market after 1987 and 1989 (Wu and Su, 1998). Japanese market also influences most of the Asia-Pacific stock markets which shows the importance of it (Ghosh et al. 1999). Because of this reason, we choose 1990 as the starting date of this study to cover the impact of after 1989 period.

The interrelations among international stock markets have received a great deal of attention recently. In addition, cross-market interdependence in returns and volatilities appear to be bi-directional between the US and foreign markets [23]. Since national stock markets operate in diverse time zones with the result that markets are nonsynchronous, we expect especially Japan and the US stock markets have dynamic linkages. Against the US innovations, all European and Asian-Pacific markets responded most strongly with a one-day lag and, thereafter, the responses tapered rapidly (Eun and Shin, 1989). It is also argued by Kiymaz and Berument (2003) who examined that the highest volatility occurs on Mondays for Japan and on Fridays United States, and on Thursdays for the United Kingdom. Dornau [8] examined the causality between the US, Europe, and Japanese stock markets considering one-day time lag covering by the period from 15 October, 1985 to 20 October, 1997. It considers the financial crises that the Japanese market experienced so the data is divided into four periods like October, 1985 to October 1987, March 1988 to October 1989, March 1990 to December 1992 and January 1993 to October 1997, respectively. However, that study finds linear Granger causality from NYSE to NIKKEI in the first, second and the fourth periods. It finds a bi-directional linear Granger causality between NIKKEI and NYSE in the third period.

In most of the studies above, interrelation of international stock markets are analysed using cointegration analysis, linear Granger causality and impulse response functions in the framework of Vector Autoregressive (VAR) model. The mentioned studies have showed that the US stock market affects the other stock markets linearly, but visa versa has not been supported, with the exception of Dornau's (1999) study. However, finding of later study is weak. The main concern of this study is latter finding might be caused of not uncovering non-linear relationships. That is why the main purpose of this study is to show the bi-directional relationship between the US and developed stock markets considering the non-linear Granger causality test.

To the best of our knowledge, there is no other study that looks at the non-linear Granger causality on these indices. In this study, the modified Baek and Brock (1992) test, fully developed in Hiemstra and Jones (1994) is used to examine the non-linear dynamic linkages between the US and the other stock markets. First, stationarity of the each series are tested. Second, linear Granger causality test is applied to find the relation of DOW with the other markets without any error correction term since the series do not have any long run relationships. Third, the non-linear Granger causality test is applied. The study finds significant non-linear Granger causality from Nikkei225 to DOW and from CAC40 to DOW, which can not be captured by the linear Granger causality tests. FTSE100 and DOW have bi-directional relation in both types of tests. In short, in addition to linear dependencies, stock markets may exhibit highly non-linear dependencies.

The rest of the paper is organized as follows: the next section discusses the linear and non-linear granger causality tests. The third section presents the data set and the empirical results of the test, and the last section concludes the remarks of the study.

3.1.1 Testing Methodology

3.1.1.1 Testing for linear Granger Causality

Granger's (1969) causality definition is the source of causality tests between two stationary series. Formally, a time series Y_t Granger-causes another time series X_t if series X_t can be predicted better by using past values of Y_t than by using only the historical values of X_t. In other words, Y_t does not Granger-cause X_t if

$$Pr(X_{t+m} \mid \boldsymbol{X}_{t-k}) = Pr(X_{t+m} \mid \boldsymbol{X}_{t-k}, \boldsymbol{Y}_{t-k}), \qquad (3.1)$$

where $Pr(\cdot)$ denotes conditional probability, $\boldsymbol{X}_{t-k} \equiv (X_t, X_{t-1},..., X_{t-k})$, and $\boldsymbol{Y}_{t-k} \equiv (Y_t, Y_{t-1},..., Y_{t-k})$. Suppose that X_t and Y_t are Dow Jones and Nikkei price indices, respectively. Testing causal relations between two series can be based on the following bivariate autoregression :

$$X_t = \alpha_0 + \sum_{k=1}^{n} \alpha_k X_{t-k} + \sum_{k=1}^{n} \beta_k Y_{t-k} + \varepsilon_{x,t}, \qquad (3.2.1)$$

$$Y_t = \phi_0 + \sum_{k=1}^{n} \phi_k X_{t-k} + \sum_{k=1}^{n} \vartheta_k Y_{t-k} + \varepsilon_{y,t}, \tag{3.2.2}$$

where α_0 and ϕ_0 are constants, α_k, β_k, ϕ_k, and θ_k are parameters, and $\varepsilon_{X,t}$ and $\varepsilon_{Y,t}$ are uncorrelated disturbance terms with zero means and finite variances. The null hypothesis that Y_t does not Granger-cause X_t is rejected if the β_k coefficients for $k = 1,2,...,n$ in equation (2.1) are jointly significantly different from zero using a standard joint test (e.g., an F test). Similarly, in equation (3.2.2), if X_t Granger-causes Y_t, the ϕ_k coefficients for $k = 1,2,...,n$ will jointly be different from zero. A bi-directional causality (or feedback) relation exists if both the β_k and ϕ_k coefficients are jointly different from then zero. Using this test, within the framework of a vector autoregression (VAR) model, we will examine the causality of stock indices.

3.2 Testing for Non-linear Granger Causality

The problem of linear approach to causality testing is that such tests can have low power detecting certain kinds of non-linear causal relations (Baek and Brock, 1992). The interest in uncovering non-linear casual relationships started with Baek and Brock who proposed a non-parametric statistical method for uncovering these relationships. Their approach uses the correlation integral, an estimator of spatial probabilities across time, to detect relations between time series. Using their model, non-linear casual relations have been found between money and income (Baek and Brock, 1992), aggregate stock returns and macroeconomic factors (Hiemstra and Kramer, 1993)and producer and consumer price indices (Jaditz and J. Jones, 1993)

Hiemstra and Jones (1994) modify Baek and Brock's test to allow the variables to which the test is applied to exhibit short-term temporal dependence, rather than the Baek and Brock assumption that the variables are mutually independent and identically distributed.

Consider two stationary time series $\{X_t\}$ and $\{Y_t\}$, t =1,2,...,T. Denote the m-length lead vector of X_t by X_t^m, and the Lx-length and Ly-length lag vectors of X_t and Y_t, respectively, by X_{t-Lx}^{Lx} and Y_{t-Ly}^{Ly}. For given values of m, Lx, and $Ly \geq 1$ and for $e>0$, Y does not strictly Granger cause X if:

$$\Pr\left(\left\| X_t^m - X_s^m \right\| < e \middle| \; \left\| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \right\| < e, \left\| Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly} \right\| < e \right)$$

$$= \Pr\left(\left\| X_t^m - X_s^m \right\| < e \middle| \; \left\| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \right\| < e \right) \quad (3.3)$$

where Pr(·) denotes probability and || · || denotes the maximum norm. The probability on the LHS of equation (3.3) is the conditional probability that two arbitrary m-length lead vectors of $\{X_t\}$ within a distance e of each other, given that the corresponding Lx-length lag vectors of $\{X_t\}$ and Ly-length lag vectors of

$\{Y_t\}$ are within e of each other. The probability on the RHS of equation (3) is the conditional probability that two arbitrary m-length lead vectors of $\{X_t\}$ are within a distance e of each other given that their corresponding Lx-length lag vectors are within a distance e of each other. A test based on equation (3.3) can be implemented as follows:

$$\frac{C_1(m+Lx, Ly, e)}{C_2(Lx, Ly, e)} = \frac{C_3(m+Lx, e)}{C_4(Lx, e)} \tag{3.4}$$

where C_1, C_2, C_3, and C_4 are the correlation-integral estimators of the joint probabilities which are discussed in detail by Hiemstra and Jones (1994). For given values of m, Lx and $Ly \geq 1$ and for $e>0$ under the assumption that $\{X_t\}$ and $\{Y_t\}$ are strictly stationary and weakly dependent, if $\{Y_t\}$ does not strictly Granger cause $\{X_t\}$ then,

$$\sqrt{n}\left[\frac{C_1(m+Lx, Ly, e, n)}{C_2(Lx, Ly, e, n)} - \frac{C_3(m+Lx, e, n)}{C_4(Lx, e, n)}\right] \rightarrow N(0, \sigma^2(m, Lx, Ly, e) \tag{3.5}$$

where $\sigma^2(m, Lx, Ly, e)$ and an estimator discussed detailed in Hiemstra and Jones (1994).

3.3 Data and Empirical Results

The data consist of daily closing price indices of four countries: the US, Japan, France and the UK. The study period is from August 3, 1990 to July 14, 2006. The stock indices that represent these four markets are the Dow Jones Industrial Average Index (DOW) taken for the US, the Nikkei 225 Stock Index (Nikkei225), French Stock Market Index (CAC40), and the Financial Time Stock Exchange 100 Share Index (FTSE100) in the US dollar which are constructed via Datastream.

This study extends the understanding of the relationship between Dow Jones and other developed countries stock market indices by testing for non-linear causalities, in addition to linear linkages. In this section, we examine the linear Granger causality which requires that all data series involved are stationary; otherwise the inference from the F-statistic might be spurious because the test statistics will have nonstandard distributions. We take natural logarithms of all series. Firstly, we use the Augmented Dickey-Fuller unit root test of Said and Dickey (1974) to check stationarity for the all stock market index series of the four countries. We use Campbell and Perron's (1991) reduction method to choose the optimum lag length. We start from the maximum 24 lags and stop at the lag value where t-statistic is significant. The results of the unit root tests are shown in Table 1, indicate that there is a unit root in all level series but not in the first difference series. Therefore, we conclude that each series follow an $I(1)$ process.

The following step is to check the cointegration relation between the corresponding series since the appropriate formulation of a Granger causality analysis may need to incorporate an error correction term into the test if the variables are cointegrated. Granger (1988) indicates that causality tests might reach incorrect conclusions if they fail to include an error correction term. It is possible that they share a common stochastic trend (i.e., they are cointegrated), although all series individually contain a stochastic trend. Moreover, if two series are cointegrated, then an error correction term should be included in the bivariate autoregressions as follows:

$$\Delta X_t = \alpha_0 + \sum_{k=1}^{n} \alpha_k \Delta X_{t-k} + \sum_{k=1}^{n} \beta_k \Delta Y_{t-k} + \delta ECT_{t-1} + \varepsilon_{x,t}, \qquad (3.6.1)$$

$$\Delta Y_t = \phi_0 + \sum_{k=1}^{n} \phi_k \Delta X_{t-k} + \sum_{k=1}^{n} \vartheta_k \Delta Y_{t-k} + \phi ECT_{t-1} + \varepsilon_{y,t}, \qquad (3.6.2)$$

where $ECT_{t\text{-}1}$ is an error correction term derived from the long-run cointegrating relationship. The error correction term can be estimated by using the residual from a cointegrating regression.

[See Table 1]

We apply Johansen's (1991) maximum likelihood method to examine whether or not DOW and corresponding country stock market indices are cointegrated. Table 2 reports the Johansen cointegration Trace test statistics. The results indicates that one sided test of the null hypothesis that the series are not cointegrated is fail to reject for each pair wise indices. As shown in the table 2, there is no cointegration vector for any of the stock market indices with DOW. Therefore, we conclude that we should not include error correction term in the Granger causality test equations in any of the series.

As reported above, the test results of Trace test indicate that there is no cointegration between stock market indices, which does not mean that there is no long-run relationship. There might be a long-run relationship between stock indices, but it might be a non-linear relationship. That is why Johansen Trace cointegration test might not catch the possible long-run relationship between the stock indices examined. Since we do not know the non-linear form of the series, we do not examine the long-run relationship. We just search for short run relationships. Therefore, we use non-linear Granger causality test.

[See Table 2]

3.3.1 Linear Granger-Causality Test Results

We begin with estimating the bivariate VAR models in (3.2.1) and (3.2.2). The lag length is chosen as two by Akaike information criteria (AIC) in bivariate VAR system. The pairwise Granger causality test results, given in Table 3, show that DOW is a Granger cause of NIKKEI225, CAC40 and FTSE100 at 1% level for all series. But the bidirectional linear relation can not be seen in the results.

CAC40 and NIKKEI225 is not a Granger cause of DOW at 5% level. FTSE100 is a Granger cause of DOW at 1% level. Only FTSE100 shows a bi-directional linear relation with DOW.

Wu and Su (1998) find that the US market has a very strong influence on Japanese stock market while the Japanese market has a weak significant effect on the US market. Beside these findings, Eun and Shim (1989) also show that the US stock market is the most influential market on France, Japan, and the UK. However, their findings indicate that there is no strong evidence of the influence of Japan, France and the UK on the US stock market. The evidence of these two studies are parallel to our findings in the framework of linear Granger causality test.

[See Table 3]

After removing the linear dependencies in the series using VAR system, we examine the linear dependencies in the residuals by using Ljung-Box Q-test. The null hypothesis of no serial correlation in residuals is rejected for all series at lag six and twelve, where the results are reported in Table 4 panel A. Next, we examine non-linear dependencies in the residuals by McLeod and Li's (1983) Q^2 test. The results in Table 4 Panel B examines that the null of no serial correlation in squared residuals is rejected for all series suggesting that all series have significant non-linear dependencies.

[See Table 4]

3.3.2 Non-linear Granger Causality Results

As mentioned in the above section, the Q^2–tests of McLeod and Li (1983) not only indicates non-linear dependency in error terms, but also suggests that non-linear linkages could be uncovered. Therefore, we test for the presence of non-linear dependencies using the McLeod and Li's Q^2 test. We found that all series show significant non-linear dependencies. Now, we can proceed by testing for non-linear causality.

Granger (1969) argues that univariate and multivariate nonlinear models represent the proper way to model a real world that is "almost certainly nonlinear". The recent focus on nonlinear structure in stock price movements is motivated by the richer types of asset behavior that nonlinear models provide researchers. Large stock price swings and abrupt changes in stock market volatility can only be properly modeled with nonlinear models (Hsieh, 1991). Based on that idea, we apply the modified Baek and Brock (1992) test, fully developed in Hiemstra and Jones (1994) to the residuals extracted from the VAR model, so we can examine non-linear Granger causality dynamics. To implement the modified Baek and Brock test, the values for the lead length, m, the lag lengths, Lx and Ly, and the scale parameter, e, have to be selected. Unfortunately, there are no methods developed in the literature to select the optimal values for these variables, unlike in linear causality tests. This study follows the Monte Carlo evidence of Hiemstra and Jones (1993), and sets the lead lag length at $m = 1$ and $Lx=Ly$ for all cases. Also, we set lag length as two which is determined in VAR model using AIC and a common scale parameter of $e = 1.0\sigma$ are used where $\sigma = 1$ denoted the standard deviation of the standardized series.

Table 5 presents the results of non-linear Granger causality test for each residual series. There is strong evidence of non-linear Granger causality from DOW to other stock market indices and also from these indices to DOW, too. The test statistics is significant for each cases at 1% level at lag length two. These results are interesting and they are the main contribution of this study since non-linear Granger causality test shows bi-directional relation between Dow and the other stock markets. However, it was not the case in linear Granger causality for NIKKEI225 and CAC40. These suggest that non-linear causality is uncovered by the test.

[See Table 5]

3.4 Summary and Conclusion

Interactions among stock markets, increasing with globalization process, encourage economists to assess whether any relationships exist. This study examines linear and non-linear causality tests conducted among stock indices of France, Japan, the UK, and the US using linear and non-linear Granger causality tests. The results of linear Granger causality test show that the US stock market Granger causes these stock markets while the UK stock market Granger causes the US stock market. However, Japan and France do not Granger causes the US. Highlighting the importance of testing for non-linear linkages in addition to linear linkages, the results of Hiemstra and Jones (1994) non-linear test suggest that Japan, France, and the UK non-linear Granger causes the US, and *vice-versa*. Under the light of that linear Granger causality tests generally have low power against non-linear relationships, the overall statistical analysis of this paper clearly supports a non-linear modeling of the relationship between the US and the other countries we examined. The efficient market hypothesis implies that price changes in equities and bonds reflect the arrival and processing of relevant new information. By using daily for four stock market prices we find a significant bi-directional non-linear Granger causality relationship in four cases, implying a degree of market inefficiency in the sense that lagged information from one stock market price can be used to forecast changes in another stock market price. The contribution of that paper is to show with the evidence that the general believe of the US stock market is not effected by the other equity markets is not true.

Following the efficient market hypothesis, there should not be any nonlinear relationships between those markets. Having a nonlinear relation shows that information does not processed and that information can be used to forecast changes in the other stock market.

Tables of Chapter 3

Table 1. Unit root test results for the stock price indices

	Level		First Differences	
Series	ADF_{μ}[a]	ADF_{τ}[b]	ADF_{μ}	ADF_{τ}
DOW	-1.730 (13)	-1.173 (13)	-18.15* (12)	-18.20* (12)
NIKKEI 225	-1.689 (21)	-2.034 (21)	-14.05* (20)	-14.05* (20)
FTSE 100	-0.997 (19)	-1.451 (19)	-16.12* (18)	-16.11* (18)
CAC 40	-0.794 (24)	-1.855 (24)	-14.17* (23)	-14.17* (23)

Notes: †,*,** indicate significance at the 10, 5, and 1 percent levels, respectively.

[a]Test allows for a constant; one-sided (lower-tail) test of the null hypothesis that the variable has a unit root; 10, 5, 1 percent significance critical value equals -2.576, -2.863, and -3.441, respectively.

[b]Test allows for a constant and a linear trend; one-sided (lower-tail) test of the null hypothesis that the variable has a unit root; 10, 5, 1 percent critical values equals -3.134, -3.428, and -3.973, respectively.

Table 2. Multivariate cointegration test results between the US and other stock market price indices

Countries	Null Hypothesis	Trace[a]
Japan	$r = 0$ $r \leq 1$	8.525
France	$r = 0$ $r \leq 1$	10.728
UK	$r = 0$ $r \leq 1$	10.258

[†] Statistical significance at the 10 %.

[a] One-sided test of the null hypothesis that the variables are not cointegrated; 5 and 1 percent critical values equal 15.41, and 20.04, respectively. Reported critical values are Osterwald-Lenum [22] critical values.

Table 3. Pairwise Granger causality tests between the US and stock price indices

Countries	Null Hypothesis	Test values	
		F-value	*P*-value
Japan	(ΔNikkei225) ≠> (ΔDOW)	2.532	0.079
	(ΔDOW) ≠> (ΔNikkei225)	124.049†	0.000
France	(ΔCAC40) ≠> (ΔDOW)	1.539	0.214
	(ΔDOW) ≠> (ΔCAC40)	663.368**	0.000
UK	(ΔFTSE100) ≠> (ΔDOW)	4.540	0.010
	(ΔDOW) ≠> (ΔFTSE100)	143.304**	0.000

Notes: †,*,** denote rejections of the null hypothesis at 10%, 5%, and 1% significance levels, respectively; and the symbol "≠>" implies does not Granger-cause.

Table 4. Residual diagnostics of VAR(2) model

	Panel A: Ljung-Box Q test		Panel B: McLeod and Li Q^2 test	
Series	$Q(6)$	$Q(12)$	$Q^2(6)$	$Q^2(12)$
$\varepsilon_{\text{DOW,Nikkei225},t}$	4.629	18.003	627.5	997.0
	(0.592)	(0.115)	(0.000)	(0.000)
$\varepsilon_{\text{Nikkei225,DOW},t}$	4.749	10.853	344.7	449.9
	(0.576)	(0.541)	(0.000)	(0.000)
$\varepsilon_{\text{DOW, FTSE100},t}$	5.338	18.664	615.7	975.9
	(0.501)	(0.096)	(0.000)	(0.000)
$\varepsilon_{\text{FTSE100,DOW},t}$	24.634	34.490	794.7	1275.0
	(0.000)	(0.000)	(0.000)	(0.000)
$\varepsilon_{\text{DOW,CAC40},t}$	4.133	17.508	623.5	981.0
	(0.658)	(0.131)	(0.000)	(0.000)
$\varepsilon_{\text{CAC40,DOW},t}$	21.232	26.294	551.5	700.7
	(0.002)	(0.009)	(0.000)	(0.000)

Note: This table provides the diagnostics tests for error terms obtained from VAR model. The Q-test is the Ljung-Box test and the Q^2-test is the McLeod-Li test, at 6 and 12 lags. *p*-values for statistical significance are given in parentheses.

Table 5. Pairwise Nonlinear-Granger causality tests between the DOW and stock price indices

Countries	Null Hypothesis	Ly=Lx	CS	TVAL
Japan	(ΔNikkei225) ≠> (ΔDOW)	2	0.021	6.907**
	(ΔDOW) ≠> (ΔNikkei225)	2	0.011	4.138**
France	(ΔCAC40) ≠> (ΔDOW)	2	0.045	12.705**
	(ΔDOW) ≠> (ΔCAC40)	2	0.012	4.539**
UK	(ΔFTSE100) ≠> (ΔDOW)	2	0.021	7.958**
	(ΔDOW) ≠> (ΔFTSE100)	2	0.015	5.475**

Notes: This table provides the results the modified Baek and Brock test statistics applied to the residuals from the bivariate VAR(2) model for the stock market first differences. CS and TVAL are the difference between the two conditional probabilities in Equation (4) and the sandardized test statistic in Equation (5), respectively.

†,*,** denote rejections of the null hypothesis at 10%, 5%, and 1% significance levels, rspectively; and the symbol "≠>" implies does not nonlinear-Granger cause. The test statistic is asymptotically distributed N (0,1). The critical values at 10%, 5%, and 1% significance levels are 1.96, 1.64, and 2.33, respectively.

Chapter 4

On the Nonlinear Causality Between Inflation, Inflation Uncertainty and Stock Returns in G3 Countries

4.1 Introduction

The link between inflation and inflation uncertainty is an important indicator in determining the monetary policy for the monetary authority. It is generally agreed that the welfare cost of inflation is highest when the future inflation rate is unpredictable. The most famous argument about the inflation and its cost on welfare is outlined by Friedman (1977)'s Nobel lecture suggesting that an increase in average inflation will raise nominal uncertainty about the future inflation which may cause an adverse output effect. Ball (1992) finds evidence to provide a formal justification of Friedman's well-known insight by employing a game of asymmetric information.

Another approach to determine the relationship between inflation uncertainty and output is studied in the finance literature. Fama and Schwert (1977) investigate the assets which are hedges against the expected and unexpected components of inflation rate during the 1953-1971 period. U.S. government bonds and bills are a complete hedge against expected inflation, and private residential real estate was a complete hedge against both expected and unexpected inflation. The most anomalous result of their study is that common stock returns are negatively related to the expected component of the inflation rate, and also to the unexpected component. Their result supports the idea of Friedman's adverse output effect.

Morley (2002) investigates the nature of the relationship between output and stock prices, and consumption and stock prices, with respect to the different financial structures that exist primarily in the European Union (EU). He finds evidence of a long-run relationship for both relationships, for the UK and US. The stock market is regarded as an important determinant of the economy in a number of respects. One of them is suggested by Friedman (1988) implying that the money demand function should include a return on shares, as it acts as a proxy for personal sector wealth, as well as the interest rate, even though Keynes felt there was no fundamental difference between stock prices and interest rates.

The empirical evidence in the literature supports the view that the stock market and economy are closely linked in the UK and US, which have established stock markets and are usually regarded as being financial market based economies. In the UK and US, financial systems depend on a market based system of control in which the market discipline comes from acquisitions and takeovers, not from banking system. Therefore, output and consumption react to changes in stock prices in both countries. The UK and US have a significantly closer relationship between stock prices and output and consumption. Moreover, Fischer and Merton (1984) showed that output and consumption are more strongly affected by the return on stocks than bonds. Morley (2002) finds that there is a strong evidence of a long run relationship between stock prices and both output and consumption for the major industrialized countries including US and UK by using Kalman-Filter technique.

The main concern of this study is to analyze the causation among inflation, inflation uncertainty and stock market returns (proxy for output growth) to test the well-known theories in economics literature for G3 countries. In the economics literature, alternative to Friedman hypotheses, Cukierman and Meltzer (1986) propose a model to explain credibility, ambiguity and inflation under asymmetric information. According to their argument, central banks tend, in the presence of higher inflation uncertainty, to create inflation surprises to realize real economic gain. In other words, Cukierman-Meltzer conclude that inflation and inflation uncertainty have positive correlation, and the direction of causality is from inflation uncertainty to inflation. However, the opportunistic response by central bank is not the only possible outcome. Holland (1995) argues that more inflation uncertainty can lead to a lower average inflation rate, opposite of the Cukierman-Meltzer hypothesis, if the central bank tries to minimize the welfare losses arising from more inflation uncertainty. It is the stabilization motive of the monetary authority, the so-called "stabilizing Fed hypothesis". He claims that as inflation-uncertainty rises due to increasing inflation, the monetary authority responds by contracting money supply growth, in order to eliminate inflation-uncertainty and the associated negative welfare effects. At final point, a raise in inflation uncertainty causes a fall in average inflation. In other words, Friedman hypotheses suggests that increase in inflation incresases inflation uncertainty and therefore decreases output. However, Cukierman-Meltzer hypothesis suggests that increase in inflation uncertainty increases inflation, following an output increase due to opportunistic central banks.

In this study, all corresponding theories are tested for Japan, USA and the UK using inflation, inflation uncertainty and stock market returns.

Testable Hypotheses	**Sign of the Effect**
(1) Inflation Granger-causes inflation uncertainty	
Friedman (1977), Ball (1992)	+
Pourgerami and Maskus (1987)	-
(2) Inflation uncertainty Granger-causes output growth	
Friedman (1977)	-
Dotsey and Sarte (2000), Cukierman-Meltzer (1986)	+
(3) Inflation uncertainty Granger-causes inflation	
Cukierman and Meltzer (1986)	+
Holland (1995)	-

Fountas and Karanasos (2007) investigates the causal effect of real and nominal macroeconomic uncertainty on inflation and output growth using GARCH for inflation uncertainty for the period 1957-2000 in G7 countries. They find mixed evidence regarding the effect of inflation uncertainty on inflation and output growth. They first find that inflation is a primary determinant of inflation uncertainty, as argued by Friedman (1977). Second, the uncertainty associated with the rate of inflation has mixed effects on output growth. In other words, Friedman's belief that inflation uncertainty can be detrimental to the economy's real sector receives only some support in their study. Third, they obtain mixed evidence in favor of the Cukierman Meltzer hypothesis. Thus, as expected, countries are anticipated to react differently to a change in the degree of uncertainty surrounding the inflation rate. In that sense, this study will be the first one that relates stock market and inflation and inflation uncertainty to test different hypothesis in the economics literature.

The recent studies concentrated on testing the above arguments rely on linear Granger causality tests. The problem of linear approach to causality testing is such tests generally have low power against non-linear Granger causality test (Baek and Brock, 1992). Baek and Brock (1992) propose a non-parametric statistical method for uncovering a kind of non-linear causal relationships. Hiemstra and Jones (1994) modify the test of Baek and Brock (1992). Hence, the main purpose of this study is to show the bi-directional relationship between the inflation and its uncertainty, and inflation uncertainty and stock market returns for Japan, US and the UK considering the non-linear Granger causality test by Hiemstra and Jones (1994). To the best of our knowledge, there is no other study that investigates the non-linear Granger causality on inflation and inflation uncertainty, and inflation uncertainty and stock market returns before. The findings of this study show significant non-linear Granger causality from inflation to inflation uncertainty and from inflation uncertainty to inflation, and from inflation uncertainty to stock retuns, and from stock returns to inflation uncertainty which can not be captured by the linear Granger causality tests. In short, in addition to some linear dependencies, inflation uncertainty and stock returns and inflation and its uncertainty present highly non-linear dependencies.

Generalized autoregressive conditional heteroskedasticity (GARCH) models, introduced by Engle (1982) and Bollerslev (1986), allow us to proxy uncertainty using the conditional variance of unpredictable shocks to the inflation. Engle (1983) finds out a high rate of inflation does not necessarily imply a high variance of inflation, therefore his findings not support Friedman hypothesis. Engle's study for US shows that high level of inflation in the 1970's were predictable and were not associated with higher inflation variability. Hwang (2001) provides support for Engle's claim with robust results for high inflation period of the 1970s and the volatile period from 1929 to 1945. On the other hand, Brunner and Hess (1993), Foster (1978), Garcia and Perron (1996), Caporale Mckiernan (1997), Conrad and Karanasos (2005) and Berument and Dincer (2005) provide supporting evidence on the Friedman's hypothesis. Conrad and Karanasos (2005) represents the ARFIMA-FIGARCH model to prove inflation rises inflation uncertainty in Japan, US and the UK and the reverse direction is approved for Japan only. Daal et al. (2005) evidence support Friedman hypothesis using Granger causality in a VAR framework for many developed and emerging countries but the hypothesis in the opposite direction has mixed results. Grier and Perry (1998) also find evidence supporting the notion that inflation significantly raises inflation uncertainty for G-7 countries, as predicted by Friedman. However, they find weak evidence on inflation uncertainty Granger-causing inflation as predicted by Cukierman and Meltzer. Fountas et al. (2004) investigates the relationship between inflation and inflation uncertainty in six EU countries for the 1960-1999 period. Using EGARCH models to generate a measure for inflation uncertainty, they support evidence for the Friedman hypothesis. However, they find less robust evidence regarding the direction of the impact of a change in inflation uncertainty on inflation. Berument and Dincer (2005) examine the relationship between inflation and inflation uncertainty in the G-7 countries by using the Full Information Maximum Likelihood Method with extended lags for the 1957-2001 period. The estimation results of their paper support the Friedman-Ball hypothesis that inflation Granger-causes inflation uncertainty for all the G-7 countries. Moreover, Berument et al. (2008) show that there is a negative relation between inflation and output growth in Turkey for the 1988 to 2007 period. Ozdemir and Fisunoglu (2008) analyze the disinflation program applied countries and find strong evidence for Friedman hypothesis, but weak evidence for Cukierman and Meltzer hypothesis concluding that inflation is expensive not only through the known channels of distorted prices but also through the channel of a highly uncertain inflation.

The rest of the paper is organized as follows: the next section discusses the linear and non-linear Granger causality tests. The third section presents the data and the empirical results. The last section concludes the remarks of the study.

4.2 Estimation Methodology

4.2.1 Methods for Linear Granger Causality

Granger's (1969) causality definition is the source of causality tests between two stationary series. Formally, a time series Y_t Granger-causes another time series X_t if series X_t can be predicted better by using past values of Y_t than by using only the historical values of X_t. In other words, Y_t does not Granger-cause X_t if

$$Pr(X_{t+m} \mid \boldsymbol{X}_{t-k}) = Pr(X_{t+m} \mid \boldsymbol{X}_{t-k}, \boldsymbol{Y}_{t-k}), \tag{4.1}$$

where $Pr(\cdot)$ denotes conditional probability, $\boldsymbol{X}_{t-k} \equiv (X_t, X_{t-1},..., X_{t-k})$, and $\boldsymbol{Y}_{t-k} \equiv (Y_t, Y_{t-1},..., Y_{t-k})$. Suppose that X_t and Y_t are Dow Jones and Nikkei price indices, respectively. Testing causal relations between two series can be based on the following bivariate autoregression:

$$X_t = \alpha_0 + \sum_{k=1}^{n} \alpha_k X_{t-k} + \sum_{k=1}^{n} \beta_k Y_{t-k} + \varepsilon_{x,t}, \tag{4.2.1}$$

$$Y_t = \phi_0 + \sum_{k=1}^{n} \phi_k X_{t-k} + \sum_{k=1}^{n} \vartheta_k Y_{t-k} + \varepsilon_{y,t}, \tag{4.2.2}$$

where α_0 and ϕ_0 are constants, α_k, β_k, ϕ_k, and θ_k are parameters, and $\varepsilon_{X,t}$ and $\varepsilon_{Y,t}$ are uncorrelated disturbance terms with zero means and finite variances. The null hypothesis that Y_t does not Granger-cause X_t is rejected if the β_k coefficients for $k = 1,2,...,n$ in equation (4.2.1) are jointly significantly different from zero using a standard joint test (e.g., an F test). Similarly, in equation (4.2.2), if X_t Granger-causes Y_t, the ϕ_k coefficients for $k = 1,2,...,n$ will jointly be different from zero. A bi-directional causality (or feedback) relation exists if both the β_k and ϕ_k coefficients are jointly different from then zero. Using this test, within the framework of a vector autoregression (VAR) model, we will examine the causality of stock indices.

4.2.2 Testing for Non-linear Granger Causality

The problem of linear approach to causality testing is that such tests can have low power detecting certain kinds of non-linear causal relations (Baek and Brock, 1992). The interest in uncovering non-linear casual relationships started with Baek and Brock who proposed a non-parametric statistical method for uncovering these relationships. Their approach uses the correlation integral, an estimator of spatial probabilities across time, to detect relations between time series. Using their model, non-linear casual relations have been found between money and income (Baek and Brock, 1992), aggregate stock returns and macroeconomic factors (Hiemstra and Kramer, 1993)and producer and consumer price indices (Jaditz and J. Jones, 1993)

Hiemstra and Jones (1994) modify Baek and Brock's test to allow the variables to which the test is applied to exhibit short-term temporal dependence, rather than the Baek and Brock assumption that the variables are mutually independent and identically distributed.

Consider two stationary time series $\{X_t\}$ and $\{Y_t\}$, t =1,2,...,T. Denote the m-length lead vector of X_t by X_t^m, and the Lx-length and Ly-length lag vectors of X_t and Y_t, respectively, by X_{t-Lx}^{Lx} and Y_{t-Ly}^{Ly}. For given values of m, Lx, and $Ly \geq 1$ and for $e>0$, Y does not strictly Granger cause X if:

$$\begin{aligned} &\Pr\left(\left\| X_t^m - X_s^m \right\| < e \middle| \left\| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \right\| < e, \left\| Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly} \right\| < e \right) \\ &= \Pr\left(\left\| X_t^m - X_s^m \right\| < e \middle| \left\| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \right\| < e \right) \qquad (3) \end{aligned}$$

where $\Pr(\cdot)$ denotes probability and $\| \cdot \|$ denotes the maximum norm. The probability on the LHS of equation (3) is the conditional probability that two arbitrary m-length lead vectors of $\{X_t\}$ within a distance e of each other, given that the corresponding Lx-length lag vectors of $\{X_t\}$ and Ly-length lag vectors of $\{Y_t\}$ are within e of each other. The probability on the RHS of equation (3) is the conditional probability that two arbitrary m-length lead vectors of $\{X_t\}$ are within a distance *e* of each other given that their corresponding *Lx*-length lag vectors are within a distance *e* of each other. A test based on equation (3) can be implemented as follows:

$$\frac{C_1(m+Lx,Ly,e)}{C_2(Lx,Ly,e)}=\frac{C_3(m+Lx,e)}{C_4(Lx,e)} \tag{4}$$

where C_1, C_2, C_3, and C_4 are the correlation-integral estimators of the joint probabilities which are discussed in detail by Hiemstra and Jones (1994). For given values of *m*, *Lx* and $Ly \geq 1$ and for $e>0$ under the assumption that $\{X_t\}$ and $\{Y_t\}$ are strictly stationary and weakly dependent, if $\{Y_t\}$ does not strictly Granger cause $\{X_t\}$ then,

$$\sqrt{n}\left[\frac{C_1(m+Lx,Ly,e,n)}{C_2(Lx,Ly,e,n)}-\frac{C_3(m+Lx,e,n)}{C_4(Lx,e,n)}\right]\rightarrow N\,(0,\sigma^2(m,Lx,Ly,e) \tag{5}$$

where $\sigma^2(m,Lx,Ly,e)$ and an estimator discussed detailed in Hiemstra and Jones.

4.3 Data and Empirical Results

We first test for the relationships between stock returns, inflation and inflation uncertainty using Japan, US and the UK data as these countries represent the most financially capitalized markets. We use monthly data on the Consumer Price Index (CPI) obtained from International Financial Statistics (IFS) database as proxies for the price level. The data range from January 1957 to October 2006. The monthly CPI series used in this study have a monthly seasonal pattern. Hence, prior to calculating the inflation series, the monthly CPI series are deseasonalized. Then, the inflation series is measured by the monthly difference of the log CPI_t [π_{t}=100.log (CPI_t / CPI_{t-1})]. Stock price index are monthly NIKKEI225, FTSE100 and S&P 500 index values obatined from Datastream for Japan, the UK and US, respectively. US stock data is for 1957-2006 period, Japan and the UK stock data are for 1984-2006 period. Stock price return is measured by the monthly difference of the log $INDEX_t$ [r_t = 100.log($INDEX_t$ / $INDEX_{t-1}$].

Table 1 presents summary statistics of inflation rates of three countries. The results indicate that the distributions of the inflation series are skewed to the right. The distributions of the British and Japanese inflation rates have fat tails. The large values of the Jarque--Bera (JB) statistic imply a deviation from normality, and the significant Q-statistics of the squared deviations of the inflation rate from its sample mean indicate the existence of ARCH effects. This evidence is also supported by the LM statistics, which are highly significant.

[See Table 1]

This study extends the understanding of the relationship between inflation and inflation uncertainty, and inflation uncertainty and stock returns in G-3 countries testing for non-linear causalities, in addition to linear linkages. We use the AR(k)-GARCH(p,q) model generating the inflation uncertainty. In the AR(k)-GARCH(p,q) model, the mean equation is defined as following:

$$\pi_t = \beta_0 + \sum_{i=0}^{k} \beta_i \pi_{t-i} + \varepsilon_t \qquad (4.6)$$

where π_t denotes the inflation, and ε_t is conditionally normal with mean zero and variance $h_{\pi t}^2$. In other words, that is $\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_{\pi t}^2)$, where Ω_{t-1} is the information set up to time t-1. The structure of the conditional variance is:

$$h_{\pi t}^2 = c + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \delta_j h_{\pi,t-j}^2 \qquad (4.7)$$

where c is a positive constant and $(\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \delta_j) < 1$. As Bollerslev (1986) shows, $c > 0$ and $\alpha_i \geq 0$ (for $i = 1,\ldots,p$) and $\delta_i \geq 0$ (for $i = 1,\ldots,q$) is sufficient for the conditional variance to be positive. The parameters of an AR(k)-GARCH(p,q) model can be estimated by quasi-maximum likelihood estimator (QMLE) obtained by analogous methods that described by Baillie et al. (1996).

Table 2 summaries the AR(17)-GARCH(1,1), AR(10)-GARCH(1,1) and AR(6)-GARCH(1,1) models for Japan, the UK, and US, which are estimated using the QMLE method as implemented by Laurent and Peters (2002) in Ox, respectively. The values of the Ljung-Box test statistics (Q) of the residual series indicate that there is no serial correlation in the residual series in neither 6th or 12th order, except for US 12th order.

[See Table 2]

We test for the stationarity properties of our data using the Augmented Dickey Fuller test. The results of these tests, reported in Table 3, imply that we can treat the inflation rate and the return of stock price as stationary processes. In all cases, we conclude that all series follow an I(0) process.

[See Table 3]

4.3.1 Linear Granger-Causality Test Results

We examine the linear Granger causality which requires that all data series involved are stationary; otherwise the inference from the F-statistic might be spurious because the test statistics will have nonstandard distributions (Granger, 1998). We estimate the bivariate VAR models given in (2.1) and (2.2) equations. The pairwise Granger causality test results, given in Table 4, show that inflation Granger causes inflation uncertainty for 4 and 8 lags at 5 percent significance level for all three series, which supports Friedman hypothesis. On the other hand, inflation uncertainty does not linear Granger cause inflation in the UK and US with an exception of Japan. The latter results indicate that the Cukierman-Meltzer hypothesis holds for Japan, while it does not hold for the UK and US. Conrad and Karanasos (2005) find mixed results for the causation of inflation uncertainty on inflation in favor of our results, but we have contradicted results for the UK. In their study, the UK series provides an evidence lags uncertainty about inflation for at eight has a positive impact on inflation for at 8 lags as predicted by Cukierman-Meltzer, whereas they provide an evidence for at 12 lags inflation uncertainty has negative impact on inflation as predicted by Holland hypothesis.

[See Table 4]

Having confusing results of the studies on linear Granger causalities on inflation and its uncertainty can be conducted with central bank independency. The findings of Grier and Perry (1998) seem consistent with `opportunistic' central bank behavior as in Cukierman-Meltzer. In Japan and France, whose central bank independence average is 0.220, inflation rises with the inflation uncertainty. On the other hand, in US and Germany, whose central banks independence average is 0.585 on an independence scale that goes from zero to one using by Cukierman's (1982) ratings, inflation falls by an increased inflation uncertainty which favors Holland hypothesis. Unfortunately, the idea of different responses to inflation uncertainty are correlated with measures of central bank independency is not supported by Conrad and Karanasos (2005), where US and Japan have independent central banks according to the index provided by Alesina and Summer (1993) but their responses to increased uncertainty are different. The results of that study favors Conrad and Karanasos (2005) results which lets us not argue that the most independent central banks are in countries where inflation falls in response to increased uncertainty. The mixture findings of the studies in the literature may be the result of the uncovered nonlinear causalities.

Panel C and Panel D in Table 4 gives the results of linear Granger causality test between stock returns and inflation uncertainties. None of the results are significant at 5% significance level for any countries. Only, in US, inflation uncertainty granger causes stock returns at 10% significance level, supporting Cukierman-Meltzer. Therefore, we concentrate on the nonlinear Granger causality between the inflation and its uncertainty for the countries included in the sample.

[See Figure 1]

To detect both linear/nonlinear and parametric/nonparametric dynamic relationships between the inflation and inflation uncertainty, inflation uncertainty and stock returns of these countries, we benefit from the scatter plot diagrams of the inflation versus inflation uncertainty series, given in Figure 1 and Figure 2, respectively. Each scatter plots of the entire data looks unclear, especially in the lower left corner in each figure The scatter plots pretend to have nonlinear dynamic symptoms between the series while they do not show there are clear linear dynamics. Moreover, from Figure 1 and 2, it is obvious that the relationships of those series are nonparametric (Haerdle 1994).

4.3.2 Non-linear Granger Causality Results

We use the modified Baek and Brock (1992) test, fully developed in Hiemstra and Jones (1994), to test the nonlinear causality relation between the inflation and inflation uncertainty; and between inflation uncertainty and stock returns. To implement the modified Baek and Brock test, the values for the lead length, m, the lag lengths, Lx and Ly, and the scale parameter, e, have to be selected. Unlike in linear causality tests, there are no methods developed in the literature to select the optimal values for these variables. This study follows the Monte Carlo evidence of Hiemstra and Jones (1993), and at sets the lead lag length at m=1 and Lx=Ly for all cases. Also, we set lag length as two which is determined in VAR model using AIC and a common scale parameter of $e=1.0\sigma$ are used where $\sigma=1$ denoted the standard deviation of the standardized series.

4.3.2.1 Causality between inflation and inflation uncertainty

Table 5 presents the results of Hiemstra and Jones's (1994) nonlinear Granger causality test for inflation and its uncertainty. The results show that the null hypothesis that inflation does not nonlinear Granger cause inflation uncertainty and visa-versa at 4 and 8 lags for Japan, the UK and US are rejected at 5 percent significance level, while the null hypothesis is failed to reject at 8 lag for Japan at 10 percent significance level. This result shows that there is a bi-directional nonlinear Granger causality between both series with the latter finding. In the frame of the formation of the nonparametric test and the scatter plots given in Figure 1, we can not conclude on the sign of that nonlinear relation.

[See Figure 2]

4.3.2.2 Causality between inflation uncertainty and stock returns

Table 6 represents the non-linear Granger causality test results for inflation uncertainty and stock market returns. At lag 4, the null hypothesis that inflation uncertanity does not granger cause stock return is rejected at 5% significance level for all countries. At 8 lags, the null hypothesis is failed to reject for all series. Moreover, the null hypothesis that stock return does not nonlinear granger cause inflation uncertainty is rejected at 5% significance level for all countries. Therefore , we can conclude that at lag 4, there is bi-directional relationship between these variables, contrary to the result of linear models. Stock market returns is used as a proxy of output and the results are supporting the claim that inflation uncertainty changes the stock market returns, and visa versa.

[See Table 6]

4.4 Summary and Conclusion

In this study, the relationship between inflation and inflation uncertainty; and inflation uncertainty and stock return have been investigated in G3 countries for the period 1957-2006 for US, and 1984-2006 for UK and Japan. GARCH models are used to generate a measure of inflation uncertainty and then not only linear but also non-linear Granger methods are employed to test for causality between average inflation and inflation uncertainty; and inflation uncertainty and stock returns. In all G3 countries, inflation significantly raises inflation uncertainty, as predicted by Friedman (1977) and Ball (1992). However, in all countries, except Japan, inflation uncertainty does not cause inflation, implying that either output effect expected by Cukierman-Meltzer (1986) as there is no output effect through the channel of inflation uncertainty or stabilizing Fed policy expected by Holland are supported. In contraction to those results, the nonlinear Granger causality test results show a bi-directional nonlinear Granger causality between the series for these countries. The relationship between the inflation uncertanity and the stock returns are analyzed to see the output effect of the considered hypotheses. Although we find support for Friedman hypothesis for Japan using linear causality test, we could not support that hypothesis with the response of the stock market where it is used as a proxy for output growth. On the other hand, the empirical results show that both variables nonlinear granger cause of the other.

Those results are promising in terms of policy implications. An increase in inflation uncertainty that would change either the structure of inflation dynamics or the long-run level of inflation has the potential to disrupt credibility and accountability and undermine the success of the regime. We can conclude from those results that, for mostly in high inflation countries, if inflation uncertainty causes inflation, inflation targeting regime might be good and bring additional gains over exchange rate regimes in decreasing inflation and promotes macroeconomic stability. Therefore, the results of this study are crucial to re-examine those hypothesis for the future researches. Stock market is also used as a hedge against inflation uncertainty.

Tables of Chapter 4

Table 1. Summary statistics for inflation series

Countries	μ	σ	S	K	JB	Q_6	Q_{12}	Q_6^2	Q_{12}^2	ARCH-LM(6)	ARCH-LM(12)
Japan			1.70*	5.71*	1101.2*	369.3*	719.3*	313.8*	460.4*	189.4*	213.8*
	0.126	0.239	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
UK	0.206	0.221	2.23*	11.28*	3666.1*	1095.2*	1848.2*	129.8*	156.6*	157.4*	160.5*
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
USA	0.144	0.128	1.01*	2.37*	241.1*	1127.8*	2090.9*	514.3*	849.1*	297.7*	310.6*
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

tes: μ denotes the average inflation rate over the period February 1957–October 2006, and σ its standard /iaion. S and K are the estimated skewness and kurtosis, respectively. JB is the Jarque–Bera statistic for normality. e columns beneath "$Q_{(m)}$" and "$Q^2_{(m)}$" give the Ljung-Box test statistics for inflation and the squared deviations of inflation rate from its sample mean for up to mth order serial correlation, respectively. The "ARCH-LM(m)" gives ARCH-LM test statistics for the series for up to m th order of ARCH effects. Numbers in parentheses are p-values icates significance at the 0.05 level

Table 2: Estimation results of AR(k)-GARCH(1,1) model for the inflation rate series

Panel A: The estimated AR(17)-GARCH(1,1) model for Japanese inflation rate

$$\pi_t = \underset{(1.62)}{0.06} - \underset{(-0.49)}{0.02}\pi_{t-1} + \underset{(0.04)}{0.01}\pi_{t-2} + \underset{(2.59)}{0.11}\pi_{t-3} + \underset{(0.87)}{0.04}\pi_{t-4} + \underset{(3.92)}{0.16}\pi_{t-5} + \underset{(1.43)}{0.07}\pi_{t-6} + \underset{(1.22)}{0.06}\pi_{t-7} + \underset{(2.565)}{0.11}\pi_{t-8} + \underset{(2.77)}{0.13}\pi_{t-9}$$

$$+ \underset{(2.99)}{0.19}\pi_{t-10} + \underset{(1.59)}{0.07}\pi_{t-11} - \underset{(-2.89)}{0.12}\pi_{t-12} - \underset{(-0.63)}{0.03}\pi_{t-13} - \underset{(-0.98)}{0.04}\pi_{t-14} + \underset{(1.55)}{0.07}\pi_{t-15} + \underset{(0.46)}{0.02}\pi_{t-16} + \underset{(1.45)}{0.06}\pi_{t-17} + \varepsilon_t$$

$$h_{\pi t} = \underset{(2.73)}{0.002} + \underset{(2.73)}{0.22}\varepsilon_t^2 + \underset{(10.11)}{0.74}h_{\pi,t-1}$$

$Q(6)$= 11.417 [0.076], $Q(12)$= 18.235 [0.108]

Panel B: The estimated AR(10)-GARCH(1,1) model for the US inflation rate

$$\pi_t = \underset{(1.89)}{0.11} + \underset{(5.80)}{0.32}\pi_{t-1} + \underset{(1.99)}{0.12}\pi_{t-2} - \underset{(-0.63)}{0.04}\pi_{t-3} + \underset{(0.99)}{0.06}\pi_{t-4} + \underset{(1.73)}{0.11}\pi_{t-5} + \underset{(1.15)}{0.04}\pi_{t-6} + \underset{(1.14)}{0.05}\pi_{t-7} + \underset{(0.72)}{0.03}\pi_{t-8} + \underset{(1.34)}{0.05}\pi_{t-9} + \underset{(3.25)}{0.13}\pi_{t-10} + \varepsilon_t$$

$$h_{\pi t} = \underset{(2.31)}{0.0004} + \underset{(2.32)}{0.25}\varepsilon_t^2 + \underset{(8.43)}{0.73}h_{\pi,t-1}$$

$Q(6)$= 5.345 [0.500], $Q(12)$= 25.828 [0.011]

Panel C: The estimated AR(6)-GARCH(1,1) model for the UK inflation rate

$$\pi_t = \underset{(2.49)}{0.16} + \underset{(6.51)}{0.31}\pi_{t-1} + \underset{(4.31)}{0.23}\pi_{t-2} + \underset{(1.32)}{0.06}\pi_{t-3} - \underset{(-0.19)}{0.02}\pi_{t-4} + \underset{(2.98)}{0.14}\pi_{t-5} + \underset{(2.02)}{0.11}\pi_{t-6} + \varepsilon_t$$

$$h_{\pi t} = \underset{(0.98)}{0.004} + \underset{(1.92)}{0.50}\varepsilon_t^2 + \underset{(1.28)}{0.43}h_{\pi,t-1}$$

$Q(6)$= 6.087 [0.413], $Q(12)$= 14.140 [0.291]

Notes: t-statistics for each coefficient is given in parenthesis. The Q-test is the Ljung-Box test and its F statistics is given in parenthesis.

Table 3. Unit root test results for the inflation and stock return series

Series	Level	
	$Z(t_\mu)^a$	$Z(t_\tau)^b$
Inflation of Japan	-17.109*	-18.745*
Inflation uncertainty of Japan	-4.607*	-5.518*
Inflation of the UK	-11.199*	-11.364*
Inflation uncertainty of the UK	-9.692*	-10.331*
Inflation of the US	-10.199*	-10.232*
Inflation uncertainty of the US	-5.532*	-5.623*
NIKKEI225 Return	-16.17*	-16.18*
FTSE100 Return	-16.25*	-16.31*
S&P 500 Return	-23.1*	-23.2*

Notes: *, **, *** indicate significance at the 1%, 5%, and 10% levels, respectively.

[a] Test allows for a constant; One-sided test of the null hypothesis that the variable is nonstationary; 1%, 5%, and 10% critical values equal -3.458, -2.871, and -2.593, respectively.

[b] Test allows for a constant and a linear trend; One-sided test of the null hypothesis that the variable is nonstationary; 1%, 5%, and 10% critical values equal -3.997, -3.431, and -3.161, respectively.

Table 4. Linear Granger-causality test results between inflation, inflation uncertainty and stock returns

		Japan	UK	US
Panel A	H_0:Inflation does not Granger-cause inflation uncertainty			
	Four lags	35.730* [0.000] (+)	41.644* [0.000] (+)	2.583* [0.036] (+)
	Eight lags	18.726* [0.000] (+)	20.862* [0.000] (+)	2.064* [0.037] (+)
Panel B	H_0:Inflation uncertainty does not Granger-cause inflation			
	Four lags	10.613* [0.000] (+)	2.185 [0.069] (+)	1.045 [0.383] (+)
	Eight lags	2.198* [0.026] (+)	1.458 [0.169] (+)	0.705 [0.686] (+)
Panel C	H_0:Inflation uncertainty does not Granger-cause stock returns			
	Four lags	1.074[0.369](+)	0.226[0.923](+)	2.074[0.082] (+)
	Eight lags	0.713[0.679] (+)	0.468[0.877] (+)	1.495[0.155]
Panel D	H_0:Stock returns does not Granger-cause inflation uncertainty			
	Four lags	1.234[0.296](+)	1.178[0.320](+)	0.202[0.936] (+)
	Eight lags	0.855[0.554](+)	1.2429[0.274](+)	1.129[0.341] (+)

Notes: †,*,** denote rejections of the null hypothesis at 10%, 5%, and 1% significance levels, respectively; the numbers in the [·] are the p-values.

In panel A and B, (+) shows that the sum of the lagged coefficients is positive.

Table 5. Pair wise nonlinear-Granger causality tests between the inflation and inflation uncertainty

Countries	Null Hypothesis	*Ly=Lx*	CS	TVAL
Japan	$\pi_t \not\Rightarrow h_{\pi t}$	4	0.032	3.877*
	$h_{\pi t} \not\Rightarrow \pi_t$	4	0.061	5.816*
	$\pi_t \not\Rightarrow h_{\pi t}$	8	0.005	0.951
	$h_{\pi t} \not\Rightarrow \pi_t$	8	0.065	5.643*
UK	$\pi_t \not\Rightarrow h_{\pi t}$	4	0.012	2.159*
	$h_{\pi t} \not\Rightarrow \pi_t$	4	0.095	6.055*
	$\pi_t \not\Rightarrow h_{\pi t}$	8	0.016	1.765*
	$h_{\pi t} \not\Rightarrow \pi_t$	8	0.098	5.634*
US	$\pi_t \not\Rightarrow h_{\pi t}$	4	0.017	2.146*
	$h_{\pi t} \not\Rightarrow \pi_t$	4	0.077	6.261*
	$\pi_t \not\Rightarrow h_{\pi t}$	8	0.014	1.935*
	$h_{\pi t} \not\Rightarrow \pi_t$	8	0.079	5.781*

Notes: This table provides the results of the modified Baek and Brock test statistics applied for the inflation and its uncertainty. CS and TVAL are the difference between the two conditional probabilities in Equation (4) and the standardized test statistic in Equation (5), respectively.

†,*,** denote rejections of the null hypothesis at 10%, 5%, and 1% significance levels, respectively; and the symbol "≠>" implies does not nonlinear-Granger cause. The test statistic is asymptotically distributed *N* (0,1). The critical values at 10%, 5%, and 1% significance levels are 1.64, 1.96 and 2.33, respectively.

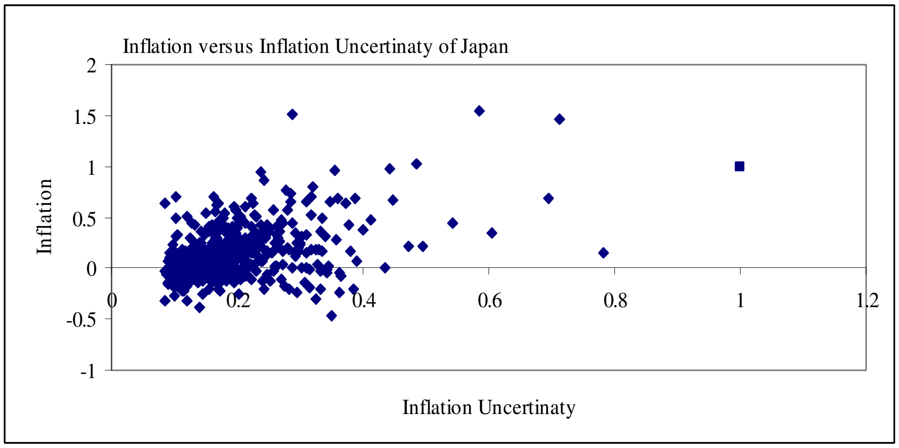
Table 6. Pair wise nonlinear-Granger causality tests between the inflation uncertainty and stock returns

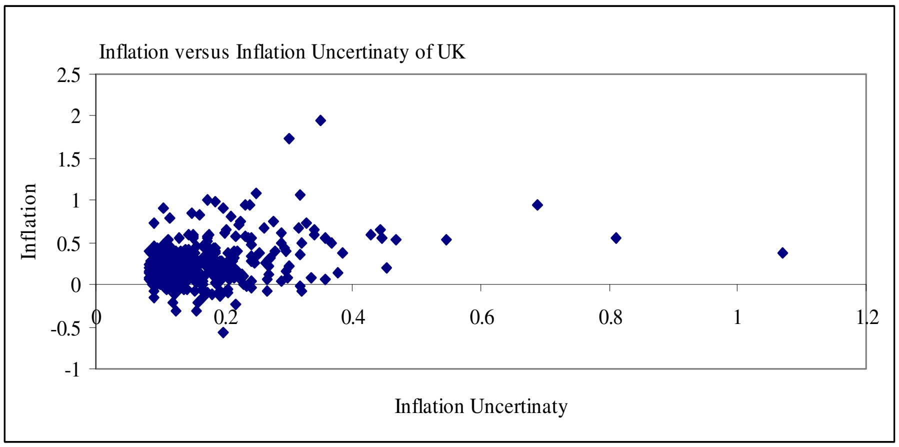
Countries	Null Hypothesis	*Ly=Lx*	CS	TVAL
Japan	$h_{\pi t} \neq> r_t$	4	0.004	1.87*
	$r_t \neq> h_{\pi t}$	4	0.001	1.85*
	$h_{\pi t} \neq> r_t$	8	0.004	1.60
	$r_t \neq> h_{\pi t}$	8	0.003	1.61
UK	$h_{\pi t} \neq> r_t$	4	0.006	1.87*
	$r_t \neq> h_{\pi t}$	4	0.003	1.87*
	$h_{\pi t} \neq> r_t$	8	0.004	1.59
	$r_t \neq> h_{\pi t}$	8	0.002	1.61
US	$h_{\pi t} \neq> r_t$	4	0.005	2.04**
	$r_t \neq> h_{\pi t}$	4	0.003	1.87*
	$h_{\pi t} \neq> r_t$	8	0.004	1.59
	$r_t \neq> h_{\pi t}$	8	0.003	1.61

Notes: This table provides the results of the modified Baek and Brock test statistics applied for the inflation and its uncertainty. CS and TVAL are the difference between the two conditional probabilities in Equation (4) and the standardized test statistic in Equation (5), respectively.

†,*,** denote rejections of the null hypothesis at 10%, 5%, and 1% significance levels, respectively; and the symbol "≠>" implies does not nonlinear-Granger cause. The test statistic is asymptotically distributed *N* (0,1). The critical values at 10%, 5%, and 1% significance levels are 1.64, 1.96 and 2.33, respectively.

Figure 1. Inflation versus inflation uncertainty for Japan, UK and US





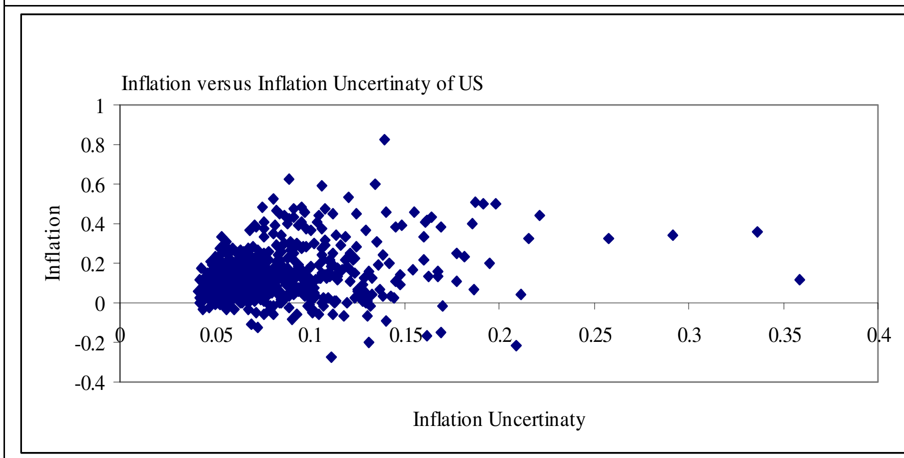
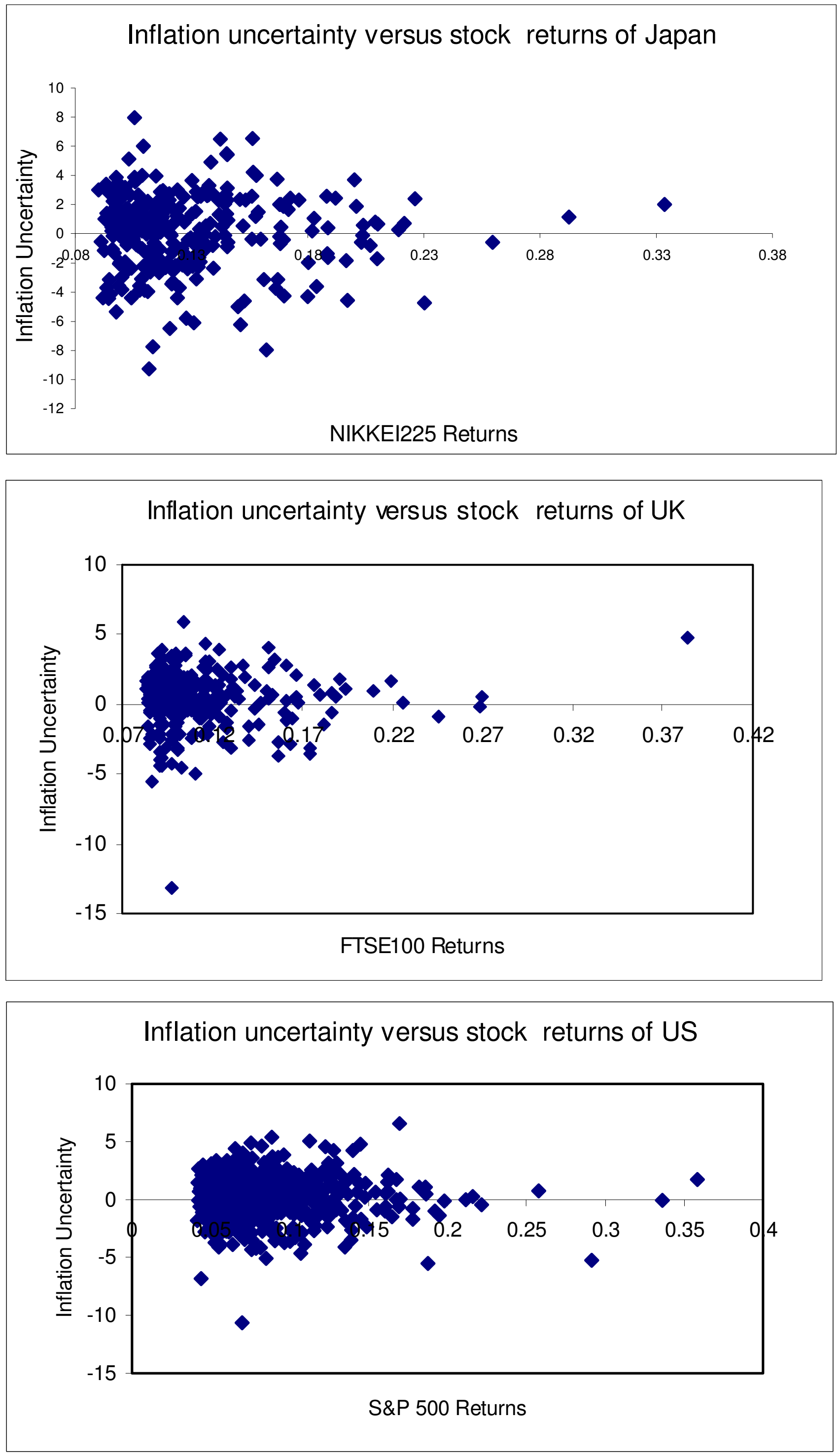


Figure 2. Inflation uncertainty versus stock returns for Japan, UK and US



References

References for Chapter 2

1. Adams, G., McQueen G., Wood R., 2004. The Effects of Inflation News on High Frequency Stock Returns, Journal of Business, 77(3) 547-574

2. Andersen, T., Bollerslev, T., 1998. Deutschmark-dollar volatility; intra-day activity patterns, macroeconomic announcements, and longer-run dependencies, Journal of Finance, 53, 219-265.

3. Andersen, Torben G and Bollerslev, Tim, 1997. Heterogeneous Information Arrivals and Return Volatility Dynamics: Uncovering the Long-Run in High Frequency Returns, Journal of Finance, American Finance Association, vol. 52(3), pages 975-1005, July.

4. Balduzzi, P., Elton, E.J., Green, T.C., 2001. Economic news and bond prices: Evidence from the US Treasury market, Journal of Financial and Quantitative Analysis, 36, 523--543.

5. Bali, T.,Tang, Y., 2007. Stock Returns, Inflation, and Output, FMA 2007 Annual Conference, Unpublished manuscript

6. Beber, A., Brandt, M.W., 2005. The effect of macroeconomic news on beliefs and preferences: Evidence from the option market, Working Paper, Duke University.

7. Becker, K., Finnerty, J., Friedmam, J., 1995. Economic news and equity market linkages between the U.S. and U.K., Journal of Banking and Finance, 19, 1191-1210.

8. Blanchard, O. J., 1981. Output, the stock market, and interest rates, American EconomicReview, 71, 132--143.

9. Boyd, J., Hu, J., Jagannathan, R., 2005. The Stock Market's Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks, Journal of Finance, 60(2), 649-672.

10. Christiansen C., 2000. Macroeconomic announcement effects on the covariance structure of government bond returns, Journal of Empirical Finance, 7, 7479--507.

11. Christie-David, R., Chaudry, M., Lindley, J.T., 2003. The effects of unanticipated macroeconomic news on debt markets, The Journal of Financial Research, 26(3), 319-339.

12. Ederington, L.H., Lee, J.H., 1993. How markets process information: news releases and volatility, Journal of Finance, 48, 1161-1189.

13. Ederington, L.H., Lee, J.H., 1996. The creation and resolution of market uncertainty: The impact of information releases on implied volatility, Journal of Financial and Quantitative Analysis, 31, 513-539.

14. Fama, E. F. and K.R. French, 1992, The Cross-Section of Expected Stock Returns, Journal of Finance, 47, 427-466.

15. Fama, E. F. and K.R. French, 1995 Size and Book to Market Factors in Earnings and Returns, Journal of Finance, 50, 131-155

16. Flannery, M.J., Protopapadakis, A., 2002. Macroeconomic factors do influence agree gate stock returns, Review of Financial Studies, 15, 751--782.

17. Fleming, M.J., Remolona, E.H., 1999. Price formation and liquidity in the US Treasury market: The response to public information, Journal of Finance, 54, 1901--1915.

18. Fornari, F., Mele, A., 2001. Volatility smiles and the information content of news, Applied Financial Economics, 11,179-186.

19. Funke, N. Matsuda A., 2006. Macroeconomic News and Stock Returns in the United States and Germany, German Economic Review, 7(2) 189-210.

20. Glosten;Lawrence R., Ravi Jagannathan and David E. Runkle, On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, The Journal of Finance, 48, 5.,1779-1801

21. Graham, M., Nikkinen, J., Sahlström, P., 2003. Relative importance of scheduled macroeconomic news for stock market investors, Journal of Economics and Finance, 27, 153-165.

22. Gürkaynak, R., Wolfers, J., 2006. Macroeconomic Derivatives: An Initial Analysis of Market-Based Macro Forecasts, Uncertainty and Risk, CEPR Discussion Papers, 5466.

23. Hardouvelis, G., 1986. Macroeconomic Information and Stock Prices, First Boston Working Paper Series, FB 86-13 (New York: Columbia University).

24. Heuson, A., Su, T., 2003. Intra-day behavior of treasury sector index option implied volatilities around macroeconomic announcements, Financial Review, 38, 161-177.

25. Kim and Verrecchia, 1991a,Trading volume and price reactions to public announcements. Journal of Accounting Research, 29, 302-321.

26. Kim, M., Kim, M., 2003. Implied volatility dynamics in the foreign exchange markets, Journal of International Money and Finance, 22, 511-528.

27. Kroner, F. K., Ng, K. V., 1998. Modeling Asymmetric comovements of assets returns, Review of Financial Studies, 11(4), 817-844.

28. Li, L., Engle, R.F., 1998. Macroeconomic announcements and volatility of Treasury futures, Discussion Paper, 98-27, Department of Economics, University of California, San Diego.

29. Li , L.,Hu, F. Z., 1998. Responses of Stock Market to Macroeconomic Announcements Across Economic States, IMF Working Paper, 98/79 (Washington: International Monetary Fund).

30. McQueen, G., and Roley, V. (1993). Stock prices, news and business conditions. Review of Financial Studies, 6, 683-707

31. Jones, C.M., Lamont, O., Lumsdain, R., 1998. Macroeconomic news market volatility, Journal of Financial Economics, 47, 315-337.

32. Jones, B., Lin, C. -T., Masih, A., Mansur, M., 2005. Macroeconomic announcements, volatility, and interrelationships: An examination of the UK interest rate and equity markets, International Review of Financial Analysis, 14, 356-375.

33. McQueen and Roley, 1993.

34. Nikkinen, J., Sahlström, P., 2004. Impact of the federal open market committee's meetings and scheduled macroeconomic news on stock market uncertainty, International Review of Financial Analysis, 13, 1-12.

35. Nofsinger, J., Prucyk, B., 2003. Option volume and volatility response to scheduled economic news releases, Journal of Futures Markets, 23, 315-345.

36. Nelson, D., 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach, Econometrics, 59(52), 347-70

37. Orphanides, A., 1992, When good news is bad news: Macroeconomic news and the stock market, Working paper, Board of Governors of the Federal Reserve System.

38. Pearce, D.K., Roley, V., 1985. Stock prices and economics news, Journal of Business, 58, 49-67

39. Veronesi, P., 1999. Stock market overreaction to bad news in good times:A rational expectations equilibrium model, Review of Financial Studies,12, 975--1007.

40. Vähämaa, S., Watska, S., & Äijö, J. (2005). What moves option-implied bond market expectations, Journal of Futures Markets, 25, 817-843.

41. Stock, J., Watson, M., 1989. New indexes of coincident and leading economic indicators in J. Olivier and Stanley Fisher, eds.: NBER Macroeconomics Annual, Cambridge, Massachusetts.

References for Chapter 3

1. H. Akaike, A new look at the statistical model identification"". IEEE Transactions on Automatic Control 19 (6): (1974) 716-723.

2. I. Asimakopoulos, D. Ayling and W. M. Mahmood, Non-linear Granger causality in the currency futures returns, Economics Letters 68 (2000) 25-30.

3. A.H. Abhyankar, Linear and non-linear Granger causality: evidence from the FT-SE 100 Stock Index futures market, Journal of Futures Markets 18 (5) (1998) 519-540.

4. E. Baek and W. Brock, A General Test for Non-linear Granger Causality: Bivariate Model. Working Paper, Iowa State University and University of Wisconsin, Madison, WI. (1992).

5. H. Berument and O. Ince, Effect of S&P500's Return on Emerging Markets: Turkish Experience, Applied Financial Economics Letters, 1 (2005) 59-64.

6. H. Berument, N. Dincer and H. Olgun, The Center and Periphery Relations In International Stock Markets Forthcoming in Applied Financial Economics Letters (2007).

7. J.Y. Campell and P. Perron, Pitfalls and Opportunities: What Macroeconomists Should Know about Unit Roots, O.J. Blanchard and S. Fischer (eds.) NBER Macroeconomic Annual 1991, 141-201, The MIT Press. (1991).

8. R. Dornau, Shock Around the Clock-On the Causal Relations Between International Stock Markets, the Strength of Causality and the Intensity of Shock Transmission: An Econometric Analysis, International Journal of Intelligent Systems in Accounting, Finance & Management, 8 (1999) 253-270.

9. C. Eun and S. Shin, International Transmission of Stock Market Movements, The Journal of Finanal Quantitative Analysis, Vol. 24, No.2 (1989) 241-25.

10. R.A Fujihara and M. Mougoue, An examination of linear and non-linear causal relationships between pre variability and volume in petroleum futures markets. Journal of Futures Market 4 (1997) 385-416.

11. George M. Von Furstenberg and Bang Nam Jeon, International stock price movements: links and messages. Brooking Papers on Economic Activity, No. 1. (1989) 125-179.

12. C. W. J Granger, Investigating Causal Relations by Econometrics Models and Cross SpectralMeods, Econometrica 37 (1969) 424-438.

13. C. W. J Granger, Some Recent Developments in A Concept of Causality, Journal of Econometrics 39 (1988) 199-211.

14. C. W. J Granger, Forecasting in Business and Economics, 2nd ed. (Academic Press, San Diego).(1989).

15. A. Ghosh, R. Saidi and K.H. Johnson, Who moves the Asia-Pacific stock markets-US or Japan? Empirical evidence based on the theory of cointegration, The Financial Review 34 (1999) 159-179.

16. C. Hiemstra and C. Kramer, Nonlinearity and endogeneity in macro-asset pricing, Working Paper, University of Strathclyde and International Monetary Found (1993).

17. C. Hiemstra and J.D. Jones, Testing for linear and non-linear Granger causality in the stock price-volume relation. Journal of Finance 5 (1994) 1639-1664.

18. D.A. Hsieh, Testing of non-linear dependence in daily foreign exchange rates. Journal of Business 62 (1989) 339-368.

19. D.A. Hsieh, Chaos and non-linear dynamics: application to financial markets. Journal of Finance, 5 (1991) 1839-1877.

20. T. Jaditz and J. Jones, Granger causality between the consumer and wholesale price indicies, Working Paper, Bureau of Labor Statistics and Securities and Exchange Commision, (1993).

21. S. Johansen, Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models, Econometrica 58 (1991) 165-188.

22. H. Kiymaz and H. Berument, The Day of the Week Effect on Stock Market Volatility and Volume: International Evidence, Review of Financial Economics, 12(4) (2003) 363-380.

23. W. Lin, R. F Engle and T Ito, Do bulls and bears move across borders? International transmission of stock returns and volatility, Review of Financial Studies, 7 (1994) 507-538.

24. A.I. McLeod and W. K. Li, Diagnostic checking ARMA time series models using squared residual autocorrelations. Journal Time Series Analysis 4 (1983) 269-73.

25. M. Osterwald-Lenum, A note with fractiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics: four cases. Oxford Bulletin of Economics and Statistics, 54 (1992) 461-472.

26. S.E. Said and D.A., Testing for Unit Roots in Autoregressive-Moving Average Models of Unknown Order, Biometrika, 71 (1984) 599-607.

27. J.A. Scheinkman and B. LeBaron, Non-linear dynamics and stock returns, Journal of Business, 62 (1989) 311-337.

28. C. Wu and Y. Su, Dynamic relations among international stock markets, International Review of Economics and Finance, 7(1) (1998) 63-84.

References for Chapter 4

1. Alesina, Alberto and Lawrence H. Summers (1993), "Central bank independence and macroeconomic performance: some comparative evidence", Journal of Money, Credit and Banking 25: 51-162.

2. Baek, Ehung and William Brock (1992), "A General Test for Non-linear Granger Causality: Bivariate Model", Working Paper, Iowa State University and University of Wisconsin, Madison, WI.

3. Baillie, Richard T., Tim Bollerslev, and Hans O. Mikkelsen, (1996), "Fractionally integrated generalized autoregressive conditional heteroskedasticity", Journal of Econometrics 74(1): 3-30.

4. Ball, Laurence (1992), "Why does high inflation raise inflation uncertainty?", Journal of Monetary Economic 29: 371-388.

5. Bollerslev, Tim (1986), "Generalised Autoregressive Conditional Heteroskedasticity", Journal of Economics 31: 307-326.

6. Berument, Hakan (1999), "The impact of inflation uncertianty on interest rates in the UK", Scottish Journal of Political Economy 46: 207-218.

7. Berument, Hakan and Nergis Dincer (2005), "Inflation and Inflation Uncertainty in the G-7 Countries", Physica A 348: 371-379.

8. Berument, Hakan, Ali Inamlik, and Hasan Olgun (2008), "Inflation and Growth: Positive or Negative Relationship?", Journal of Applied Sciences 8(2): 192-204.

9. Brunner, Allan D. and Gregory D. Hess (1993), "Are higher levels of inflation less predictable? A state-dependent conditional heteroscedasticity approach", Journal of Business and Economic Statistics 11: 187-197.

10. Caporale, Tony and Barbara McKierman (1997), "High and variable inflation: further evidence on the Friedman hypothesis", Economics Letters 54: 65-68.

11. Campbell, John Y. and Pierre Perron (1991), "Pitfalls and Opportunities: What Macroeconomists Should Know about Unit Roots",O.J. Blanchard and S. Fischer (eds.) NBER Macroeconomic Annual 141-201, The MIT Press.

12. Conrad, Christian and Menelaos Karanasos (2005), "On the inflation-uncertainty hypothesis in the USA, Japan and the UK: a dual long memory approach", Japan and the World Economy 17: 327 - 343.

13. Cukierman, Alex and Allan H. Meltzer (1986), "A theory of ambiguity, credibility, and infation under discretion and asymmetric information", Econometrica 54: 1099-1128.

14. Daal, Elton, Naka Atsuyuki and Benito Sanchez (2005), "Re-examining inflation, inflation uncertainty in developed and emerging countries", Economic Letters 89: 180-186.

15. Dotsey, M., Sarte, P., 2000. Inflation uncertainty and growth in a cash-in-advance economy. Journal of Monetary Economics 45 (3), 631e655.

16. Engle, Robert F. (1982),"Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation", Econometrica 50: 987-1007.

17. Engle, Robert F. (1983), "Estimates of the variance of US inflation based upon the ARCH model", Journal of Money, Credit and Banking 15: 286-301.

18. Fama, F. Eugene and G. William Schwert (1977) Asset returns and inflation, Journal of Financial Economics Volume 5, Issue 2, November 1977, Pages 115-146

19. Fischer, S. and Merton, R. (1984) Macroeconomics and Finance: the role of the stock market, Carnegie-Rochester Conference Series on Public Policy, 21.

20. Friedman, Milton (1977), "Nobel lecture: Inflation and Unemployment", Journal of Political Economy 85: 451-472.

21.Foster, Edward (1978), "The variability of inflation", Review of Economics and Statistics 60: 346-350.

22. Fountas, Stilianos., A. Ioannidis, and Menelaos Karanasos, 2004 Inflation, Inflation Uncertainty and a Common European Monetary Policy, Manchester School 72(2): 221-242

23. Fountas, Stilianos and Menelaos Karanasos, 2007 Inflation, output growth, and nominal and real uncertainty: Empirical evidence for the G7, Journal of International Money and Finance 26, 229-250

24. Garcia, Rene and Pierre Perron (1996), "An analysis of the real interest rate under regime shifts", Review of Economics and Statistics 83: 111-125.

25. Granger, Clive W. J. (1969), "Investigating Causal Relations by Econometrics Models and Cross Spectral Methods", Econometrica 37: 424-438.

26. Granger, Clive W. J. (1988), "Some Recent Developments in A Concept of Causality", Journal of Econometrics 39: 199-211.

27. Granger, Clive W. J. (1989), Forecasting in Business and Economics, 2nd ed., Academic Press, San Diego.

28. Grier, Kevin B. and Mark J. Perry (1998), "On inflation and inflation uncertainty in the G7 countries", Journal of International Money and Finance 17: 671-689.

29. Härdle, Wolfgang (1994), Applied Nonparametric Regression, Cambridge University Press.

30. Hiemstra, Craig and Charles F. Kramer (1993), "Nonlinearity and endogeneity in macro-asset pricing", Working Paper, University of Strathclyde and International Monetary Found.

31. Hiemstra, Craig and Jonathan D. Jones (1994), "Testing for linear and non-linear Granger causality in the stock price--volume relation", Journal of Finance 5: 1639--1664.

32. Holland, Steven (1995), "Inflation and uncertainty: tests for temporal ordering", Journal of Money, Credit, and Banking 27: 827-837.

33. Hwang, Yung (2001), "Relationship between inflation rate and inflation uncertainty", Economics Letters, 73, 179-186.

34. Jaditz, Ted and Jonathan Jones. (1993), "Granger causality between the consumer and wholesale price indicies", Working Paper, Bureau of Labor Statistics and Securities and Exchange Commision.

35. Laurent, S. and J. P. Peters, (2002), "G@RCH 2.2: an Ox package for estimating and forecasting various ARCH models", Journal of Economic Surveys 3: 447-485.

36. McLeod, Allan I. and William K. Li (1983), "Diagnostic checking ARMA time series models using squared residual autocorrelations", Journal Time Series Analysis 4: 269--73.

37. Morley, Bruce (2002), "Output, consumption and the stock market implications for European convergence", Applied Economics, 2002, 34, 317-323

38. Ozdemir, Zeynel A. and Mahir Fisunoglu (2008), "On the inflation-uncertainty hypothesis in Jordan, Philippines and Turkey: A long memory approach", International Review of Economics and Finance 17: 1-12.

39. Pourgerami, A., Maskus, K., 1987. The effects of inflation on the predictability of price changes in Latin America: some estimates and policy implications. World Development 15 (1), 287e290.

40. Phillips, Peter C. and Pierre Perron (1988), "Testing for a unit root in time series regression", Biometrica 75: 335-346.

41. Stilianos Fountas a, Menelaos Karanasos (2007), Inflation, output growth, and nominal and real uncertainty: Empirical evidence for the G7, Journal of International Money and Finance 26 229-250

42. Friedman, M. (1988) Money and the stock market, Journal of Political Economy, 96, 221-45.

43. Tobin, J. (1969) A general equilibrium approach to monetary theory, Journal of Money Credit and Banking, 1, 15-29.

44. Bayoumi, T. (1993) Financial deregulation and household saving, Economic Journal, 103, 1432-43.

45. Fischer, S. and Merton, R. (1984) Macroeconomics and Finance: the role of the stock market, Carnegie-Rochester Conference Series on Public Policy,