UNIVERSIDAD CARLOS III DE MADRID

working papers

Working Paper 11-45
Economic Series
July, 2011

Departamento de Economía
Universidad Carlos III de Madrid
Calle Madrid, 126
28903 Getafe (Spain)
Fax (34) 916249875

The Reaction of Stock Market Returns to Anticipated Unemployment*

Jesús Gonzalo† — Universidad Carlos III de Madrid

Abderrahim Taamouti‡ — Universidad Carlos III de Madrid

July 10, 2011

ABSTRACT

We empirically investigate the short-run impact of *anticipated* and *unanticipated* unemployment rates on stock prices. We particularly examine the nonlinearity in stock market's reaction to unemployment rate and study the effect at each individual point (quantile) of stock return distribution. Using *nonparametric* Granger causality and *quantile* regression based tests, we find that, contrary to the general findings in the literature, *only anticipated* unemployment rate has a *strong* impact on stock prices. Quantile regression analysis shows that the causal effects of anticipated unemployment rate on stock return are usually heterogeneous across quantiles. For quantile range [0.35, 0.80], an increase in the anticipated unemployment rate leads to an increase in the stock market price. For the other quantiles the impact is statistically insignificant. Thus, an increase in the anticipated unemployment rate is in general a good news for stock prices. Finally, we offer a reasonable explanation of why unemployment rate should affect stock prices and how it affects them. Using Fisher and Phillips curve equations, we show that high unemployment rate is followed by monetary policy action of Federal Reserve (Fed). When unemployment rate is high, the Fed decreases the interest rate, which in turn increases the stock market prices.

Keywords: Stock market returns; anticipated unemployment; unanticipated unemployment; nonparametric tests; conditional independence; Granger causality in distribution; Granger causality in quantile; local bootstrap; monetary policy; Federal funds rate; money supply.

Journal of Economic Literature classification: C14, C58, E44, G12

∗ Financial support from the Spanish Ministry of Education through grants SEJ 2007-63098 is acknowledged.

† Economics Department, Universidad Carlos III de Madrid. Address: Departamento de Economía Universidad Carlos III de Madrid Calle Madrid, 126 28903 Getafe (Madrid) Espan˜a. TEL: +3491 624-9853; FAX: +34-91 6249329; e-mail: ataamout@eco.uc3m.es.

‡ Corresponding author : Economics Department, Universidad Carlos III de Madrid. Address: Departamento de Economía Universidad Carlos III de Madrid Calle Madrid, 126 28903 Getafe (Madrid) España. TEL: +34-91 6249863; FAX: +34-91 6249329; e-mail: ataamout@eco.uc3m.es

1 Introduction

Stock market analysts argue that stock prices rebound after an unemployment rate increase announcement. However, in the literature there is no clear academic consensus on the impact of unemployment announcement on stock market return. Most of the conclusions about stock prices-unemployment rate relationship are based on *linear mean regression* analysis. In the present paper we investigate nonlinearity in the stock market's reaction to unemployment rate and examine the impact at different quantiles of stock return distribution. We conduct a rigorous analysis of short-run impact of *anticipated* and *unanticipated* unemployment rates on stock market prices. Using *nonparametric* Granger causality and *quantile* regression based tests, we find that, contrary to the general findings in the literature, *only anticipated* unemployment rate has a *strong* impact on stock prices. We also propose a monetary policy explanation of why and how unemployment rate affects stock prices.

Many papers have been written to examine the links between stock market prices and real economy. Given the importance of the issue for policy makers there is still a great interest in studying these relationships. The existing papers have analyzed two directions of causality: from stock market prices to real economy and from real economy to stock market prices. The present paper focus on the latter direction of causality. The main differences with the existing literature is we examine the reaction of both *distribution function* and individual *quantiles* of stock market returns to *anticipated* and *unanticipated* unemployment rates, whereas most of the papers only looked at the conditional *mean* effect, thus they ignored non-linear dependence and the dependence in the quantiles of the conditional stock returns distribution. The reason for choosing unemployment rate to represent real economy is because, in addition to its accuracy, it is considered as a gauge of the economy's growth rate. It is one of the important indicators used by the Federal Reserve to determine the health of the economy when setting monetary policy.

Started with Chen, Roll, and Ross (1986), many articles have tried to show reliable associations between macroeconomic variables and security returns. Other papers before [see Bodie (1976), Fama (1981), Geske and Roll (1983), Pearce and Roley (1983)] have shown that aggregate stock returns are negatively related to inflation and money growth. Chen, Roll, and Ross (1986, pages 383-384) wrote *"A rather embarrassing gap exists between the theoretically exclusive importance of systematic "state variables" and our complete ignorance of their identity. The comovements of asset prices suggest the presence of underlying exogenous influences, but we have not yet determined which economic variables, if any, are responsible".* With respect to the empirical relevance of macroeconomic factors to equity returns, Chan, Karceski, and Lakonishok (1998, page 175) wrote " *The macroeconomic factors generally make a poor showing. Put more bluntly, in most cases, they are as useful as a randomly generated series of numbers in picking up return covariation. We are at a loss to explain this poor performance."* Motivated by these conclusions, Flannery and Protopapadakis

(2002) have examined the impact of 17 macroeconomic variables, including unemployment rate, on mean and volatility of stock returns. After estimating a GARCH model of daily equity returns, where realized returns and their conditional volatility depend on the 17 macro series' announcements, they find that the unemployment rate doesn't affect the mean (average) stock returns but it affects its variance.

A recent related paper by Boyd, Hu, and Jagannathan (2005) [hereafter BHJ(2005)] has studied the impact of *unanticipated* unemployment rate on stock returns. This paper finds that on average, an announcement of rising unemployment is good news for stocks during economic expansions and bad news during economic contractions. The main differences between BHJ(2005) and our paper can be summarized as follows: **(1)** BHJ(2005) focus *only* on *conditional mean* effect using mean regression analysis, whereas we investigate the effect on *conditional distribution* and individual *quantiles* using a *nonparametric approach* and *conditional quantile* regression; **(2)** BHJ(2005) examine the impact of *only* unanticipated unemployment rate on stock returns, whereas we examine and compare the impact of *both* anticipated and unanticipated unemployment rates on stock returns; and **(3)** BHJ(2005) find that *unanticipated* unemployment rate affects the mean stock returns, whereas we find that *only* anticipated unemployment rate has an impact on *conditional distribution* and *quantiles* of stock returns.

The present paper can be viewed as an extension of the previous research. We test the above relationships using *new nonparametric* causality tests and *quantile* regression-based tests. The *nonparametric* causality tests allow to capture non-linearity and dependence in low and high-order moments, whereas the quantile regression-based tests help to identify and examine the effect at different quantiles, including the median, of stock returns distribution. To our Knowledge this is the first paper that investigates the reaction of conditional distribution and quantiles of stock returns to anticipated and unanticipated unemployment rates.

To achieve our aims and conclusions, we first follow the approach considered by Barro (1977, 1978), Barro and Rush (1980), Sheffrin (1979), Makin (1982) among many others, to decompose actual growth rate of unemployment rate into "*anticipated*" and "*unanticipated*" components. Barro (1977, 1978) use an autoregressive model to divide observed money growth rate into anticipated and unanticipated components. Thus, our measures of anticipated and unanticipated growth rates of unemployment rate are taken from an autoregressive (AR) model.

Second, we test the reaction of conditional distribution of stock market returns to anticipated and unanticipated unemployment rates using a recent nonparametric Granger causality tests proposed by Bouezmarni, Roy, and Taamouti (2010). The test statistic can detect nonlinearity and dependence in both low and high-order moments. It is based on comparison of conditional distribution function estimates using an L_2 metric, where the distribution functions are estimated using Nadaraya-Watson method. Using monthly data for the period 1950-2009 on S&P 500 stock index and unemployment rate, we find, contrary to the conventional t-statistic, very convincing evidence that the *anticipated* unemployment growth rate Granger causes the conditional distribution function of S&P 500 stock returns. We also find that *unanticipated* unemployment growth rate doesn't affect the conditional distribution function of stock returns. Thus, the unemployment rate affects the conditional distribution of stock return *only* through its anticipated component. Further, the traditional tests of Granger causality in mean show that the two components of unemployment rates do not affect stock returns.

Third, the nonparametric test discussed before helps to detect the impact of anticipated unemployment rate on stock return distribution. However, the rejection of Granger non-causality in distribution hypothesis doesn't inform us about level(s) of return distribution where the causality exists. To overcome this problem, we consider conditional quantile regression-based tests to identity the impact of unemployment rate components on individual quantiles of conditional stock return distribution. This will give a broader picture of the effect in various scenarios. Using the same data as before, the quantile regression analysis confirms our previous results and show that only anticipated unemployment rate affects stock return quantiles. The causal effect is usually heterogeneous across stock return quantiles. For quantile range [0.35, 0.80], we find that an increase in anticipated unemployment rate leads to an increase in stock prices. Thus, an increase in the anticipated unemployment rate is in general a good news for stock prices. This effect is statistically significant event at 1% significance level. For the quantile range [0.05, 0.35) the effect is rather negative and statistically insignificant even at 10% significance level.

Finally, we offer a reasonable explanation of why and how the unemployment rate affects stock market prices. Using monetary policy measures (Federal funds rate and money supply), we identify two possible channels of the impact of unemployment rate on stock prices. The first one involves Federal funds rate and can be summarized as follows: unemployment rate affects Federal funds rate which in turn affects stock market prices. Using existing economic theory (Fisher and Phillips curve equations), we show that Federal funds rate reacts negatively to unemployment rate, and this is probably to stimulate the economy and create more jobs. Many papers [see Rigobon and Sack (2002), Craine and Martin (2003), Bernanke and Kuttner (2005), and references therein] also show that there is a negative impact of Federal funds rate on stock market returns. Thus, the signs in the channel through Federal funds rate can be summarize as follows: a decrease (increase) in unemployment rate is followed by an increase (decrease) in Federal funds rate which in turn leads to a decrease (increase) in stock market price (return). The second channel is through money supply. We find that anticipated unemployment rate affects money supply growth rate and that the latter affects immediately Federal funds rate, which in turn affects stock market returns. There is also a possibility of a direct impact of money supply growth rate on stock market returns: unemployment rate affects money supply growth rate which in turn affects stock market returns.

The paper is organized as follows. In Section 2, we describe the data and discuss the methodology we

Table 1: Descriptive statistics of monthly unemployment rate and its growth rate

	Mean	**Median**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera (Prob.)**
UR	5.680	5.600	1.556	0.639	3.486	0.000
g_u	0.00026	0.000	0.016	0.551	6.517	0.000

follow to measure the anticipated and unanticipated components of unemployment growth rate. In Section 3, we use nonparametric Granger causality tests to test the statistical significance of the impact of anticipated and unanticipated unemployment rates on conditional distribution function of stock returns. In Section 4, we examine the Granger causality in mean versus Granger causality in quantiles of stock returns using the unemployment rate components. In Section 5, we identify the channels that explain how unemployment rate affects stock prices based on monetary policy action of Federal Reserve. In Section 6, we check the robustness of our results using quarterly data and an alternative statistical procedure. Section 7 concludes.

2 Data and Methodology

2.1 Monthly unemployment announcements

This section aims to describe our data and discuss the methodology that we follow to measure the anticipated and unanticipated components of unemployment rate that is announced by the Bureau of Labor Statistics (BLS). The first Friday of each month, the BLS of the U.S. Department of Labor announces the employment and unemployment rates in the United States for the previous month, along with many characteristics of such persons (gender, age, color, origin, education,...) The unemployment rate represents the number of unemployed persons as a percent of the labor force. According to BLS, "*persons are classified as unemployed if they do not have a job, have actively looked for work in the prior four weeks, and are currently available for work. Persons who were not working and were waiting to be recalled to a job from which they had been temporarily laid off are also included as unemployed.*" To collect the data on unemployment, the Government conducts a monthly sample survey called the Current Population Survey (CPS) to measure the extent of unemployment in the country. The CPS has been conducted in the United States every month since 1940. It has been expanded and modified several times since then. The U.S. Department of Labor releases revisions of past unemployment announcements for the previous three months, after which the announcement is considered final. BLS offers a long and accurately dated time series on unemployment rate.

In addition to its accuracy, we choose unemployment rate among many other macroeconomic variables because it is considered as a gauge of the economy's growth rate. It is one of the important indicators used by the Federal Reserve to determine the health of the economy when setting monetary policy and investors use unemployment statistics to look at which sectors are losing jobs faster.

The sample used here contains monthly seasonally adjusted unemployment rate and covers the period from January 1950 to December 2009 for a total of 721 observations. Summary statistics for unemployment rate, say UR_t, and its growth rate, say $g_{u,t} = \log(UR_t) - \log(UR_{t-1})$, are presented in Table 1. The unconditional distributions of monthly unemployment rate and its growth rate show the expected excess kurtosis and positive skewness. The sample mean of growth rate is almost zero, the value of sample skewness is also close to zero, and its sample kurtosis is greater than the normal distribution value of three. Finally, the zero p-value of the Jarque-Bera's test of the growth rate of unemployment rate indicates that this variable cannot be normally distributed.

We also perform an Augmented Dickey-Fuller test [hereafter ADF-test] for the nonstationarity of unemployment rate and its growth rate. Using an ADF-test with only an intercept and with both an intercept and trend, we find that the two variables are stationary. Since the value of the ADF-test statistic with intercept and trend (-3.474) is close to the corresponding 5% critical value (-3.417), our analysis in the next sections will be based on the growth rate of unemployment rate. Several empirical studies also use growth rate of unemployment rate. Consequently, the causality relations have to be interpreted in terms of growth rates.

2.2 Measuring anticipated and unanticipated unemployment rates

This paper aim to examine the reaction of stock market return to anticipated and unanticipated growth rates of unemployment rate. We follow the approach considered by Barro (1977, 1978), Barro and Rush (1980), Sheffrin (1979) Makin (1982) and many others, to decompose actual growth rate of unemployment rate into "*anticipated*" and "*unanticipated*" components. Barro (1977, 1978) use autoregressive models to divide observed money growth rate into anticipated and unanticipated components. Our measures of the anticipated and unanticipated growth rates of unemployment rate are taken from an autoregressive (AR) process. Compared to many other linear and nonlinear processes, van Dijk, Teräsvirta and Franses (2002) and Deschamps (2008) argue that autoregressive processes are appropriate to model the unemployment rate.

The equation used to decompose the observed growth rate into anticipated and unanticipated components is given by:

$$g_{u,t} = \mu + \sum_{j=1}^{p} \beta_j g_{u,t-j} + u_t,$$

where $g_{u,t}$ is the growth rate of unemployment rate at time t, $(\mu, \beta_1, ..., \beta_p)'$ is the vector of parameters to estimate, and u_t is an error term. We apply the Box and Jenkins procedure and Akaike information criterion (AIC) to select the autoregressive order p that corresponds to the best model for the growth rate of unemployment rate. We select a model that has the lowest AIC value. Using the data described before, the minimum value of AIC corresponds to $p = 12$. Further, the results of the estimation of an AR(12) model

Table 2: Estimation results of AR(12) model

Ind. Variables	**Coefficient**	**T-Statistic**
Const.	0.00035	0.618
$g_{u,t-1}$	0.086	2.319
$g_{u,t-2}$	0.166	4.483
$g_{u,t-3}$	0.124	3.326
$g_{u,t-4}$	0.084	2.251
$g_{u,t-5}$	0.057	1.519
$g_{u,t-6}$	0.019	0.504
$g_{u,t-7}$	0.011	0.310
$g_{u,t-8}$	0.038	1.030
$g_{u,t-9}$	-0.004	-0.111
$g_{u,t-10}$	-0.117	-3.174
$g_{u,t-11}$	0.064	1.750
$g_{u,t-12}$	-0.142	-3.854
$R^2(\%)$	14.50	-
F-statistic	9.801	-

are reported in Table 2. From these, we see that all parameter estimates are significant except the constant term and the coefficients of lags $6, 7, 8$ and 9. The coefficient of determination (R-squared) is equal to 14.5%, which indicates that the past of unemployment rate explain more than 14% of the the actual value of its growth rate. Finally, to validate the estimated model we consider an AR residual Portmanteau tests for autocorrelations and the results are presented in Table 3. The latter shows that the estimated AR(12) model appears adequate in that the residuals in general seem serially uncorrelated.

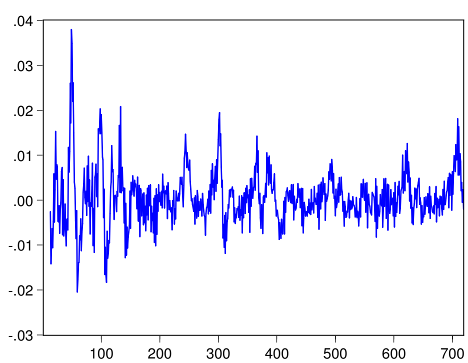
Thus, we obtain the following estimated autoregressive model which is used to decompose observed growth rate into anticipated, say $g^e_{u,t}$, and unanticipated, say $g^u_{u,t}$, components:

$$\begin{aligned} g^e_{u,t} &= E_{t-1}(g_{u,t}) \simeq \hat{g}_{u,t} = \underset{(0.618)}{3.5\ 10^{-4}} + \underset{(2.319)}{0.086}\ g_{u,t-1} + \underset{(4.483)}{0.166}\ g_{u,t-2} + \underset{(3.326)}{0.124}\ g_{u,t-3} + \underset{(2.251)}{0.084}\ g_{u,t-4} \\ &+ \underset{(1.519)}{0.057}\ g_{u,t-5} + \underset{(0.504)}{0.019} g_{u,t-6} + \underset{(0.310)}{0.011} g_{u,t-7} + \underset{(1.030)}{0.038} g_{u,t-8} - \underset{(1.030)}{0.004} g_{u,t-9} \underset{(-3.174)}{-0.117}\ g_{u,t-10} \\ &+ \underset{(1.750)}{0.064}\ g_{u,t-11} \underset{(-3.854)}{-0.142}\ g_{u,t-12}. \end{aligned} \tag{1}$$

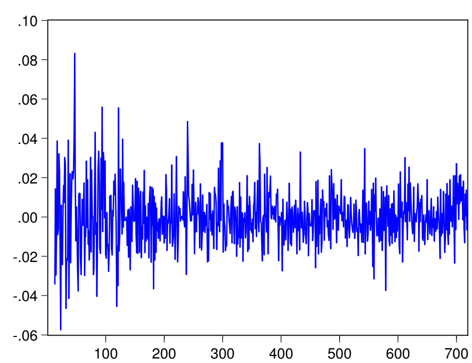
The residuals $\hat{u}_t = g_{u,t} - g^e_{u,t}$ measure the "unanticipated" growth rate of unemployment rate. The anticipated and unanticipated components are displayed in Figure 1. We see that the anticipated component is smoother than the unanticipated one and that the average values of the two components are almost equal to zero [see

Table 3: VAR residual Portmanteau tests for autocorrelations

Lags	**Q-Stat**	**Prob.**	**Adj Q-Stat**	**Prob.**	**df**
13	2.090	0.148	2.116	0.145	1
14	4.294	0.116	4.365	0.112	2
15	6.006	0.111	6.113	0.106	3
16	6.011	0.198	6.119	0.190	4
17	6.568	0.254	6.690	0.244	5
18	6.576	0.361	6.698	0.349	6
19	9.852	0.197	10.064	0.185	7
20	11.738	0.163	12.005	0.151	8



(a) Anticipated Growth Rate



(b) Unanticipated Growth Rate

Figure 1: Anticipated and unanticipated growth rates of unemployment rate.

Table 4: Descriptive Statistics of anticipated and unanticipated growth rates

	Mean	**Median**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera (Prob.)**
g_u^e	0.0006	0.0004	0.0060	1.004	7.870	0.000
g_u^u	-0.0000	-0.0008	0.0150	0.439	5.293	0.000

Table 5: Descriptive Statistics of SP 500 Stock Returns

	Mean	**Median**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera (Prob.)**
S&P 500 Return (r)	0.0025	0.0039	0.018	-0.680	5.549	0.000

Table 4]. Finally, the ADF-tests show that the two components are stationary.

2.3 Monthly stock return

The stock market is given by the monthly S&P 500 Index. As for unemployment rate, the sample runs from January 1950 to December 2009 for a total of 721 observations. Stock returns are computed using the standard continuous compounding formula: If we denote the time t logarithmic price of stock market by p_t, then the continuously compounded stock return from time $t-1$ to t is defined by $r_t = p_t - p_{t-1}$. Summary statistics for stock return are presented in Table 5. From these, we see that the S&P 500 price movements exhibit expected excess kurtosis and negative skewness. The sample kurtosis is greater than the normal distribution value of three. The p-value of Jarque-Bera test statistic indicates that stock returns cannot be normally distributed. Finally, we perform ADF-tests for nonstationarity of the S&P 500 stock returns. The results, using both ADF-test with only an intercept and with an intercept and trend show that the S&P 500 stock return is stationary, which validates the asymptotic distribution theory of the test statistics that we consider in the next sections.

3 Stock market's reaction: Nonparametric analysis

We begin our analysis by testing whether stock market return reacts to anticipated and unanticipated unemployment rates in a broader framework that allows us to leave free the specification of the underlying model. Nonparametric tests are well suited for that. They do not impose any restriction on the model linking the dependent variable to the independent variables.

Most of the empirical work on the stock price-unemployment rate relation focuses exclusively on the traditional linear Granger causality tests [see Boyd, Hu, and Jagannathan (2002), Flannery and Protopapadakis

(2002) and references therein]. Although such tests have high power in uncovering linear causal relations, their power against nonlinear causal relations can be very low [see Baek and Brock (1992), Hiemstra and Jones (1993), Bouezmarni, Roy, and Taamouti (2010), Bouezmarni, Rombouts, and Taamouti (2009)]. For that reason, traditional Granger causality tests might overlook a significant nonlinear relation between stock returns and unemployment rate.

We test whether past and present changes in the anticipated and unanticipated unemployment rates affect the conditional distribution of stock return. The null hypothesis is defined when the distribution of stock return conditional on its own past and past (present) changes in the anticipated or unanticipated unemployment rate is equal to the distribution of stock return conditional only on its own past, almost everywhere. This corresponds to testing the conditional independence between stock return and past (present) changes in the anticipated or unanticipated unemployment rate conditionally on past stock return. It is also a test of Granger non-causality in distribution, as opposed to the existing regression based tests that examine only Granger non-causality in mean. In the mean regression the dependence is only due to the mean dependence, thus one ignores the dependence described by high-order moments and quantiles. Granger causality tests provide useful information on whether knowledge of past (present) changes in the anticipated and unanticipated components of the unemployment rate improves short-run forecasts of current and future movements in stock return. The test that we consider here [hereafter non-linear Granger causality test or nonparametric Granger causality test] can detect any type of Granger causality (linear, non-linear) and at any level (quantile) of the conditional distribution of stock return. We consider a new nonparametric test statistic proposed recently by Bouezmarni, Roy, and Taamouti (2010) [hereafter BRT(2010)].

Before we show how the nonparametric test works, let $\left\{(r_t,\ z_t)'\right\}_{t=1}^{T}$ be a sample of T observations on weakly dependent random variables in $\mathbb{R} \times \mathbb{R}$, with joint distribution function F and density function f. Here the random variable z_t represents either the anticipated or unanticipated component of growth rate of the unemployment rate. Assume now that we are interested in testing the conditional independence between r_t and z_{t-1} (z_t) conditionally on r_{t-1}. This corresponds to test the null hypothesis

$$H_0^D : \Pr\left\{F\left(r_t \mid r_{t-1}, z_{t-1}(\text{or } z_t)\right) = F\left(r_t \mid r_{t-1}\right)\right\} = 1 \tag{2}$$

against the alternative hypothesis

$$H_1^D : \Pr\left\{F\left(r_t \mid r_{t-1}, z_{t-1}(\text{or } z_t)\right) = F\left(r_t \mid r_{t-1}\right)\right\} < 1. \tag{3}$$

Since the conditional distribution functions $F\left(r_t \mid r_{t-1}, z_{t-1}(\text{or } z_t)\right)$ and $F\left(r_t \mid r_{t-1}\right)$ are unknown, we use a nonparametric approach to estimate them. We follow BRT(2010) to use Nadaraya-Watson approach proposed by Nadaraya (1964) and Watson (1964). For simplicity of exposition, hereafter we focus our discussion on testing the impact of lagged anticipated and unanticipated unemployment rates on stock return. The test can be defined in a similar way when we test the instantaneous effects. If we denote $\overline{V}_{t-1} = (r_{t-1}, z_{t-1})' \in \mathbb{R}^2$ and $\bar{v} = (r, z)'$, for $z = g_u^e,\ g_u^u$, then the Nadaraya-Watson estimator of the conditional distribution function of r_t given z_{t-1} and r_{t-1} is defined by:

$$\hat{F}_{h_1}(r_t|\bar{v}) = \frac{\sum_{t=2}^{T+1} K_{h_1}(\bar{v} - \overline{V}_{t-1})\, \mathrm{I}_{A_{R_t}}(r_t)}{\sum_{t=2}^{T+1} K_{h_1}(\bar{v} - \overline{V}_{t-1})}, \tag{4}$$

where $K_{h_1}(.) = h_1^{-2} K(./h_1)$, for $K(.)$ a kernel function, $h_1 = h_{1,T}$ is a bandwidth parameter, and $\mathrm{I}_{A_{R_t}}(.)$ is an indicator function defined on the set $A_{R_t} = [R_t, +\infty)$. Similarly, the Nadaraya-Watson estimator of the conditional distribution function of r_t given only r_{t-1} is defined by:

$$\hat{F}_{h_2}(r_t|r) = \frac{\sum_{t=2}^{T+1} K^*_{h_2}(r - r_{t-1})\, \mathrm{I}_{A_{R_t}}(r_t)}{\sum_{t=2}^{T+1} K^*_{h_2}(r - r_{t-1})}, \tag{5}$$

where $K^*_{h_2}(.) = h_2^{-1} K^*(./h_2)$, for $K^*(.)$ a different kernel function, and $h_2 = h_{2,T}$ is a different bandwidth parameter. Notice that the Nadaraya-Watson estimators of the conditional distribution functions are positive and monotone. To test the null hypothesis (2) against the alternative hypothesis (3), BRT(2010) propose the following test statistic

$$\hat{\Gamma} = \frac{1}{T} \sum_{t=2}^{T+1} \left\{ \hat{F}_{h_1}(r_t|\overline{V}_{t-1}) - \hat{F}_{h_2}(r_t|r_{t-1}) \right\}^2 w(\overline{V}_{t-1}), \tag{6}$$

where $w(.)$ is a nonnegative weighting function of the data $\overline{V}_{t-1}$, for $2 \leq t \leq T+1$. The test statistic $\hat{\Gamma}$ depends obviously on the sample size and it is close to zero if conditionally on r_{t-1}, the variables r_t and z_{t-1} are independent and it diverges in the opposite case. Assuming $\beta-$mixing dependent variables, BRT(2010) establish the asymptotic distribution of the nonparametric test statistic in (6). They show that the test is asymptotically pivotal under the null hypothesis and follows a normal distribution. Since the distribution of their test statistic is only valid asymptotically, for finite samples they suggest to use a local bootstrap version of the test statistic. In a finite sample, the asymptotic normal distribution does not generally provide a satisfactory approximation for the exact distribution of nonparametric test statistic. Further, simple resampling from the empirical distribution will not conserve the conditional dependence structure in the data. Hence, the importance of using the local smoothed bootstrap suggested by Paparoditis and Politis (2000). The latter improves quite a lot the finite sample properties (size and power) of the nonparametric test. BRT(2010) report the results of a Monte Carlo experiment to illustrate the size and power of their test which is based on local smoothed bootstrap. In the simulation study, they considered two groups of data generating processes (DGPs) that correspond to linear and nonlinear regression models with different forms of heteroscedasticity. They used four DGPs to evaluate the empirical size and five DGPs to evaluate the power. They also considered two different reasonable sample sizes, $T = 200$ and $T = 300$. For each DGP and sample size, they have generated 500 independent realizations and for each realization, 500 bootstrapped samples were obtained. Since optimal bandwidths are not available, they have considered the bandwidths $h_1 = c_1 T^{-1/4.75}$ and $h_2 = c_2 T^{-1/4.25}$ for various values of c_1 and c_2 ($c_1 = c_2 = 2$, $c_1 = c_2 = 1.5$, $c_1 = c_2 = 1$, and $c_1 = 0.8$ and $c_2 = 0.7$), which corresponds to the most practical. These bandwidths satisfy the assumptions needed to derive the asymptotic distribution of the test statistic. Based on 500 replications, the standard error of the rejection frequencies in their simulation study is 0.0097 at the nominal level $\alpha = 5\%$ and 0.0134 at $\alpha = 10\%$. Globally, the size of the test is fairly well controlled even with series of length $T = 200$. At 5%, all rejection frequencies are within 2 standard errors. However, at 10%, three rejection frequencies are between 2 and 3 standard errors (two at $T = 200$ and one at $T = 300$). They find no strong evidence of overrejection or underrejection. Finally, the empirical power of their test performs quite well. In most cases, the test produces the greatest power when $c_1 = c_2 = 1$. Thus, BRT(2010) test which is based on the local smoothed bootstrap is a valid test and appropriate to test the Granger non-causality in distribution. Thus, in the next sections we will use the local smoothed bootstrap to compute the *p-values.*

3.1 Linear versus non-linear Granger causality

To test for linear Granger causality (or feedback) from anticipated and unanticipated components of growth rate of unemployment rate to stock market return, we consider the following linear regression model

$$r_t = \mu + \beta\, r_{t-1} + \alpha\, z_{t-1} + \varepsilon_t, \tag{7}$$

where r_t is the stock return at time t, z_{t-1} represents either the anticipated or unanticipated component of growth rate of unemployment rate at time $t-1$, and ε_t is an error term. Here we say that z_{t-1} does not Granger cause r_t if the null hypothesis $H_0 : \alpha = 0$ is true. To test for the instantaneous Granger causality between anticipated (resp. unanticipated) component of unemployment rate and stock return, in Equation (7) we replace z_{t-1} by $z_t = g^e_{u,t}$ (resp. $z_t = g^u_{u,t}$). In section 4.1, we consider other extensions of linear regression model given by Equation (7).

We first use the conventional t-statistic to test the above null hypothesis H_0. To avoid the impact of the dependence in the error terms on the inference, we consider a t-statistic which is based on the commonly used HAC robust variance estimator. The results for linear feedback and instantaneous Granger causality tests, say LN, are presented in Table 6. The *p-value* for testing the instantaneous Granger causality between anticipated (resp. unanticipated) growth rate and stock return is equal to 0.926 (resp. 0.310) [see Panel A in Table 6]. At 5%, 10% and even 30% significance levels, we find that instantaneous changes in anticipated and unanticipated unemployment rates have no impact on stock market returns. Further, the *p-value* for testing the feedback Granger causality from anticipated (resp. unanticipated) unemployment rate to stock return is equal to 0.089 (resp. 0.114) [see Panel B in Table 6]. Thus, at 5% significance level, there's no statistical evidence for the feedback effect of changes in anticipated and unanticipated unemployment rates

Table 6: P-values of linear and nonlinear Granger causality tests

Test statistic / H_0	From g_u^e to r	From g_u^u to r
	Panel A: *Instantaneous Effect*	
LN	0.926	0.310
BRT, $c = 2$	0.036	0.244
BRT, $c = 1.5$	0.048	0.320
BRT, $c = 1$	0.052	0.192
BRT, $c_1 = 0.8$, $c_2 = 0.7$	0.060	0.152
	Panel B: *Feedback Effect*	
LN	0.089	0.114
BRT, $c = 2$	0.000	0.324
BRT, $c = 1.5$	0.000	0.280
BRT, $c = 1$	0.000	0.230
BRT, $c_1 = 0.8$, $c_2 = 0.7$	0.000	0.132

Note: *P-values for the tests of the instantaneous and feedback Granger non-causality in mean (LN) and distribution (BRT) from anticipated and unanticipated unemployment growth rates to stock market returns.*

on stock market return. Consequently, we may conclude that there is no linear impact of unemployment rate on stock market prices.

We now test for nonlinear Granger causality (feedback) from anticipated and unanticipated components of unemployment rate to stock market return. To do so, we test the null hypothesis (2) against the alternative hypothesis (3) using the nonparametric test statistic given by (6). The results for testing the instantaneous and feedback Granger causality in distribution, say BRT, are presented in Table 6. The latter reports the *p-values* computed using the local smoothed bootstrap. Contrary to the conventional t-statistic, at 5% significance level, we find strong evidence that the *lagged* anticipated unemployment rate Granger causes the conditional distribution function of stock market return. Further, we see that there's a weak evidence of an instantaneous causality between anticipated unemployment rate and stock return. However, we also find convincing evidence that there is no instantaneous and feedback Granger causality from unanticipated unemployment rate to stock return, even at 10% significance level. Hence, we conclude that unemployment rate affects the distribution of stock return *only* through its anticipated component.

The rejection of Granger non-causality in distribution hypothesis from anticipated unemployment rate to stock market return does not inform us about the level of stock return distribution where the causality exists. To overcome this problem, in the next section we use quantile regression analysis to identity the effect of anticipated and unanticipated unemployment rates at each quantile of stock return distribution.

4 Quantile analysis

While the big majority of regression models are concerned with examining the conditional mean of a dependent variable, there is an increasing interest in methods of modeling other aspects of the conditional distribution. One important and popular approach, quantile regression, models the quantiles of the dependent variable given a set of conditioning variables. As originally developed by Koenker and Bassett (1978), quantile regression model provides estimates of linear relationship between a set of covariates and a specified quantile of the dependent variable. Quantile regression offers a more complete description of the conditional distribution than conditional mean analysis. For example, it can describe how the median, or the 10th or 90th quantile of the response variable, are affected by regressor variables. Moreover, quantile regressions do not require strong distributional assumptions and they are robust compared to mean regressions against outliers, and can thus be estimated with greater precision than conventional moments [see Harvey and Siddique (2000)]. Further, under some asymmetric loss functions, conditional quantiles may be optimal forecasts.

To see how the estimation and inference work for quantile regressions, we first denote the αth quantile of the conditional distribution of stock return by $Q_\alpha\left(r_t \mid I_{t-1}\right)$, where I_{t-1} is an information set containing the past (present) of the variables of interest. Observe that the null hypothesis (2) is equivalent to

$$H_0^Q : Q_\alpha\left(r_t \mid r_{t-1}, z_{t-1}(\text{or } z_t)\right) = Q_\alpha\left(r_t \mid r_{t-1}\right), \quad \forall\alpha \in (0,1), \text{ a.s.,} \tag{8}$$

where z_{t-1} (resp. z_t) represents either the anticipated or unanticipated component of growth rate of the unemployment rate at time $t-1$ (resp. t). If the null hypothesis H_0^Q holds, then we say that the components of the unemployment rate do not Granger cause the distribution of stock return. In other words, Granger non-causality in distribution from z to r is equivalent to Granger non-causality in all quantiles from z to r. One advantage of testing H_0^Q instead of H_0^D is that the former can help to identify the levels of the conditional distribution of stock return at which the causality(ies) exist(s). We also consider a Granger non-causality at a given quantile α using the following null hypothesis

$$H_0^{Q_\alpha} : Q_\alpha\left(r_t \mid r_{t-1}, z_{t-1}(\text{or } z_t)\right) = Q_\alpha\left(r_t \mid r_{t-1}\right), \text{ for a given } \alpha \in (0,1). \tag{9}$$

If $H_0^{Q_\alpha}$ holds, then we say that the components of the unemployment rate do not Granger cause the αth quantile of stock market return.

Now to examine the Granger causality (feedback) in quantiles from z to r, we consider the following quantile regression model

$$r_t = \theta\left(\alpha\right)' w_{t-1} + \varepsilon_t^{(\alpha)}, \text{ for a given } \alpha \in (0,1). \tag{10}$$

where $w_{t-1} = (1, z_{t-1}, r_{t-1})'$, for $z_{t-1} = g_{u,t-1}^e$, $g_{u,t-1}^u$, $\theta\left(\alpha\right) = \left(\mu\left(\alpha\right), \beta_1\left(\alpha\right), \beta_2\left(\alpha\right)\right)'$ is an unknown vector of parameters associated with the αth quantile, and $\varepsilon_t^{(\alpha)}$ is an unknown error term also associated with the

αth quantile and which satisfies the unique condition:

$$Q_\alpha\left(\varepsilon_t^{(\alpha)} \mid r_{t-1}, z_{t-1}\right) = 0, \tag{11}$$

that is, the conditional αth quantile of the error term is equal to zero. Observe that the null hypothesis $H_0^{Q_\alpha}$ (H_0^{Q}) is general in the sense that it does not specify the functional form of the quantile function which can be linear or nonlinear. However, in equation (10) we consider that this functional form is linear, we thus implicitly assume that the dependence at each quantile of stock return distribution is linear. Further, for the purposes of estimation and inference the i.i.d. errors assumption is not needed. Finally, under Assumption (11), the αth conditional quantile of r_t is given by:

$$Q_\alpha\left(r_t \mid r_{t-1}, z_{t-1}\right) = \theta\left(\alpha\right)' w_{t-1}.$$

Based on the quantile regression in (10), the lagged anticipated and unanticipated components of the unemployment rate do not Granger cause the *αth quantile* of stock market return if $H_{lin,0}^{Q_\alpha} : \beta_1\left(\alpha\right) = 0$ is true. The latter hypothesis corresponds to a *feedback* Granger non-causality in the *αth quantile* of stock return distribution. We can similarly define an *instantaneous* Granger non-causality in the αth quantile between the components of the unemployment rate and stock return by replacing in Equation (10) z_{t-1} with z_t.

Using Koenker and Bassett (1978), the quantile regression estimator of the vector $\theta\left(\alpha\right)$ is the solution to the following minimization problem:

$$\hat{\theta}\left(\alpha\right) = \underset{\theta(\alpha)}{\arg\min}\left(\sum_{t: r_t > \theta(\alpha)' w_{t-1}} \alpha \mid r_t - \theta\left(\alpha\right)' w_{t-1} \mid + \sum_{t: r_t < \theta(\alpha)' w_{t-1}} \left(1-\alpha\right) \mid r_t - \theta\left(\alpha\right)' w_{t-1} \mid\right). \tag{12}$$

The quantile regression estimator in (12) minimizes a weighted sum of the absolute errors $\varepsilon_t^{(\alpha)}$, where the weights α and $(1-\alpha)$ are symmetric and equal to $\frac{1}{2}$ for the median regression case and asymmetric otherwise. The estimator $\hat{\theta}\left(\alpha\right)$ can be obtained as the solution to a linear programming problem. Several algorithms for obtaining a solution to this problem have been proposed in the literature [see Koenker and D'Orey (1987), Barrodale and Roberts (1974), Koenker and Hallock (2001) and Portnoy and Koenker (1997)]. Further, under some regularity conditions, the estimator $\hat{\theta}\left(\alpha\right)$ is asymptotically normally distributed with different forms of the asymptotic covariance matrix depending on the model assumptions [see Koenker (2005)]

$$\sqrt{T}\left(\hat{\theta}\left(\alpha\right) - \theta\left(\alpha\right)\right) \overset{d}{\sim} \mathcal{N}\left(0, \Sigma_\alpha\right). \tag{13}$$

Thus, tests can be constructed using critical values from the normal distribution with asymptotic justification. Computation of an estimator of the covariance matrix Σ_α is very important in quantile regression analysis. Generally speaking, we distinguish between three classes of estimators for Σ_α: **(1)** methods for estimating the Σ_α in i.i.d. settings; **(2)** methods for estimating Σ_α for independent but not-identical distribution; **(3)** bootstrap resampling methods for both i.i.d. and independent and non identically distributed settings [see Koenker (2005)]. However, the estimator most commonly used in practice and the more efficient in small samples is based on the design matrix bootstrap [see Buchinsky (1995)]. The design matrix bootstrap estimator of Σ_α was suggested initially by Efron (1979, 1982) and is given by:

$$\hat{\Sigma}_\alpha^* = \frac{T}{B} \sum_{j=1}^{B} \left(\hat{\theta}_j^* (\alpha) - \hat{\theta} (\alpha) \right) \left(\hat{\theta}_j^* (\alpha) - \hat{\theta} (\alpha) \right)', \tag{14}$$

where $\hat{\theta}_j^* (\alpha)$ is the quantile regression estimator based on the jth bootstrap sample, for $j = 1, ..., B$. The bootstrap samples $\left\{ (r_t^*, z_t^*)' \right\}_{t=1}^T$ are drawn from the empirical joint distribution of r and z. The design matrix bootstrap is the most natural form of bootstrap resampling, and is valid in settings where the error term $\varepsilon_t^{(\alpha)}$ and regressors $(z_{t-1}, r_{t-1})'$ are not independent. Buchinsky (1995) examined, via Monte Carlo simulations, six different estimation procedures of the asymptotic covariance matrix Σ_α: design matrix bootstrap; error bootstrapping; order statistic; sigma bootstrap; homoskedastic kernel and heteroskedastic kernel. In his study, Monte Carlo samples are drawn from real data sets and the estimators are evaluated under various realistic scenarios. His results favor the design bootstrap estimation of Σ_α for the general case. Consequently, in the empirical application we use a t-statistic which is based on the standard errors obtained from the design matrix bootstrap estimator. For robustness check, in Section 6 we consider other testing procedures based on Markov Chain Marginal Bootstrap (MCMB) introduced by He and Hu (2002) [see also Kocherginsky, He, and Mu (2005)].

4.1 Mean Analysis

We start by examining the impact of anticipated and unanticipated unemployment rates on the conditional mean of stock market return. To do so, we consider the following regression models:

$$r_t = \omega_r + \alpha_1 \; g_{u,t} + \alpha_2 \; g_{u,t-1} + \alpha_3 \; g_{u,t}^e + \alpha_4 \; g_{u,t-1}^e + \alpha_5 \; g_{u,t}^u + \alpha_6 \; g_{u,t-1}^u + \alpha_7 \; r_{t-1} + e_t, \tag{15}$$

where in

$$\begin{aligned}
&\text{Model 1: } \omega_r, \alpha_1, \alpha_2, \alpha_7 \neq 0, \; \alpha_3, \; \alpha_4, \; \alpha_5, \; \alpha_6 = 0,\\
&\text{Model 2: } \omega_r, \alpha_3, \alpha_7 \neq 0, \; \alpha_1, \; \alpha_2, \; \alpha_4, \; \alpha_5, \; \alpha_6 = 0,\\
&\text{Model 3: } \omega_r, \alpha_5, \alpha_7 \neq 0, \; \alpha_1, \; \alpha_2, \; \alpha_3, \; \alpha_4, \; \alpha_6 = 0,\\
&\text{Model 4: } \omega_r, \alpha_3, \alpha_5, \alpha_7 \neq 0, \; \alpha_1, \; \alpha_2, \; \alpha_4, \; \alpha_6 = 0,\\
&\text{Model 5: } \omega_r, \alpha_4, \alpha_7 \neq 0, \; \alpha_1, \; \alpha_2, \; \alpha_3, \; \alpha_5, \; \alpha_6 = 0,\\
&\text{Model 6: } \omega_r, \alpha_6, \alpha_7 \neq 0, \; \alpha_1, \; \alpha_2, \; \alpha_3, \; \alpha_4, \; \alpha_5 = 0,\\
&\text{Model 7: } \omega_r, \alpha_4, \alpha_6, \alpha_7 \neq 0, \; \alpha_1, \; \alpha_2, \; \alpha_3, \; \alpha_5 = 0,
\end{aligned} \tag{16}$$

and $E\left[e_t \mid I_{t-1} \text{ (or } I_t)\right] = 0$, with I_{t-1} (resp. I_t) represents the set of covariates at time $t-1$ (resp. t) that defines each of the above models. The parameters in the mean regressions are unknown and will be estimated using OLS. Tests for statistical significance will be performed using the conventional t-statistics calculated using heteroskedasticity autocorrelation consistent (HAC) estimator of variance. The results of the estimation and inference using the data described in section 2 are presented in Table 7, in which the *p-values* are given between parentheses. From these, we see that the constant terms in all mean regression models are positive and statistically significance at 5% and 1% significance levels. We find that the unemployment growth rate and its anticipated and unanticipated components have a negative immediate impact on the conditional mean of stock market return, whereas their lagged effects are positive. However, none of the coefficients of the immediate and lagged effects is statistically significant at 5% and 10% significance levels. The coefficient of determination (R^2) indicates that the regression equations with lagged anticipated and unanticipated unemployment rates explain better the conditional mean return.

Table 7: Conditional Mean Regressions: Estimation and Inference

Mean	M1	M2	M3	M4	M5	M6	M7
Const.	0.0021 (0.005)	0.0023 (0.001)	0.0023 (0.001)	0.0023 (0.001)	0.0021 (0.004)	0.0022 (0.003)	0.0021 (0.004)
$g_{u,t}$	−0.0276 (0.570)						
$g_{u,t-1}$	0.0204 (0.716)						
$g^e_{u,t}$		−0.0148 (0.926)		−0.0149 (0.927)			
$g^e_{u,t-1}$					0.1448 (0.235)		0.1448 (0.235)
$g^u_{u,t}$			−0.0368 (0.310)	−0.0368 (0.310)			
$g^u_{u,t-1}$						0.0061 (0.898)	0.0061 (0.897)
r_{t-1}	0.0645 (0.160)	0.0607 (0.184)	0.0584 (0.200)	0.0583 (0.199)	0.0623 (0.184)	0.0617 (0.182)	0.0624 (0.182)
$R^2(\%)$	0.506	0.373	0.465	0.467	0.610	0.383	0.613

The above mean regression analysis shows that both anticipated and unanticipated unemployment rates have no impact on mean of stock market returns. Thus, if we only focus on mean regressions, then we must conclude that there is no causality from unemployment rate to stock market return. However, given the results of nonparametric tests, this raises the question of whether the causality exists at other levels (quantiles) of the conditional distribution of stock return. This also indicates that the mean regression analysis is not enough and can leads to wrong conclusions.

4.2 Median Analysis

We now investigate the impact of anticipated and unanticipated unemployment rates on the median of stock market return using the regression models:

$$r_t = \mu_r^{(0.5)} + \beta_1^{(0.5)}\ g_{u,t} + \beta_2^{(0.5)}\ g_{u,t-1} + \beta_3^{(0.5)}\ g_{u,t}^e + \beta_4^{(0.5)}\ g_{u,t-1}^e + \beta_5^{(0.5)} g_{u,t}^u + \beta_6^{(0.5)} g_{u,t-1}^u + \beta_7^{(0.5)}\ r_{t-1} + u_t^{(0.5)}, \tag{17}$$

where in

$$\begin{aligned}
&\text{Model 1: } \mu_r^{(0.5)}, \beta_1^{(0.5)}, \beta_2^{(0.5)}, \beta_7^{(0.5)} \neq 0,\ \beta_3^{(0.5)},\ \beta_4^{(0.5)},\ \beta_5^{(0.5)},\ \beta_6^{(0.5)} = 0,\\
&\text{Model 2: } \mu_r^{(0.5)}, \beta_3^{(0.5)}, \beta_7^{(0.5)} \neq 0,\ \beta_1^{(0.5)},\ \beta_2^{(0.5)},\ \beta_4^{(0.5)},\ \beta_5^{(0.5)},\ \beta_6^{(0.5)} = 0,\\
&\text{Model 3: } \mu_r^{(0.5)}, \beta_5^{(0.5)}, \beta_7^{(0.5)} \neq 0,\ \beta_1^{(0.5)},\ \beta_2^{(0.5)},\ \beta_3^{(0.5)},\ \beta_4^{(0.5)},\ \beta_6^{(0.5)} = 0,\\
&\text{Model 4: } \mu_r^{(0.5)}, \beta_3^{(0.5)}, \beta_5^{(0.5)}, \beta_7^{(0.5)} \neq 0,\ \beta_1^{(0.5)},\ \beta_2^{(0.5)},\ \beta_4^{(0.5)},\ \beta_6^{(0.5)} = 0,\\
&\text{Model 5: } \mu_r^{(0.5)}, \beta_4^{(0.5)}, \beta_7^{(0.5)} \neq 0,\ \beta_1^{(0.5)},\ \beta_2^{(0.5)},\ \beta_3^{(0.5)},\ \beta_5^{(0.5)},\ \beta_6^{(0.5)} = 0,\\
&\text{Model 6: } \mu_r^{(0.5)}, \beta_6^{(0.5)}, \beta_7^{(0.5)} \neq 0,\ \beta_1^{(0.5)},\ \beta_2^{(0.5)},\ \beta_3^{(0.5)},\ \beta_4^{(0.5)},\ \beta_5^{(0.5)} = 0,\\
&\text{Model 7: } \mu_r^{(0.5)}, \beta_4^{(0.5)}, \beta_6^{(0.5)}, \beta_7^{(0.5)} \neq 0,\ \beta_1^{(0.5)},\ \beta_2^{(0.5)},\ \beta_3^{(0.5)},\ \beta_5^{(0.5)} = 0,
\end{aligned} \tag{18}$$

and $Q_{0.5}\left(u_t^{(0.5)} \mid I_{t-1} \text{ (or } I_t)\right) = 0$, with I_{t-1} (resp. I_t) represents the set of covariates at time $t-1$ (resp. t) that defines each of the above models. The parameters in the median regression models are unknown and can be estimated using the method described at the beginning of section 4. Tests for statistical significance will be performed using the statistical procedures discussed in section 4. The estimation of the covariance matrix Σ_α will be done using the design matrix bootstrap estimator with $B = 5000$ replications.

The estimation and inference results are presented in Table 8. We first see that the constant terms in all median regressions are positive and statistically very significant. Second, we find that the unemployment growth rate and its anticipated component have a positive immediate and lagged effects on the conditional median of stock market return, whereas the unanticipated component has a negative immediate and lagged effects. Tests for statistical significance show that the immediate and lagged effects of unemployment growth rate and its unanticipated component are statistically insignificant at 5% and 10% significance levels. The same conclusion can be drawn for the immediate effect of the anticipated component. However, the lagged effect of anticipated unemployment growth rate is economically important and statistically very significant even at 0.2% significance level. Finally, we find that the coefficient of determination is more sizeable for models with lagged anticipated unemployment rate.

Contrary to the conventional mean regression analysis, the median regressions show that unemployment rate Granger causes the median of stock market return. However, only lagged anticipated component has a positive and statistically significant impact. A 1% increases in lagged anticipated unemployment growth rate decreases the median of stock market return by approximately 0.30 points, whereas in the mean regression analysis it decreases the mean return by approximately 0.15 points. Of course, anticipated unemployment rate could affect other levels (quantiles) of the conditional distribution of stock market return. Thus, this will be investigate in the next sub-section.

Table 8: Conditional Median Regressions: Estimation and Inference

Median	M1	M2	M3	M4	M5	M6	M7
Const.	0.0040 (0.000)	0.0038 (0.000)	0.0039 (0.000)	0.0036 (0.000)	0.0037 (0.000)	0.0039 (0.000)	0.0037 (0.000)
$g_{u,t}$	0.0199 (0.751)						
$g_{u,t-1}$	0.0409 (0.572)						
$g^e_{u,t}$		0.1471 (0.272)		0.1339 (0.317)			
$g^e_{u,t-1}$					0.2951 (0.002)		0.3044 (0.002)
$g^u_{u,t}$			-0.0113 (0.822)	-0.0332 (0.529)			
$g^u_{u,t-1}$						-0.0428 (0.474)	-0.0285 (0.628)
r_{t-1}	0.0140 (0.768)	0.0047 (0.914)	0.0101 (0.817)	0.0019 (0.965)	0.0152 (0.714)	0.0129 (0.775)	0.0215 (0.607)
$R^2(\%)$	0.075	0.107	0.012	0.141	0.867	0.094	0.894

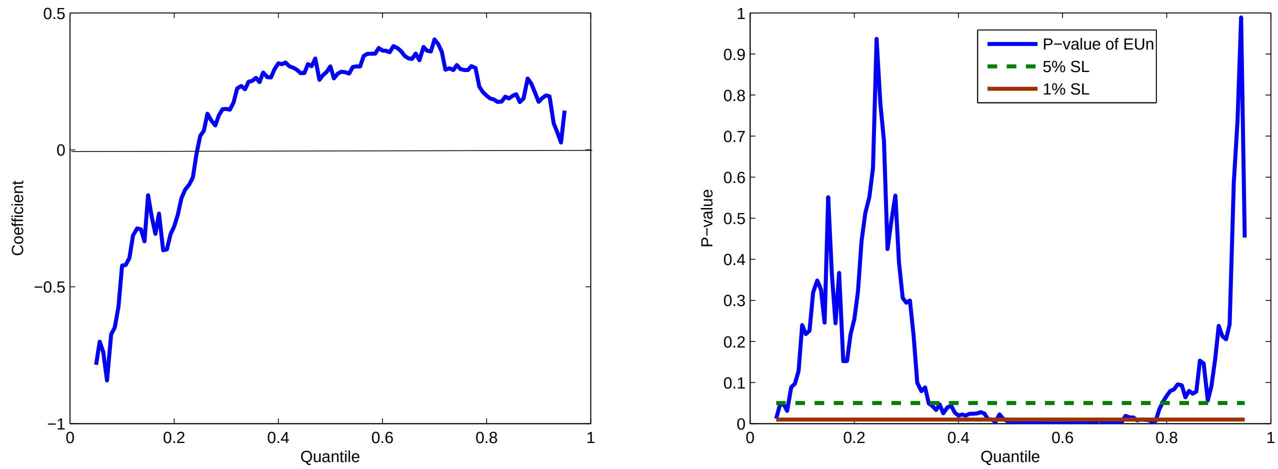
4.3 Lower and upper quantiles Analysis

Nonparametric analysis has suggested that anticipated unemployment rate can cause *any* quantile of conditional distribution of stock return *not only* its median. Thus, it is necessarily to examine the causality at other quantiles of stock return distribution. Since the nonparametric and median analyses recommend that only *lagged* unemployment rate components can explain stock market returns, in the following we concentrate our attention on studying the feedback (lagged) effects. We consider the quantile regression models:

$$r_t = \eta_r^{(\alpha)} + \lambda_1^{(\alpha)}\ g^e_{u,t-1} + \lambda_2^{(\alpha)}\ g^u_{u,t-1} + \lambda_3^{(\alpha)} r_{t-1} + v_t^{(\alpha)},\ \text{for } \alpha \in (0,1)\,, \tag{19}$$

with $Q_\alpha\left(v_t^{(\alpha)} \mid g^e_{u,t-1},\ g^u_{u,t-1}, r_{t-1}\right) = 0$. The estimation of $\eta_r^{(\alpha)}, \lambda_1^{(\alpha)}\ , \lambda_2^{(\alpha)}$, and $\lambda_3^{(\alpha)}$ and the tests for their statistical significance will be performed using the techniques discussed in section 4.

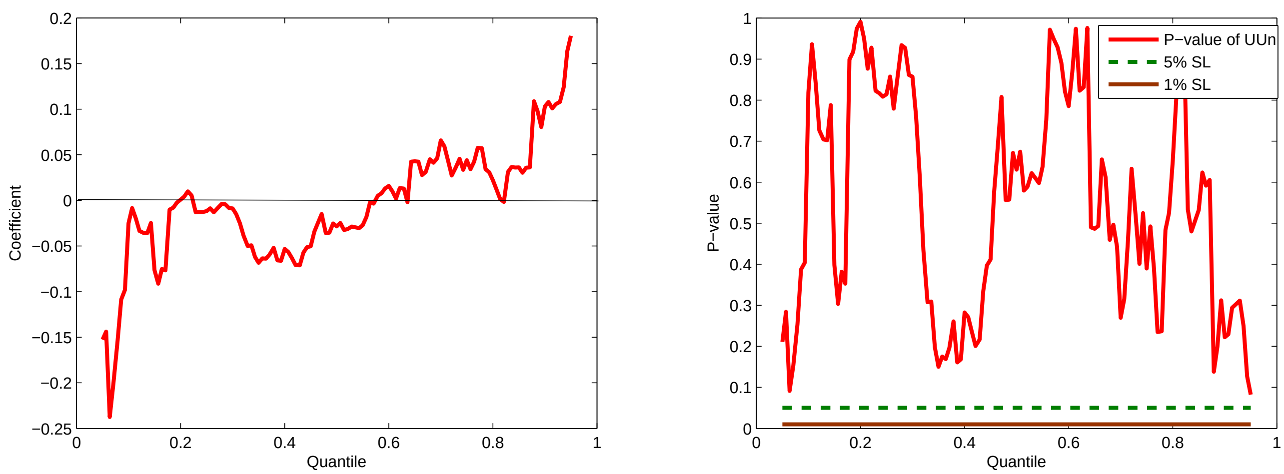
The estimation and inference results are reported in Figures 2 and 3, respectively. From these, we find that lagged anticipated unemployment rate affects negatively the quantile range (0.05, 0.25). The impact is positive for the quantile range (0.25, 0.95) [see Figure 2-(a)]. During a bear market the lagged anticipated unemployment rate affects negatively the 20% of the lower quantiles of stock return, whereas during a bull market it affects positively the 70% of the upper quantiles of stock return. Consequently, the most of the



(a) Coefficient

(b) P-value

Figure 2: Impact of anticipated unemployment growth rate on stock market return

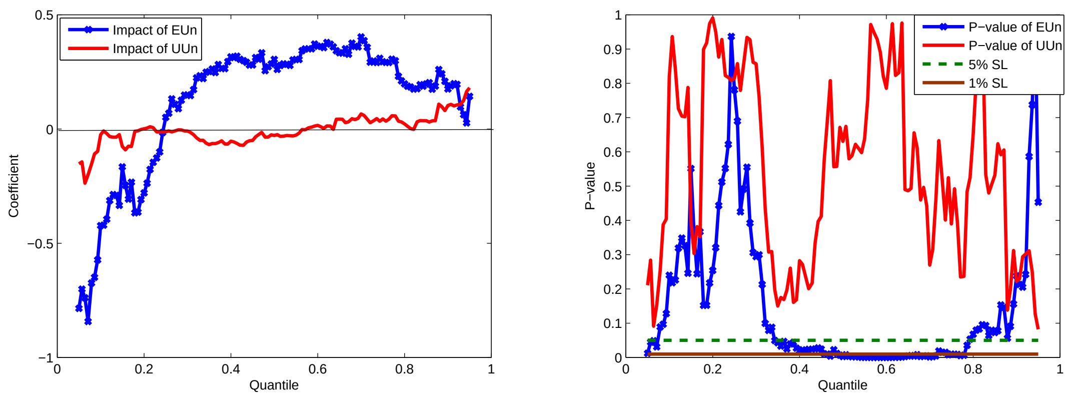


(a) Coefficient

(b) P-value

Figure 3: Impact of unanticipated unemployment growth rate on stock market return

time the anticipated unemployment rate affects positively stock market return. This is confirmed by Figure 2-(b) which shows that the effect of lagged anticipated unemployment rate is statistically significant, both at 5% and 1% levels, for quantile range (0.35, 0.77), except for very extreme lower quantiles. Hence, we can conclude that for the most of the time an increase in the lagged anticipated growth rate leads to a statistically significant increase in stock market return. Finally, Figure 3-(a) shows that contrary to the anticipated unemployment rate, unanticipated unemployment rate has no impact on stock market return: the sign of the impact changes continuously through the quantiles. This is confirmed by Figure 3-(b) where we see that the effect is statistically insignificant both at 1% and 5% significant levels and at all quantiles of stock market return.



(a) Coefficient

(b) P-value

Figure 4: Impact of unanticipated and anticipated unemployment growth rates on stock market return

Again quantile regression analysis confirms that unemployment rate affects stock market return through its anticipated component. This effect is both economically and statistically important [see Figure 4]. This provides empirical evidence that more can be learned about stock market through studying the joint dynamics of stock prices and unemployment rate. Thus, the quantile analysis produces stylized facts on how monthly aggregate stock prices and unemployment rate are intertemporally related.

5 Explaining the stock market's reaction to unemployment rate

Here we identify some possible channels through which stock market prices react to unemployment rate. We follow the argument made by Bernanke and Blinder (1992) who believe that any measure of monetary policy "*should respond to the Federal Reserve's perception of the state of the economy*". Thus, we believe that it exists a function that can explain the movements in monetary policy measures in terms of movements in unemployment rate. This function quantifies the reaction of monetary policy (changes in money supply and Federal funds rate) to changes in unemployment rate. To complete the channel(s), stock market prices must react to monetary policy measures. Some possible channels are given by the following scheme

$$\begin{array}{ccccc} & \nearrow & \text{Money} & \searrow & \\ \text{Unemployment Rate} & & \downarrow & & \text{Stock Market prices.} \\ & \searrow & \text{Federal funds rate} & \nearrow & \end{array}$$

This scheme suggests three different channels: **(1)** unemployment rate affects money, which in turn affects stock market prices; **(2)** unemployment rate affects money and the latter affects Federal funds rate, which in turn affects stock market prices; and **(3)** unemployment rate affects Federal funds rate, which in turn affects stock market prices.

The channels **(1)** and **(3)** contain two different causal directions, whereas the channel **(2)** contains three. Evidence of causal effects of Money and Federal funds rate on stock market prices (returns) can be found in the literature. Many studies have investigated the money-stock price relationship; for the review the reader can consult Homa and Jafee (1971); Palmer (1970); Hamburger and Kochin (1972); Cooper (1974); Rozeff (1974); Thornton (1993); Chan, Foresi, and Lang (1996); Thorbecke (1997); Balvers and Huang (2009) among others. These papers argue that changes in money cause changes in stock prices. Further, recently Taamouti (2011) applied parametric and nonparametric Granger causality tests to find that money has an important and significant impact on stock market returns. Moreover, other papers have investigated the impact of Federal funds rate on stock prices. The most recent papers are Rigobon and Sack (2002) and Bernanke and Kuttner (2005) who found a negative impact of Federal funds rate on stock market return. Given that the last causal links in the above channels are well established in the literature, in the next subsections we focus our attention on analyzing the causal effects from unemployment rate to Money and Federal funds rate. We also examine the causal effect of money on Federal funds rate as in the channel **(2)**.

5.1 Unemployment Rate and Federal funds rate

Here we examine the impact of unemployment rate on Federal funds rate. We start our analysis with the following simple observation which is based on real data. In Figure 5 we plot the monthly U.S. unemployment rate and Federal funds rate. The data on effective Federal Funds Rate come from Federal Reserve Bank-St Louis, dating back to July 1954. The figure shows that the two variables move in opposite directions and the movements happen with some lag: a decrease (increase) in unemployment rate is always followed by an increase (decrease) in Federal funds rate. This may reveal important relationship between unemployment rate and Federal Funds Rate.

We now explore the existing economic theories to formally investigate the reaction of Federal funds rate to unemployment rate. We consider the well known Fisher and Phillips curve equations. Let $i_{n,t}$, $i_{r,t}$, π_t, and

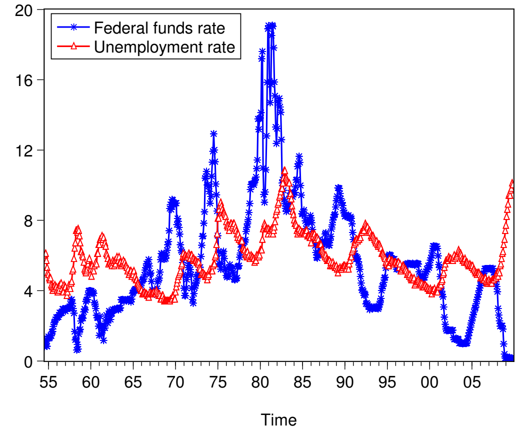


Figure 5: Unemployment rate and Federal funds rate.

u_t, be the nominal interest rate, realized real interest rate, actual rate of inflation, and the unemployment rate at time t, respectively. According to Fisher equation, the following identity holds:

$$i_{n,t} = i_{r,t} + \pi_t. \tag{20}$$

The difference between nominal interest rate $i_{n,t}$ and realized real interest rate $i_{r,t}$ is given by the actual rate of inflation π_t. Further, from the simple version of Phillips curve equation, we have

$$\pi_t = \pi^e + v - \alpha u_t, \tag{21}$$

where π^e is the expected inflation, v represents exogenous economic shocks, and α is is a positive constant. For simplicity of exposition, we implicitly assume that expected inflation and economic shocks are constant, at least at short horizon. Considering π^e and v random variables will not affect our analysis. Thus, Equation (21) implies that a rise in unemployment rate lowers inflation by the amount α. It also indicates that governments had a tool to control inflation and if they were willing to raise inflation, they would achieve a lower level of unemployment. If we plug the Fisher equation into the Phillips curve equation, we obtain

$$i_{n,t} = \pi^e + v - \alpha u_t + i_{r,t}. \tag{22}$$

Equation (22) shows that the nominal interest rate is a linear function of unemployment rate u_t and real interest rate $i_{r,t}$, given constant expected inflation and economic shocks. We now define the component of nominal interest rate response that is strictly due to a change in the unemployment rate factor as follows:

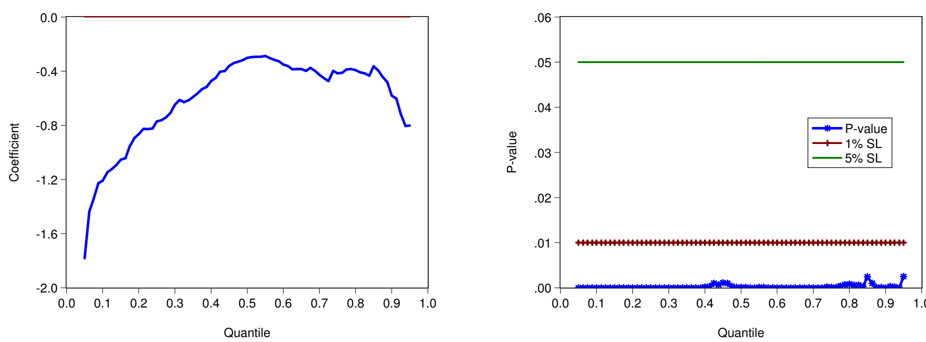
$$\frac{di_{n,t}}{du_t} \mid_{di_{r,t}=0} . \tag{23}$$

Thus, based on equations (22) and (23), we show that:

$$\frac{di_{n,t}}{du_t} \mid_{di_{r,t}=0} = -\alpha. \tag{24}$$

Since α is a positive value, the marginal effect of unemployment rate on nominal interest rate must be negative $\frac{di_{n,t}}{du_t} |_{di_{r,t}=0} < 0$. Bernanke and Blinder (1992) also found a negative reaction function of Federal funds rate to unemployment rate. Thus, high unemployment rate is followed by stimulus by the Fed which consists in lowering Federal funds rate. In turn, Federal funds rate affects stock market prices as shown by Rigobon and Sack (2002), Craine and Martin (2003), Bernanke and Kuttner (2005) and references therein.

To confirm the previous theoretical result on the negative impact of unemployment rate on Federal funds rate, we first consider the mean regression of growth rate of the Federal Funds Rate on a constant and lagged growth rate of the unemployment rate. We find that the coefficient estimate of the impact of unemployment rate is negative and equal to -0.950. The latter is statistically significant with a robust t-statistic equal to -4.454. We also applied quantile regressions and the results [see Figure 6] confirm the strong negative and statistically very significant impact of unemployment rate on Federal funds rate.



(a) Coefficient

(b) P-value

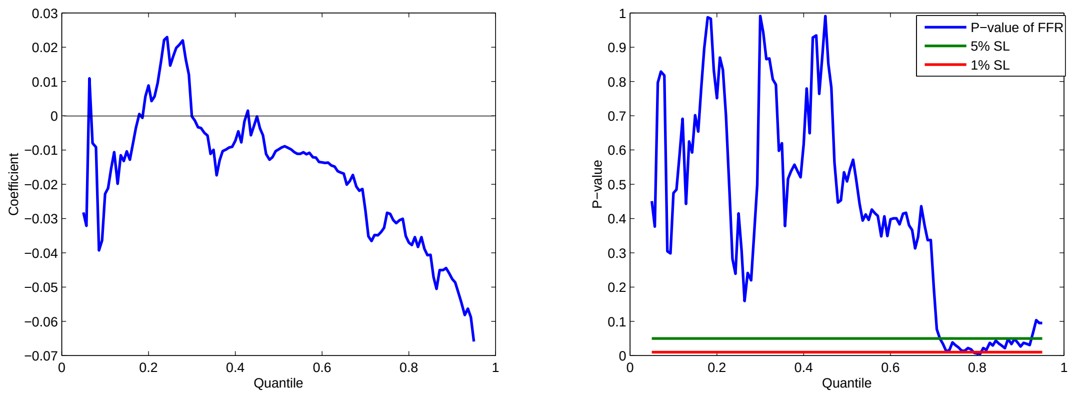
Figure 6: Impact of growth rate of the unemployment rate on Federal funds rate.

Finally, we also use quantile regressions to identify the sign of the impact of Federal funds rate, say ffr_t, on S&P 500 stock returns:

$$r_t = \pi_0^{(\alpha)} + \pi_1^{(\alpha)} ffr_t + \pi_2^{(\alpha)} ffr_{t-1} + \pi_3^{(\alpha)} r_{t-1} + \bar{\epsilon}_t^{\alpha}, \text{ for } \alpha \in [0.05, 0.95]. \tag{25}$$

Figures (7)-(a) and 7-(b) report the coefficient estimates and the p-values of tests for statistical significance of those coefficients, respectively. From these, we see that stock market returns react immediately to Federal funds rate. We find that the Federal funds rate has a negative and statistically significant impact on quantile range [0.72, 0.92]. Bernanke and Kuttner (2005) also find a negative impact of Federal funds rate on mean stock return.

The signs of different causal links in the channel through Federal funds rate (channel **(3)**) can be summarized as follows: a decrease (increase) in unemployment rate is followed by an increase (decrease) in Federal funds rate which in turn leads to an immediate decrease (increase) in stock market price. This



(a) Coefficient (b) P-value

Figure 7: Immediat impact of Federal funds rate on stock returns.

corresponds to what we found in section 4, that is a decrease (increase) in unemployment rate is followed by a statistically significant decrease (increase) in stock market prices.

5.2 Unemployment Rate and Money Supply

We now investigate the impact of unemployment rate on money supply. As in the previous subsection, here we start with the following observation. In Figure 8 we plot the S&P 500 stock price and the ratio of money supply to unemployment rate. As a measure of money supply we use the seasonally adjusted M2 money stock from Federal Reserve Bank-St Louis dating back to January 1959.[1] Figure 8 shows that the stock market prices move the same way as the money supply to unemployment rate ratio. The correlation between the two variables is very high and equal to 0.97. The high correlation may indicate important relationship between money supply, unemployment rate and stock prices. In the following, we use parametric and nonparametric tests to formally investigate the relationship between anticipated/unanticipated unemployment rate and money supply.

To nonparametrically test the impact of anticipated and unanticipated components of unemployment rate on money supply, we consider the following null hypothesis:

$$H_0^D : \Pr\{F(ms_t \mid ms_{t-1},\ z_{t-1}(z_t)) = F(ms_t \mid ms_{t-1})\} = 1, \tag{26}$$

against the alternative hypothesis

$$H_1^D : \Pr\{F(ms_t \mid ms_{t-1},\ z_{t-1}(z_t)) = F(ms_t \mid ms_{t-1})\} < 1, \tag{27}$$

[1]The money M2 includes a broader set of financial assets held principally by households. It consists of money M1 plus: **(1)** savings deposits (includes money market deposit accounts); **(2)** small-denomination time deposits (time deposits in amounts of less than $100,000); and **(3)** balances in retail money market mutual funds.

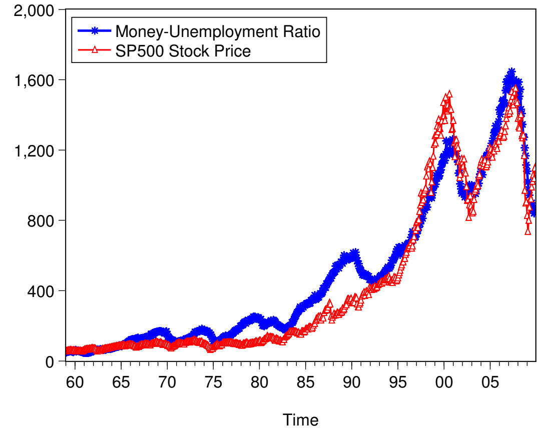


Figure 8: Money-Unemployment rate ratio and SP 500 stock price.

where z_{t-1} (resp. z_t) $= g^e_{u,t-1}, g^u_{u,t-1}$ (resp. $g^e_{u,t}, g^u_{u,t}$) and ms_t is the money supply growth rate at time t. The latter is defined as: $ms_t = \log(MS_t) - \log(MS_{t-1})$, where MS_t is the money supply a time t. The results of nonparametric tests are presented in Table 9. The latter reports the *p-values* for testing the instantaneous (**Panel A**) and lagged **(Panel B)** Granger non-causality from anticipated (column 2) and unanticipated (column 3) unemployment rates to money supply growth rate. We find strong evidence of an *immediate* impact of unemployment rate on money supply growth rate. The feedback effect is generally statistically insignificant. Consequently, the distribution function of money supply growth rate reacts immediately to changes in the unemployment growth rate. Interestingly, we find that only anticipated unemployment rate affects money supply. This possibly indicate that the Fed anticipates the unemployment growth rate and reacts accordingly.

Now, we first use the following mean regression model to identify the sign of the impact of anticipated and unanticipated unemployment rates on money supply,

$$ms_t = \delta_{ms} + \rho_1 g^e_{u,t} + \rho_2 g^e_{u,t-1} + \rho_3 g^u_{u,t} + \rho_4 g^u_{u,t-1} + \rho_5\ ms_{t-1} + \epsilon_t. \tag{28}$$

The estimation results reported in Table 10 confirm the results obtained using nonparametric test: only anticipated unemployment rate affects immediately money supply growth rate. We find that the impact is positive and statistically significant even at 1% significance level. Thus, a decrease (increase) in anticipated unemployment rate is immediately followed by a decrease (increase) in the conditional mean of money supply growth rate.

Given the previous results, we also investigate the immediate impact of anticipated and unanticipated unemployment rates on quantiles of money supply using the following quantile regressions

$$ms_t = \theta^{(\alpha)}_{ms} + \xi^{(\alpha)}_1 g^e_{u,t} + \xi^{(\alpha)}_2 g^u_{u,t} + \xi^{(\alpha)}_3 ms_{t-1} + \epsilon^{\alpha}_t, \text{ for } \alpha \in [0.05, 0.95] \tag{29}$$

Table 9: P-values of linear and nonlinear Granger causality tests

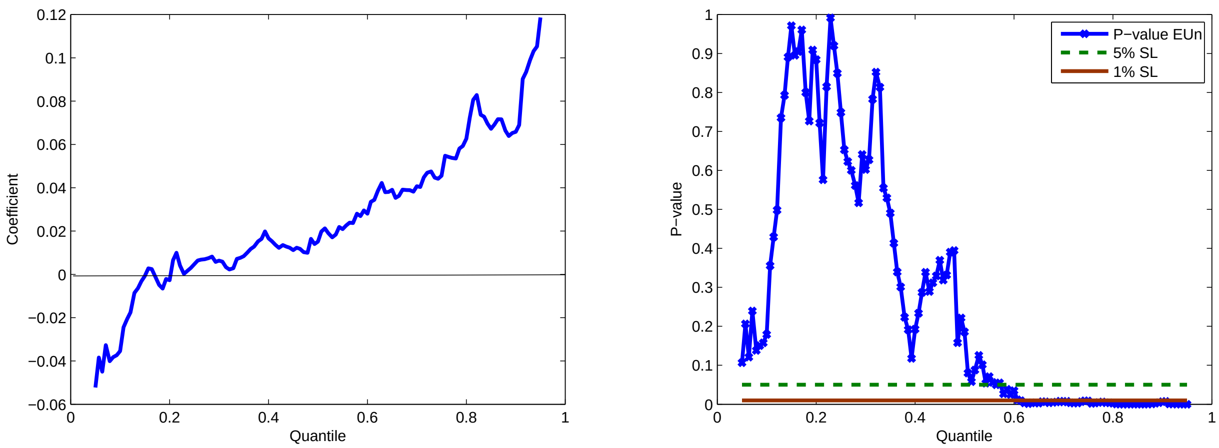
Test statistic / H_0	From g_u^e to ms	From g_u^u to ms
	Panel A: *Instantaneous Effect*	
BRT, $c = 2$	0.012	0.300
BRT, $c = 1.5$	0.012	0.216
BRT, $c = 1$	0.032	0.160
BRT, $c_1 = 0.8$, $c_2 = 0.7$	0.043	0.148
	Panel B: *Feedback Effect*	
BRT, $c = 2$	0.024	0.308
BRT, $c = 1.5$	0.048	0.336
BRT, $c = 1$	0.228	0.712
BRT, $c_1 = 0.8$, $c_2 = 0.7$	0.340	0.784

Note: *P-values for the tests of instantaneous and feedback Granger non-causality in mean (LN) and distribution (BRT) from anticipated and unanticipated unemployment growth rates to money supply growth rate.*

Table 10: Conditional Mean Regressions: Estimation and Inference

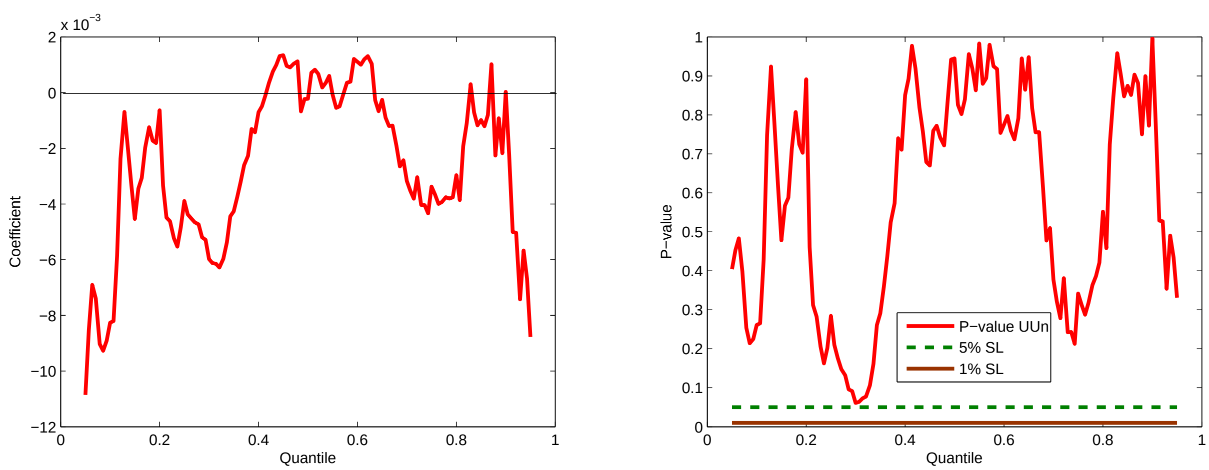
Mean	M1	M2	M3	M4
$Const.$	0.00097 (0.000)	0.00099 (0.000)	0.00098 (0.000)	0.00097 (0.000)
$g_{u,t}$	−0.0024 (0.520)			
$g_{u,t-1}$	0.0027 (0.482)			
$g_{u,t}^e$		0.0324 (0.030)		0.0488 (0.010)
$g_{u,t-1}^e$			0.0068 (0.624)	−0.0239 (0.155)
$g_{u,t}^u$		−0.0062 (0.142)		−0.0059 (.170)
$g_{u,t-1}^u$			0.0021 (0.575)	0.0037 (0.342)
ms_{t-1}	0.5931 (0.000)	0.5802 (0.000)	0.5910 (0.000)	0.5881 (0.000)
$R^2(\%)$	35.243	36.214	35.214	36.535

Once again, the estimation results [see Figures 9 and 10] confirm the previous ones and show that only anticipated unemployment rate immediately affects money supply. For the quantile range $[0.60, 0.95)$, the impact is positive and it is statistically very significant. However, for the quantile range $(0.05, 0.2]$ the sign is negative, but it is statistically insignificant even at 10% significance level. Finally, the impact of the unanticipated unemployment rate is statistically insignificant at all quantiles of the distribution of money supply growth rate.



(a) Coefficient (b) P-value

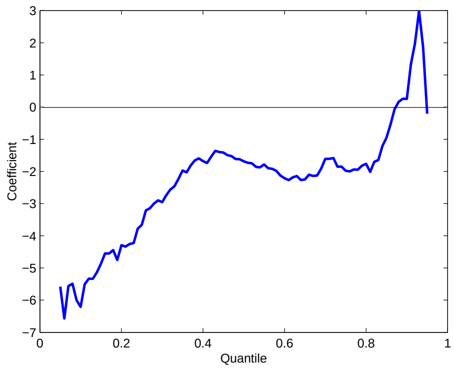
Figure 9: Impact of anticipated growth rate of the unemployment rate on money supply growth rate.



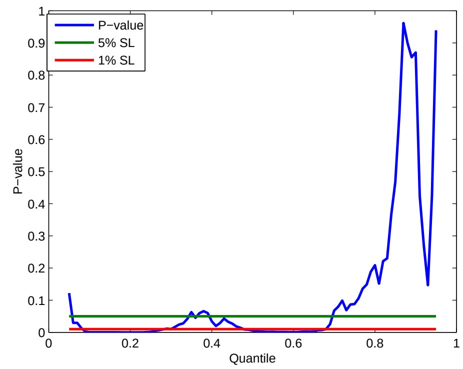
(a) Coefficient (b) P-value

Figure 10: Impact of unanticipated growth rate of the unemployment rate on money supply growth rate.

We now examine the second causal link of channel **(2)** from money supply to Federal funds rate. As it is expected, we find very strong evidence of an immediate negative impact of money supply on Federal funds rate [see Figure 11]. Finally, the immediate and negative impact of Federal funds rate on stock market return that we found in the previous subsection completes the channel **(2).**



(a) Coefficient



(b) P-value

Figure 11: Impact of money supply growth rate on Federal funds rate.

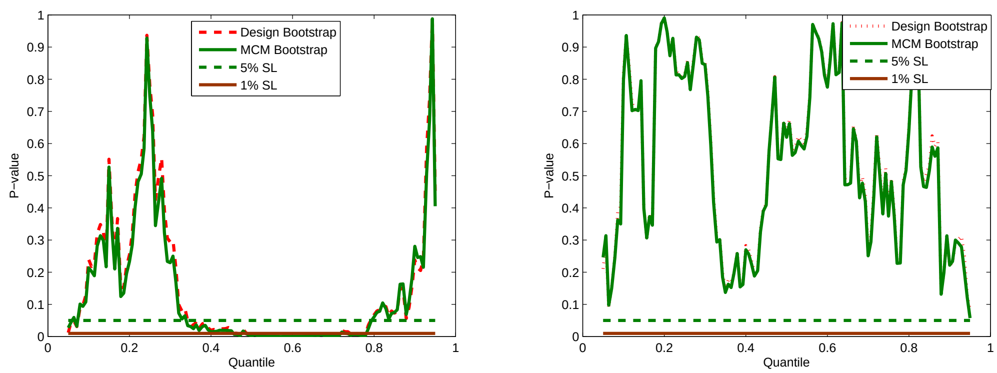
To conclude, we find that an increase (decrease) in anticipated unemployment rate leads to an immediate increase (decrease) in money supply, which in turn leads to an immediate decrease (increase) in Federal funds rate and to an immediate increase (decrease) in stock market returns. To summarize, an increase (decrease) in anticipated unemployment rate causes an increase (decrease) in stock market returns. This corresponds exactly to the positive impact that we found in sections 4.2 and 4.3. Finally, using the same data as the one in the present paper, Taamouti (2010) found a direct impact of money supply on stock prices.

6 More discussion

To check the robustness of the results found before, here we consider an alternative statistical procedure for testing the statistical significance of the impact of anticipated unemployment rate on stock market returns. This alternative procedure is given by Markov Chain Marginal Bootstrap method proposed by He and Hu (2002) and modified by Kocherginsky, He and Mu (2005). We also consider quarterly data on stock prices and unemployment rate that we use to re-examine the robustness of our previous results.

6.1 Markov chain marginal bootstrap

Markov chain marginal bootstrap (MCMB) was introduced by He and Hu (2002) as a bootstrap-based method for constructing confidence intervals or regions for a wide class of M-estimators in linear regression and maximum likelihood estimators in certain parametric models. An advantage of using He and Hu (2002) is that it reduces the dimensionality of bootstrap optimization to a sequence of easily solved one-dimensional problems. The sequence of one-dimensional solutions forms a Markov chain consistently approximates the true covariance of the vector of parameters. One problem with the MCMB method is that high autocorrelations in the MCMB sequence for specific coefficients will result in a poor estimates for the asymptotic covariance matrix. Kocherginsky, He and Mu (2005) [Hereafter KHM(2005)] propose a modification to MCMB, which alleviates autocorrelation problems by transforming the parameter space prior to performing the MCMB algorithm, and then transforming the result back to the original space. KHM(2005) show that the resulting MCMB autocorrelation algorithm (MCMB-A) is robust against heteroskedasticity.



(a) P-values of the impact of anticipated unemployment rate on stock return

(b) P-values of the impact of unanticipated unemployment rate on stock return

Figure 12: P-values: Design bootstrap versus Modified Markov chain marginal bootstrap

We apply MCMB autocorrelation algorithm to double check the statistical significance of the impact of anticipated and unanticipated components of unemployment rate on stock market return. We particularly compare the results using the design bootstrap and the modified Markov chain marginal bootstrap of KHM(2005). The empirical results are presented in Figure 12 which compares the p-values from the design bootstrap and the modified MCMB of the impact of anticipated and unanticipated unemployment growth rates on stock returns. Finally, we find that both methods yield to similar results, which confirms our previous conclusions.

6.2 Quarterly data

The quarterly data that we consider here goes from 1950Q1 to 2009Q4 for a total of 241 observations. The time period covered by the data corresponds to the one considered in the previous sections. The results of the tests for the statistical significance of the effects studied before using nonparametric and quantile regression analyses are presented in Table 11 and Figure 13, respectively.

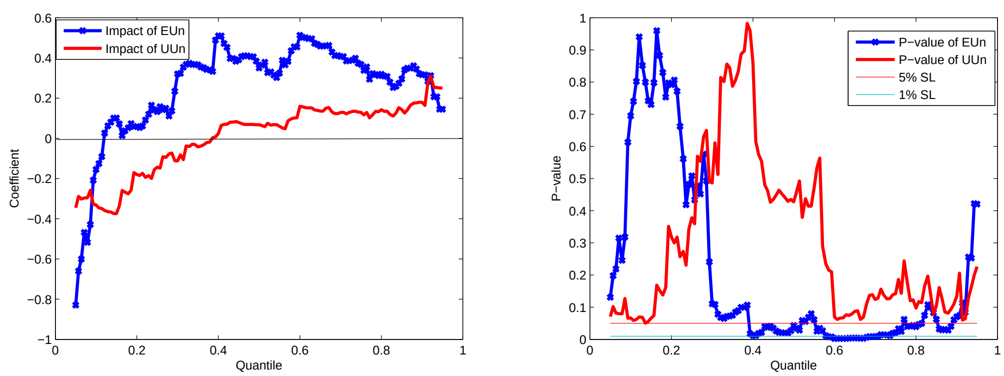
Panel A of Table 11 shows the results of testing the contemporaneous impacts of anticipated and unanticipated unemployment rates on stock market return that correspond to the null hypothesis H_0 : $\Pr\{F(r_t \mid r_{t-1},\ z_t) = F(r_t \mid r_{t-1})\} = 1$, where $z_t = g^e_{u,t}, g^u_{u,t}$. The conventional t-statistic which is based

Table 11: P-values of linear and nonlinear Granger causality tests

Test statistic / H_0	From g_u^e to r	From g_u^u to r
	Panel A: *Instantaneous Effect*	
BRT, $c = 2$	0.012	0.082
BRT, $c = 1.5$	0.016	0.140
BRT, $c = 1$	0.028	0.084
BRT, $c_1 = 0.8$, $c_2 = 0.7$	0.084	0.056
	Panel B: *Feedback Effect*	
BRT, $c = 2$	0.024	0.090
BRT, $c = 1.5$	0.012	0.120
BRT, $c = 1$	0.028	0.180
BRT, $c_1 = 0.8$, $c_2 = 0.7$	0.043	0.340

Note: *P-values for the tests of instantaneous and feedback Granger non-causality in mean (LN) and distribution (BRT) from anticipated and unanticipated unemployment growth rates to stock market returns.*

on the mean regression model indicates that the impacts of anticipated and unanticipated unemployment rates on stock market return are statistically insignificant at both 5% and 10% significance levels. However, nonparametric Granger causality tests show that only the anticipated component of the unemployment rate does affect stock market return. We find similar conclusions when we studied the feedback (lagged) effects [see Panel B of Table 11].



(a) Coefficient

(b) P-value

Figure 13: Impact of quarterly anticipated and unanticipated growth rates on quarterly stock return

We now consider quantile regressions to identify the level(s) of the effect of anticipated unemployment rate on stock market return. Figure 13 shows the results of estimating and testing the statistical significance of the impact of anticipated and unanticipated unemployment rates on quantiles of stock market returns using the regression models

$$r_t = \mu_Q^{(\alpha)} + \beta_{Q,1}^{(\alpha)}\ g_{u,t-1}^e + \beta_{Q,2}^{(\alpha)}\ g_{u,t-1}^u + \varepsilon_t^\alpha.$$

Again, the quantile analysis confirms the results that we obtain using nonparametric causality tests. Thus, the conclusions using quarterly data are similar to the ones that we got using monthly data.

7 Conclusion

We examined the nonlinearity in stock price-unemployment rate relationship. We conducted a rigorous analysis of the impact of anticipated and unanticipated unemployment rates on the distribution and quantiles of stock prices. Using *nonparametric* Granger causality and *quantile* regression based tests, we find that, contrary to the general findings in the literature, *only anticipated* unemployment rate has a *strong* impact on stock prices. Quantile regression analysis shows that the causal effects of anticipated unemployment rate on stock return are usually heterogeneous across quantiles. For the quantile range [0.35, 0.80], an increase in the anticipated unemployment rate leads to an increase in the stock market price (return). For the other quantiles the impact is statistically insignificant. Thus, an increase in the anticipated unemployment rate is generally a good news for stock market prices. Finally, we offer a reasonable explanation of why unemployment rate affects stock market prices and how it affects them. Using Fisher and Phillips curve equations, we show that high unemployment rate is followed by monetary policy action of Federal Reserve (Fed). When unemployment rate is high, the Fed decreases the interest rate which in turn increases the stock market prices.

References

[1] Baek, E., and Brock, W. (1992), "A general test for nonlinear Granger causality: Bivariate model," *Working paper*, Iowa State University and University of Wisconsin, Madison.

[2] Balvers, R.J. and Huang, D. (2009), "Money and the C-CAPM," *Journal of Financial and Quantitative Analysis*, vol. 44, pp. 337-368.

[3] Barro, R.J. (1977), "Unanticipated money growth and unemployment in the United States," *American Economic Review*, vol. 67, pp. 101-15.

[4] Barro, R.J. (1978), "Unanticipated money, output and the price level in the United States," *Journal of Political Economy*, vol 86, pp. 549-80.

[5] Barro, R. and Rush, M. (1980), "Unanticipated money and economic activity," in Rational Expectations and Economic Policy. Ed. Stanley Fischer. Chicago: U. of Chicago Press for NBER, pp. 23-48, 72-73.

[6] Barrodale, I. and Roberts, F.D.K. (1974), "Solution of an overdetermined system of equations in the norm," *Communications of the ACM*, vol. 17, pp. 319-320.

[7] Bernanke, B. and Blinder, A. (1992) "The Federal funds rate and the channels of monetary transmission," *American Economic Review*, vol. 82, pp. 901-21.

[8] Bernanke, B.S., and Kuttner, K. (2005), "What explains the stock market's reaction to Federal Reserve policy?" *The Journal of Finance*, vol. LX (3), pp. 1221-1257.

[9] Bodie, Z. (1976), "Common stocks as a hedge against inflation," *Journal of Finance*, vol. 31, pp. 459-470.

[10] Bouezmarni, T., Roy, R. and Taamouti, A. (2010), "Nonparametric tests for conditional independence using conditional distribution," *Working paper*, Université de Montreal and Universidad Carlos III de Madrid.

[11] Bouezmarni, T., Rombouts, J. and Taamouti, A. (2009), "A Nonparametric Copula Based Test for Conditional Independence with Applications to Granger Causality," *Working paper*, Université de Montreal and Universidad Carlos III de Madrid.

[12] Boyd, J.H., Hu, J. and Jagannathan, R. (2005), "The stock market's reaction to unemployment news: Why bad news is usually good for stocks,"The Journal of Finance, vol. LX (2), pp. 649-672.

[13] Buchinsky, M. (1995), "Estimating the asymptotic covariance matrix for quantile regression models: A Monte Carlo study," *Journal of Econometrics*, vol. 68, pp. 303-38.

[14] Copper, R. (1974), "Efficient capital markets and the quantity theory of money", *Journal of Finance*, vol. 19, pp. 887-908.

[15] Chan, L.K.C., Karceski, J. and Lakonishok, J. (1998). "The risk and return from factors," *Journal of Financial and Quantitative Analysis*, vol. 33, pp. 159-188.

[16] Chan, K.C., Foresi, S. and Lang, L.H.P. (1996), "Does money explain asset returns? Theory and empirical analysis," *Journal of Finance*, vol. 51, pp. 345-361.

[17] Chen, N.F., Roll, R. and Ross, S. (1986), "Economic forces and the stock market," *Journal of Business*, vol. 59, pp. 383-403.

[18] Craine, R. and Martin, V. (2003), "Monetary policy shocks and security market responses," University of California at Berkeley, Working Paper.

[19] Deschamps, P.J. (2008), "Comparing smooth transition and Markov switching autoregressive models of US unemployment," *Journal of Applied Econometrics*, vol. 23, pp. 435-462.

[20] van Dijk, D., Teräsvirta, T. and Franses, P.H. (2002), "Smooth transition autoregressive models- A survey of recent developments," *Econometric Reviews*, vol. 21 , pp. 1-47.

[21] Efron, B. (1979), "Bootstrap methods: Another look at the jackknife," *Annals of Statistics* vol. 7, pp. l-26.

[22] Efron, B. (1982), "The jackknife, the bootstrap and other resampling plans," *Society for Industrial and Applied Mathematics, Philadelphia, PA.*

[23] Fama, E.F. (1981), "Stock returns, real activity, inflation, and money," *American Economic Review*, vol. 71, pp. 545-565.

[24] Flannery, M.J and Protopapadakis, A.A. (2002), "Macroeconomic factors do influence aggregate stock returns," *The Review of Financial Studies*, vol. 15, pp. 751-782.

[25] Geske, R. and Roll, R. (1983), "The fiscal and monetary linkage between stock returns and inflation," *Journal of Finance*, vol. 38, pp. 1-34.

[26] Hamburger, J.M., and and Kochin A.L. (1972), "Money and stock prices: The channels of influence", *The Journal of Finance*, vol. 27, pp. 231-249.

[27] Harvey, C. and Siddique, A. (2000), "Conditional skewness in asset pricing tests," *The Journal of Finance*, vol. 55, pp. 1263-1295.

[28] He, X. and Hu, F. (2002), "Markov chain marginal bootstrap," *Journal of the American Statistical Association*, vol 97, pp. 783-795.

[29] Hiemstra, C. and Jones, J. (1994), "Testing for linear and nonlinear Granger causality in the stock price-volume relation," *Journal of Finance*, vol. 49, pp. 1639-1664.

[30] Homa, K.E., and Jaffee, D.W. (1971), "The supply of money and common stock prices", *Journal of Finance*, vol. 27, pp. 1045-1066.

[31] Kocherginsky, M., He, X. and Mu, Y. (2005), "Practical confidence intervals for regression quantiles," *Journal of Computational and Graphical Statistics*, vol. 14, pp. 41-55.

[32] Koenker, R. and Bassett, G. (1978), "Regression quantiles," *Econometrica*, vol. 46, pp. 33-50.

[33] Koenker, R. and D'Orey, V. (1987), "Algorithm AS 229: Computing regression quantiles," *Applied Statistics*, vol. 36, pp. 383-393.

[34] Koenker, R., and Hallock, K.F. (2001), "Quantile regression," *Journal of Economic Perspectives*, vol. 15, pp. 143-156.

[35] Koenker, R. (2005), Quantile regression. New York: Cambridge University Press.

[36] Makin, J.H. (1982), "Anticipated money, inflation uncertainty and real economic activity," *The Review of Economics and Statistics*, vol. 64, pp. 126-134.

[37] Nadaraya, E. A. (1964), "On estimating regression," *Theory of Probability and its Applications*, vol. 9, pp. 141-142.

[38] Palmer, M. (1970), "Money supply, portfolio adjustments and stock prices", *Financial Analysts Journal*, vol. 26, pp. 19-22.

[39] Paparoditis, E., and Politis, D. (2000), "The local bootstrap for kernel estimators under general dependence conditions," *Annals of the Institute of Statistical Mathematics*, vol. 52, pp. 139-159.

[40] Pearce, D.K. and Roley, V.V. (1983), "The reaction of stock prices to unanticipated changes in money: A note," *Journal of Finance*, vol. 38, pp. 1323-1333.

[41] Portnoy, S., and Koenker, R. (1997), "The Gaussian Hare and the Laplacian Tortoise: Computability of squared-error versus absolute-error estimators," *Statistical Science*, vol. 12, pp. 279-300.

[42] Rigobon, R. and Sack, B. (2002). "The Impact of monetary policy on asset prices," NBER Working Paper No. 8794.

[43] Rozeff S.M. (1974), "Money and stock prices market efficiency and the lag in effect of monetary policy," *Journal of financial Economics*, vol. 1, pp. 245-302.

[44] Sheffrin, S.M. (1979), "Unanticipated money growth and output fluctuations," *Economic Inquiry*, vol. 17, pp. 1-13.

[45] Taamouti, A. (2010), "Stock market's reaction to money supply: The action is in the tails," Universidad Carlos III de Madrid Working paper.

[46] Thorbecke, W. (1997), "On stock market returns and monetary policy" *The Journal of Finance*, vol. 52, pp. 635-654.

[47] Thornton, J. (1993), "Money, output and stock prices in the UK: Evidence on some (non) relationships", *Applied Financial Economics*, vol. 3, pp. 335-338.

[48] Watson, G. (1964), "Smooth regression analysis," *Sankhya*, vol. 26, pp. 359-372.