



Working Paper 12-37  
Economic Series  
July, 2012

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## The Reaction of Stock Market Returns to Anticipated Unemployment\*

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July 6, 2012

### 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 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

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\* The authors thank Jean-Marie Dufour, Barbara Rossi, and Enrique Santana for their several useful comments. Earlier versions of this paper were presented at the 65th European Meeting of the Econometric Society in Oslo (2011), the NBER -NSF Time Series Conference in Michigan (2011), the XXVI Simposio of the Spanish Economic Association (SAEe) in Malaga (2011), and the 4th International IFABS conference on Rethinking Banking and Finance: Money, Markets and Models in Valencia (2012). Financial support from the Spanish Ministerio de Ciencia e Innovación through grants ECO2010-19357 and Consolider-2010 and Bank of Spain (grant ER program) is gratefully acknowledged.

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# 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 existing papers only looked at the conditional *linear mean* effect. The latter papers have ignored non-linear dependence and the dependence in the quantiles of the conditional stock market 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 *linear* mean regression analysis, whereas we investigate the non-linear effect on *conditional mean and 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 a non-linear impact on *conditional mean, 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* Granger 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 each quantile of stock returns distribution. To the best of 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. We also believe it is the first to use *nonparametric tests* for testing the Granger non-causality in mean and in distribution from anticipated and unanticipated unemployment rates to stock market returns.

To achieve our goals 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 approximation 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 investigate the stock market's reaction to anticipated and unanticipated unemployment rates using two different nonparametric tests. The first one allows to test for the Granger non-causality in mean and the second one looks at the general Granger non-causality in distribution. Both tests do not require to specify the model that might link the two variables of interest, and thus they can help to avoid misleading results due to model misspecification. Moreover, the two tests are able to detect both linear and nonlinear

causal effects.

To test for Granger non-causality in mean we use the nonparametric test that have been recently proposed by Nishiyama, Hitomi, Kawasaki, and Jeong (2011) [hereafter NHKJ(2011)]. The test statistic is constructed based on moment conditions. It is also a test for omitted variables in time series regression. To apply this test, a Nadaraya-Watson [see Nadaraya (1964) and Watson (1964)] nonparametric estimator for conditional moments is needed. Using monthly data for the period 1950-2009 on S&P 500 stock index and unemployment rate, we find that only time-lagged anticipated unemployment rate Granger causes the conditional mean of stock market returns. As we will see later, this indicates that the time-lagged anticipated unemployment rate has a *nonlinear* impact on stock market returns.

The test of the reaction of *conditional distribution* of stock market returns to anticipated and unanticipated unemployment rates is also based on a recent *nonparametric* Granger causality in distribution test statistic proposed by Bouezmarni, Roy, and Taamouti (2011). This test detects nonlinearity and the dependence in low and high-order moments and quantiles. It is based on a comparison of the estimators of conditional distribution functions using an  $L_2$  metric, where the distribution functions are estimated using the Nadaraya-Watson approach. Using monthly data, 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 market returns *only* through its anticipated component.

Third, the nonparametric general Granger non-causality in distribution test discussed in the previous paragraph 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 issue, we consider conditional quantile regression-based tests to identify the impact of unemployment rate components on the 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 possibly 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 effect from money supply growth rate to 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 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 mean and conditional distribution of stock returns. In Section 4, we examine the Granger causality at each quantile of stock market 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. Section 6 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 (not reported) for unemployment rate, say  $ur_t$ , and its growth rate, say  $g_{u,t} = \log(ur_t) - \log(ur_{t-1})$ , show that the unconditional distributions of monthly unemployment rate and its growth rate exhibit 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. The zero p-value of Jarque-Bera's test for 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 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 t-statistics for testing the nonstationarity of unemployment rate are equal to  $-2.582$  and  $-2.780$ , respectively, with the corresponding 5% critical values equal to  $-2.865$  and  $-3.416$ , respectively. However, the ADF test-statistics for testing the nonstationarity of growth rate of unemployment rate, again using only an intercept and both an intercept and trend, are equal to  $-7.958$  and  $-7.961$ , respectively, with same 5% critical values as before. Thus, unemployment rate is nonstationarity, whereas its growth rate is stationary. Hence, in the next sections our analysis will be based on 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 returns 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 approximation 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) approximation. 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  $t$ ,  $(\mu, \beta_1, \dots, \beta_p)'$  is the vector of parameters to estimate, and  $u_t$  is an error term. We apply the 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  $p = 12$  (over a maximum of 30 lags). Further, the results of estimating the AR(12) model can be summarized by the following equation:

$$\begin{aligned} \hat{g}_{u,t} = & \quad 3.5 \cdot 10^{-4} + 0.086 g_{u,t-1} + 0.166 g_{u,t-2} + 0.124 g_{u,t-3} + 0.084 g_{u,t-4} \\ & \quad (0.618) \quad (2.319) \quad (4.483) \quad (3.326) \quad (2.251) \\ & + 0.057 g_{u,t-5} + 0.019 g_{u,t-6} + 0.011 g_{u,t-7} + 0.038 g_{u,t-8} - 0.004 g_{u,t-9} - 0.117 g_{u,t-10} \\ & \quad (1.519) \quad (0.504) \quad (0.310) \quad (1.030) \quad (1.030) \quad (-3.174) \\ & + 0.064 g_{u,t-11} - 0.142 g_{u,t-12}, \quad R^2 = 14.5\%, \quad \mathbf{F}\text{-statistic} = 9.801. \end{aligned} \quad (1)$$

From the above equation, 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 suggests that the past of unemployment rate explain more than 14% of the actual value of its growth rate. To validate the estimated model we consider an AR residual Portmanteau tests for autocorrelations and the results (not reported, but available upon request) suggest that the estimated AR(12) model appears adequate in that the residuals seem serially uncorrelated.

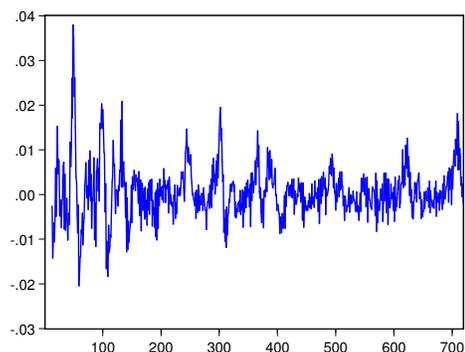
Finally, the estimated equation in (1) is used to decompose observed growth rate into anticipated,  $g_{u,t}^e$ , and unanticipated,  $g_{u,t}^u$ , components. Obviously, the anticipated component is given by the fitted values  $g_{u,t}^e = E_{t-1}(g_{u,t}) \simeq \hat{g}_{u,t}$  and the “unanticipated” growth rate of unemployment rate is measured by the residuals  $\hat{u}_t = g_{u,t} - g_{u,t}^e$ . 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 1].

### 2.3 Monthly stock return

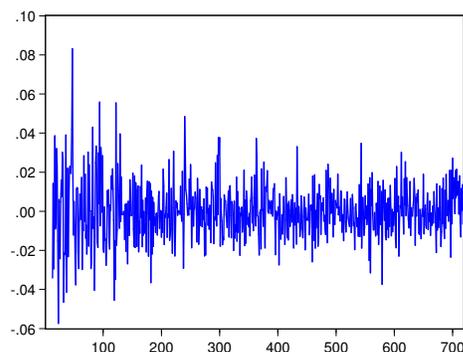
The stock market is given by the monthly S&P 500 Index. As for unemployment rate, the sample runs from January 1950 to December 2009 for a total of 721 observations. Stock returns are computed using

Table 1: 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



(a) Anticipated Growth Rate



(b) Unanticipated Growth Rate

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

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 (not reported) for stock return show 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 suggests that stock returns cannot be normally distributed. Finally, we perform ADF-tests for the 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 returns react 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 which are based on the conditional *linear* mean regression analysis;

see BHJ(2005), 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 (2012)]. For that reason, traditional linear Granger causality tests might overlook a significant nonlinear relation between stock returns and unemployment rate.

In the present section, we start by testing for the Granger non-causality in mean, and then we look at the general Granger non-causality in distribution. The idea is to first investigate the impact of anticipated and unanticipated unemployment rates on the conditional mean of stock market returns without assuming any parametric model for mean. The comparison with the results from linear regressions will help to see the nature (linear or nonlinear) of the impact, if it exists, of unemployment rate components on the conditional mean of stock returns. Thereafter, we test for the general Granger non-causality in distribution, again, without assuming any parametric model for the conditional distribution of stock returns. This second test will help us to see whether unemployment rate components affect other levels (other than the mean) of stock return distribution.

### 3.1 Nonparametric Granger Causality in Mean

To test for the Granger non-causality in mean, we use the nonparametric test that have been recently proposed by Nishiyama, Hitomi, Kawasaki, and Jeong (2011) [hereafter NHKJ(2011)]. The test statistic is constructed based on moment conditions. To apply this test, the Nadaraya-Watson nonparametric estimator of moments is needed. Before we show how the test works, let  $\{(r_t, z_t)'\}_{t=1}^T$  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  $f$ . The random variable  $z_t$  represents either the anticipated or unanticipated component of growth rate of unemployment rate. Suppose now we are interested in testing the Granger non-causality in mean from  $z_{t-1}$  to  $r_t$ . This is to test the null hypothesis

$$H_0^m : \Pr \{E[u_t | X_{t-1}] = 0\} = 1$$

against the alternative hypothesis

$$H_1^m : \Pr \{E[u_t | X_{t-1}] = 0\} < 1,$$

where  $u_t = r_t - E[r_t | r_{t-1}]$  and  $X_{t-1} = (r_{t-1}, z_{t-1})' \in \mathbb{R}^2$ . If the null hypothesis  $H_0^m$  is true, then the past changes in  $z$ , where  $z = g_u^e, g_u^u$ , can not affect the conditional mean of stock market return. NHKJ(2011) have showed that the above null and alternative hypotheses can be rewritten in terms of unconditional moment restrictions:

$$H_0^m : \Pr \{E[u_t f(r_{t-1}) h(X_{t-1})] = 0\} = 1, \quad \text{for } \forall h(x) \in s_r^\perp \quad (2)$$

against the alternative hypothesis

$$H_1^m : \Pr \{E [u_t f(r_{t-1}) h(X_{t-1})] = 0\} < 1, \text{ for some } h(x) \in s_r^\perp, \quad (3)$$

where  $h(x)$  is any function in the Hilbert space  $s_r^\perp$  that is orthogonal to the Hilbert  $L_2$  space

$$s_r = \left\{ s(\cdot) \mid E \left[ s(r_{t-1})^2 \right] < \infty \right\}.$$

Since  $E [u_t f(r_{t-1}) h(X_{t-1})]$  is unknown, we use a nonparametric approach to estimate it. We follow NHKJ(2011) and use the Nadaraya-Watson method to estimate this conditional mean. To test the null hypothesis (2) against the alternative hypothesis (3), NHKJ(2011) suggest the following test statistic

$$\hat{S}_T = \sum_{i=1}^{k_T} w_i \hat{a}_i^2, \quad (4)$$

where  $\hat{a}_i = \frac{1}{\sqrt{T}} \sum_{t=2}^T \widehat{u_t f}(r_{t-1}) \hat{h}_i(X_{t-1})$  and  $w_i$  is a nonnegative weighting function, such as  $w_i = 0.9^i$ . To avoid the technicalities and save space, we refer the reader to NHKJ(2011) for details concerning the nonparametric estimation of  $u_t f(r_{t-1})$  and  $h_i(X_{t-1})$  and on how to choose  $k_T$ .

The test statistic  $\hat{S}_T$  depends obviously on the sample size. NHKJ(2011) have showed that, under the null hypothesis,  $\hat{S}_T$  converges in distribution to  $\sum_{i=1}^{\infty} w_i \varepsilon_i^2$ , as  $T \rightarrow \infty$ , where  $\varepsilon_i$  are i.i.d.  $N(0, 1)$ . Thus, for a given summable positive sequence of weights  $\{w_i\}$ , the test statistic  $\hat{S}_T$  is pivotal and it is asymptotically distributed as an infinite sum of weighted chi-squares. To compute the critical values, NHKJ(2011) truncate the infinite sum to  $\sum_{i=1}^L w_i \varepsilon_i^2$  and simulate its distribution using the  $N(0, 1)$  random variables. One advantage of this test is that the simulation is very simple and the critical values do not dependent on the data.

NHKJ(2011) also show that their test has nontrivial power against  $\sqrt{T}$ -local alternatives. Moreover, they argue that the previously proposed tests [see Bierens (1982, 1990), Bierens and Ploberger (1997), Chen and Fan (1999), Fan and Li (1996) and Robinson (1989)] can be rewritten as special cases of their test statistic, and that the latter has an advantage over the previous ones in that it can control the power properties easily and directly. Finally, in their simulation section they use the following weighting function  $w_i = 0.9^i$  and they show that their test has quite good empirical size and power for a variety of linear and nonlinear models. They also discuss, in the section on power of the test, how one can choose the sequence of  $\{w_i\}$  such that the power is maximized.

### 3.2 Nonparametric general Granger Causality in distribution

Now we test whether the past and present changes in the anticipated and unanticipated unemployment rates affect the *conditional distribution* of stock market returns. 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 the past stock return. It is 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 will 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 linear and non-linear Granger causality 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 (2011) [hereafter BRT(2011)]. The test is based on a comparison of conditional distribution functions using an  $L_2$  metric. Suppose we are interested in testing the Granger non-causality in *distribution* from  $z_{t-1}$  ( $z_t$ ) to  $r_t$ . This is to test the null hypothesis

$$H_0^D : \Pr \{F(r_t | r_{t-1}, z_{t-1}(\text{or } z_t)) = F(r_t | r_{t-1})\} = 1 \quad (5)$$

against the alternative hypothesis

$$H_1^D : \Pr \{F(r_t | r_{t-1}, z_{t-1}(\text{or } z_t)) = F(r_t | r_{t-1})\} < 1. \quad (6)$$

Notice that in the above hypotheses, due to the lack of persistent in the returns, we only consider one lag for the unemployment rate components ( $z$ ) and stock return ( $r$ ).

Since the conditional distribution functions  $F(r_t | r_{t-1}, z_{t-1}(\text{or } z_t))$  and  $F(r_t | r_{t-1})$  are unknown, we use a nonparametric approach to estimate them. We follow BRT(2011) to use Nadaraya-Watson approach proposed by Nadaraya (1964) and Watson (1964). For simplicity of exposition we focus our discussion on testing the time-lagged impact of anticipated and unanticipated unemployment rates on stock market return. The test can be defined in a similar way for testing the contemporaneous (instantaneous) effects. If we denote  $\bar{V}_{t-1} = (r_{t-1}, z_{t-1})' \in \mathbb{R}^2$  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

$$\hat{F}_{h_1}(r_t | \bar{v}) = \frac{\sum_{t=2}^{T+1} K_{h_1}(\bar{v} - \bar{V}_{t-1}) \mathbb{I}_{A_{r_t}}(r_t)}{\sum_{t=2}^{T+1} K_{h_1}(\bar{v} - \bar{V}_{t-1})}, \quad (7)$$

where  $K_{h_1}(\cdot) = h_1^{-2}K(\cdot/h_1)$ , for  $K(\cdot)$  a kernel function,  $h_1 = h_{1,T}$  is a bandwidth parameter, and  $\mathbb{I}_{A_{r_t}}(\cdot)$  is an indicator function which is 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:

$$\hat{F}_{h_2}(r_t|r) = \frac{\sum_{t=2}^{T+1} K_{h_2}^*(r - r_{t-1}) \mathbf{I}_{A_{r_t}}(r_t)}{\sum_{t=2}^{T+1} K_{h_2}^*(r - r_{t-1})}, \quad (8)$$

where  $K_{h_2}^*(\cdot) = h_2^{-1} K^*(\cdot/h_2)$ , for  $K^*(\cdot)$  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 (5) against the alternative hypothesis (6), we follow BRT(2011) to use the following test statistic

$$\hat{\Gamma} = \frac{1}{T} \sum_{t=2}^{T+1} \left\{ \hat{F}_{h_1}(r_t|\bar{V}_{t-1}) - \hat{F}_{h_2}(r_t|r_{t-1}) \right\}^2 w(\bar{V}_{t-1}), \quad (9)$$

where  $w(\cdot)$  is a nonnegative weighting function of the data  $\bar{V}_{t-1}$ , for  $2 \leq t \leq T$ . 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. BRT(2011) establish the asymptotic distribution of the nonparametric test statistic in (9). 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 standardize the data and use the 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 largely the finite sample properties (size and power) of the test.

BRT(2011) 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 the test performs quite well. In most cases, the test produces the greatest power when  $c_1 = c_2 = 1$ .

### 3.3 Empirical results: linear versus non-linear causality

Before showing the results of nonparametric Granger non-causality in mean and distribution tests, we first examine the causal effect of anticipated and unanticipated unemployment rates using linear mean regressions

$$r_t = \omega_r + \alpha_1 g_{u,t}^e + \alpha_2 g_{u,t-1}^e + \alpha_3 g_{u,t}^u + \alpha_4 g_{u,t-1}^u + \alpha_5 r_{t-1} + e_t, \quad (10)$$

where  $e_t$  is an error term with conditional mean equal to zero. The parameters in equation (10) are unknown and will be estimated using OLS. The anticipated (resp. unanticipated) unemployment rate  $g_{u,t}^e$  (resp.  $g_{u,t}^u$ ) does not instantaneously Granger cause stock market return  $r_t$  if the null hypothesis  $H_0 : \alpha_1 = 0$  (resp.  $H_0 : \alpha_3 = 0$ ) holds. Similarly, time-lagged anticipated (resp. unanticipated) unemployment rate  $g_{u,t-1}^e$  (resp.  $g_{u,t-1}^u$ ) does not Granger cause stock market return  $r_t$  if the null hypothesis  $H_0 : \alpha_2 = 0$  (resp.  $H_0 : \alpha_4 = 0$ ) holds.

Since in equation (10) the dependent variable is given by stock return  $r_t$ , it is more likely that the error  $e_t$  is heteroscedastic. To avoid the effect of heteroscedasticity on inference, we consider a robust HAC  $t$ -statistic. The estimation and inference results using the data described in section 2 are presented in Table 2. The latter shows that the constant terms in all linear mean regressions are positive and statistically significance at 5% and 1% significance levels. We also see that anticipated and unanticipated components of unemployment growth rate have a negative and immediate linear effect on conditional mean of stock market return, whereas the time-lagged effects are positive. However, none of the coefficients of the immediate and time-lagged effects is statistically significant at 5% and 10% significance levels. The coefficient of determination indicates that the regressions with time-lagged anticipated and unanticipated unemployment rates explain better the conditional mean return.

The linear mean regression analysis shows that both anticipated and unanticipated unemployment rates have no impact on conditional mean of stock market returns. Thus, if we only focus on linear mean regressions, then we must conclude that there is no causality from unemployment rate to stock market return. This raises the question of whether the dependence in mean is *nonlinear* or it exists at other levels (other than the mean) of the conditional distribution of stock market returns. To answer these questions, in what follows we use nonparametric Granger non-causality in mean and distribution tests.

We have applied the nonparametric test statistic given in (4) to test for *nonlinear* Granger non-causality in mean from anticipated and unanticipated unemployment rates to stock market returns. We followed NHKJ(2011) to choose as a weighting function  $w_i = 0.9^i$ . We have also considered many other weighting

Table 2: Linear Granger causality in mean tests

$r_t$	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
$Const.$	0.0023 (0.001)	0.0023 (0.001)	0.0023 (0.001)	0.0021 (0.004)	0.0022 (0.003)	0.0021 (0.004)
$g_{u,t}^e$	-0.0148 (0.926)		-0.0149 (0.927)			
$g_{u,t-1}^e$				0.1448 (0.235)		0.1448 (0.235)
$g_{u,t}^u$		-0.0368 (0.310)	-0.0368 (0.310)			
$g_{u,t-1}^u$					0.0061 (0.898)	0.0061 (0.897)
$r_{t-1}$	0.0607 (0.184)	0.0584 (0.200)	0.0583 (0.199)	0.0623 (0.184)	0.0617 (0.182)	0.0624 (0.182)
$R^2(\%)$	0.373	0.465	0.467	0.610	0.383	0.613

**Note:** This table reports the estimation results that corresponds to the linear mean regressions in (10). The  $p$ -values are given between parentheses.

functions such as  $w_i = 0.5^i, 0.6^i, 0.7^i, 0.8^i$ . For all the weighting functions that we considered, we found that there is a negligible change in the critical values obtained from simulating the distribution of  $\sum_{i=1}^L w_i \varepsilon_i^2$  when the truncation  $L$  is bigger than 300. We have also followed NHKJ(2011) to choose the bandwidths  $b_1 T^{-0.3}$  and  $b_2 T^{-0.3}$  for various values of  $b_1$  and  $b_2$ :  $(b_1 = b_2 = 1)$ ,  $(b_1 = 2.5, b_2 = 3.5)$ ,  $(b_1 = b_2 = 5)$ , and  $(b_1 = 7.3, b_2 = 5.6)$ .

The results for testing the nonlinear time-lagged Granger non-causality in mean are presented in Table 3. The latter reports the test statistics and the corresponding 5% critical values. For all considered weighting functions and bandwidths, we find that only time-lagged anticipated unemployment rate Granger causes the conditional mean of stock market returns. Given the results of linear regression analysis [see table 2], this suggests that time-lagged anticipated unemployment rate has a nonlinear effect on stock market returns.

We now test for the general Granger non-causality in distribution from anticipated and unanticipated components of unemployment rate to stock market return. To do so, we test the null hypothesis (5) against the alternative hypothesis (6) using the nonparametric test statistic given in (9). The results are presented in Table 4. The latter reports the  $p$ -values computed using local smoothed bootstrap. Contrary to the linear mean regression based tests, at 5% significance level, we find strong evidence that *time-lagged* anticipated unemployment rate Granger causes the conditional distribution function of stock market return. Further, there is a weak evidence of an instantaneous causality between anticipated unemployment rate and stock market return. Moreover, we also find convincing evidence that there is no instantaneous and time-lagged 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 market returns *only* through its anticipated component. This might indicate that *time-lagged* anticipated unemployment rate affects other

Table 3: Nonparametric test (expression (4)) for nonlinear Granger Causality in mean

Test statistic / $H_0$	From $g_u^e$ to $r$	From $g_u^u$ to $r$
<b>Bandwidths</b>	<b>Panel A: <math>w_i=0.5^i</math>, Critical Value=2.60</b>	
$h_1 = 1, h_2 = 1$	4.46	0.301
$h_1 = 2.5, h_2 = 3.5$	4.45	0.279
$h_1 = 5, h_2 = 5$	4.45	0.276
$h_1 = 7.3, h_2 = 5.6$	4.44	0.275
	<b>Panel B: <math>w_i=0.6^i</math>, Critical Value=3.57</b>	
$h_1 = 1, h_2 = 1$	10.73	0.589
$h_1 = 2.5, h_2 = 3.5$	10.69	0.553
$h_1 = 5, h_2 = 5$	10.69	0.548
$h_1 = 7.3, h_2 = 5.6$	10.69	0.547
	<b>Panel C: <math>w_i=0.7^i</math>, Critical Value=5.01</b>	
$h_1 = 1, h_2 = 1$	23.01	1.15
$h_1 = 2.5, h_2 = 3.5$	22.91	1.09
$h_1 = 5, h_2 = 5$	22.90	1.09
$h_1 = 7.3, h_2 = 5.6$	22.90	1.08
	<b>Panel D: <math>w_i=0.8^i</math>, Critical Value=7.58</b>	
$h_1 = 1, h_2 = 1$	45.11	2.23
$h_1 = 2.5, h_2 = 3.5$	44.89	2.15
$h_1 = 5, h_2 = 5$	44.88	2.14
$h_1 = 7.3, h_2 = 5.6$	44.88	2.13
	<b>Panel E: <math>w_i=0.9^i</math>, Critical Value=14.38</b>	
$h_1 = 1, h_2 = 1$	82.45	4.23
$h_1 = 2.5, h_2 = 3.5$	82.02	4.11
$h_1 = 5, h_2 = 5$	82.02	4.09
$h_1 = 7.3, h_2 = 5.6$	82.03	4.09

**Note:** This table reports the test statistics and the 5% critical values of nonparametric test for testing nonlinear time-lagged Granger Causality in mean from anticipated and unanticipated unemployment growth rates to stock market returns.

Table 4: Nonparametric test (expression (9)) for nonlinear Granger Causality in distribution

Test statistic / $H_0$	From $g_u^e$ to $r$	From $g_u^u$ to $r$
<b>Bandwidths</b>	<b>Panel A: Instantaneous Effect</b>	
$c = 2$	0.036	0.244
$c = 1.5$	0.048	0.320
$c = 1$	0.052	0.192
$c_1 = 0.8, c_2 = 0.7$	0.060	0.152
	<b>Panel B: Time-lagged Effect</b>	
$c = 2$	0.000	0.324
$c = 1.5$	0.000	0.280
$c = 1$	0.000	0.230
$c_1 = 0.8, c_2 = 0.7$	0.000	0.132

**Note:** This table reports the  $p$ -values of nonparametric test for testing nonlinear instantaneous and time-lagged Granger non-causality in distribution from anticipated and unanticipated unemployment growth rates to stock market returns.

levels (other than the mean) of conditional distribution of stock market returns.

The rejection of Granger non-causality in distribution hypothesis from anticipated unemployment rate to stock market return does not inform us about levels of stock return distribution where the causality exist. To overcome this problem, in the next section we use quantile regression analysis to identify the effect 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 relationship between a set of covariates and a specified quantile of the dependent variable. It 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 regression doesn't require strong distributional assumptions and it is robust compared to mean regression against outliers, and can thus be estimated with greater precision than conventional moments [see Harvey and Siddique (2000)].

To see how the estimation and inference work for quantile regressions, we first denote the  $\alpha$ th quantile of the conditional distribution of stock return by  $Q_\alpha(r_t | I_{t-1})$ , where  $I_{t-1}$  is an information set containing

the past (present) of the covariates. Observe that the null hypothesis in (5) is equivalent to

$$H_0^Q : Q_\alpha(r_t | r_{t-1}, z_{t-1}(\text{or } z_t)) = Q_\alpha(r_t | r_{t-1}), \quad \forall \alpha \in (0, 1), \text{ a.s.}, \quad (11)$$

If  $H_0^Q$  holds for all  $\alpha$  in  $(0, 1)$ , then the changes in the components of the unemployment rate do not Granger cause the distribution of stock market returns. 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 helps to identify the levels of conditional distribution of stock market returns at which the causality exists. The null hypothesis for testing the Granger non-causality at a given  $\alpha$ th quantile of stock return is:

$$H_0^{Q\alpha} : Q_\alpha(r_t | r_{t-1}, z_{t-1}(\text{or } z_t)) = Q_\alpha(r_t | r_{t-1}), \text{ for a given } \alpha \in (0, 1). \quad (12)$$

If  $H_0^{Q\alpha}$  holds, then the changes in the components of unemployment rate do not Granger cause the  $\alpha$ th quantile of stock market return.

Now to examine the time-lagged Granger causality in quantiles from  $z$  to  $r$ , we consider the following quantile regression specifications

$$r_t = \theta(\alpha)' w_{t-1} + \varepsilon_t^{(\alpha)}, \text{ for a given } \alpha \in (0, 1), \quad (13)$$

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

$$Q_\alpha(\varepsilon_t^{(\alpha)} | r_{t-1}, z_{t-1}) = 0, \text{ for } \alpha \in (0, 1), \quad (14)$$

that is, the conditional  $\alpha$ th quantile of the error term is equal to zero. For the purposes of estimation and inference the i.i.d. errors assumption is not needed.

Observe that the null hypotheses  $H_0^Q$  and  $H_0^{Q\alpha}$  are general hypotheses in the sense that they do not specify the functional form of conditional quantiles that can be linear or nonlinear. Since there are not many nonparametric tests available for testing the Granger causality in quantiles, in equation (13), we follow most of the empirical literature to consider a linear functional form for the conditional quantiles:

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

Based on the quantile regression in (13), the time-lagged anticipated and unanticipated components of unemployment rate do not Granger cause the  $\alpha$ th quantile of stock market return if  $H_{lin,0}^{Q\alpha} : \beta_1(\alpha) = 0$  holds. The latter hypothesis corresponds to a *time-lagged* Granger non-causality in the  $\alpha$ th quantile of stock return distribution. We can similarly define an *instantaneous* Granger non-causality in the  $\alpha$ th quantile between the components of unemployment rate and stock return by replacing in equation (13)  $z_{t-1}$  with  $z_t$ .

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

$$\hat{\theta}(\alpha) = \arg \min_{\theta(\alpha)} \left( \sum_{t:r_t > \theta(\alpha)' w_{t-1}} \alpha |r_t - \theta(\alpha)' w_{t-1}| + \sum_{t:r_t < \theta(\alpha)' w_{t-1}} (1 - \alpha) |r_t - \theta(\alpha)' w_{t-1}| \right). \quad (15)$$

The estimator  $\hat{\theta}(\alpha)$  minimizes a weighted sum of the absolute errors  $\varepsilon_t^{(\alpha)}$ , where the weights  $\alpha$  and  $(1 - \alpha)$  are symmetric and equal to  $\frac{1}{2}$  for the median regression case and asymmetric otherwise. This estimator 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)]. Moreover, under some regularity conditions, the estimator  $\hat{\theta}(\alpha)$  is asymptotically normally distributed [see Koenker (2005)]

$$\sqrt{T} \left( \hat{\theta}(\alpha) - \theta(\alpha) \right) \stackrel{d}{\sim} \mathcal{N}(0, \Sigma_\alpha). \quad (16)$$

where “ $\stackrel{d}{\sim}$ ” denotes the convergence in distribution,  $\Sigma_\alpha$  is the covariance matrix of  $\hat{\theta}(\alpha)$ , and  $T$  is the sample size. Tests for statistical significance of parameter estimates can be constructed using critical values from Normal distribution.

Computation of an estimator of covariance matrix  $\Sigma_\alpha$  is very important in quantile regression analysis. Generally speaking, we distinguish between three classes of estimators: **(1)** methods for estimating  $\Sigma_\alpha$  in i.i.d. settings; **(2)** methods for estimating  $\Sigma_\alpha$  for independent but not-identically distributed settings; **(3)** bootstrap resampling methods for both i.i.d. and independent and non identically distributed settings [see Koenker (2005)]. The estimator most commonly used and the more efficient in small samples is based on the design matrix bootstrap [see Buchinsky (1995)]. The design matrix bootstrap estimator of  $\Sigma_\alpha$  suggested initially by Efron (1979, 1982) and is given by:

$$\hat{\Sigma}_\alpha^* = \frac{T}{B} \sum_{j=1}^B \left( \hat{\theta}_j^*(\alpha) - \hat{\theta}(\alpha) \right) \left( \hat{\theta}_j^*(\alpha) - \hat{\theta}(\alpha) \right)', \quad (17)$$

where  $\hat{\theta}_j^*(\alpha)$  is the quantile regression estimator based on the  $j$ th bootstrap sample, for  $j = 1, \dots, B$ . The bootstrap samples  $\{(r_t^*, z_t^*)'\}_{t=1}^T$  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 terms  $\varepsilon_t^{(\alpha)}$  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  $\Sigma_\alpha$ : 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  $\Sigma_\alpha$  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 4.2 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 Empirical Results

Nonparametric analysis has suggested that anticipated unemployment rate might cause *any* quantile of conditional distribution of stock market returns. Consequently, we need to identify the causal effect at each quantile of stock return distribution.

Since the nonparametric Granger non-causality tests have recommended that only *time-lagged* unemployment rate components explain stock market returns, in the following we concentrate our attention on testing the time-lagged effects using the quantile regression specification

$$r_t = \eta_r^{(\alpha)} + \lambda_1^{(\alpha)} g_{u,t-1}^e + \lambda_2^{(\alpha)} g_{u,t-1}^u + \lambda_3^{(\alpha)} r_{t-1} + v_t^{(\alpha)}, \text{ for } \alpha \in (0, 1), \quad (18)$$

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

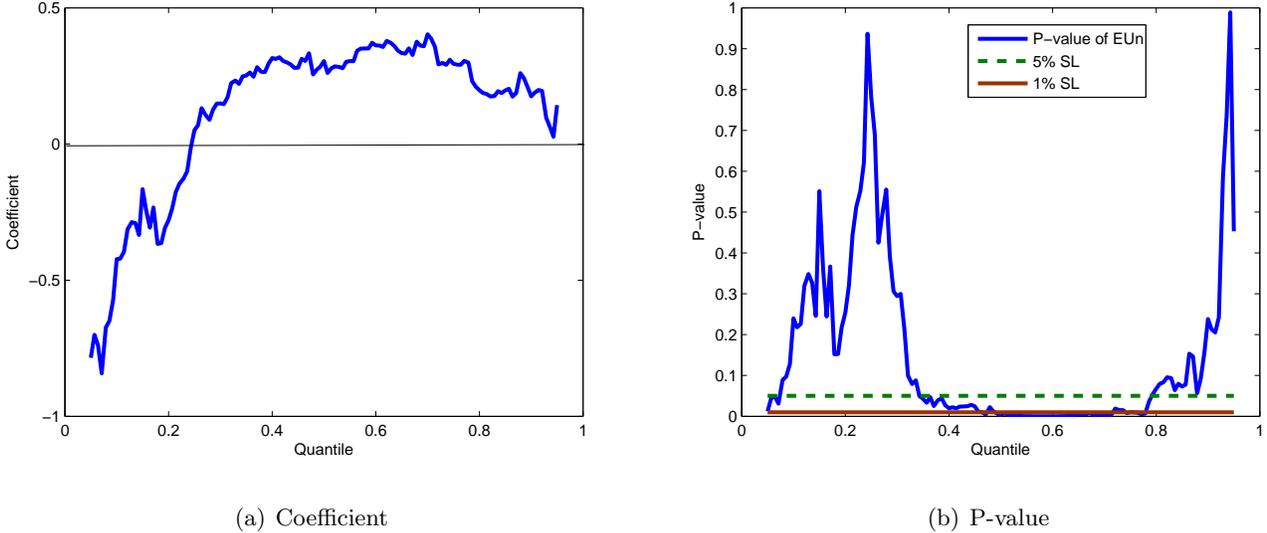


Figure 2: Causal effect of anticipated growth rate on quantiles of stock market return

The estimation and inference results for the coefficients of anticipated and unanticipated unemployment growth rates in equation (18) are reported in Figures 2 and 3, respectively. From these, we see that time-lagged anticipated unemployment rate affects negatively the quantile range (0.05, 0.25), whereas the effect is positive for the quantile range (0.25, 0.95) [see Figure 2-(a)]. This means that during a bear market the time-lagged anticipated unemployment rate affects negatively 20% of the lower quantiles of stock market returns, whereas during a bull market it affects positively 70% of the upper quantiles of stock market return.

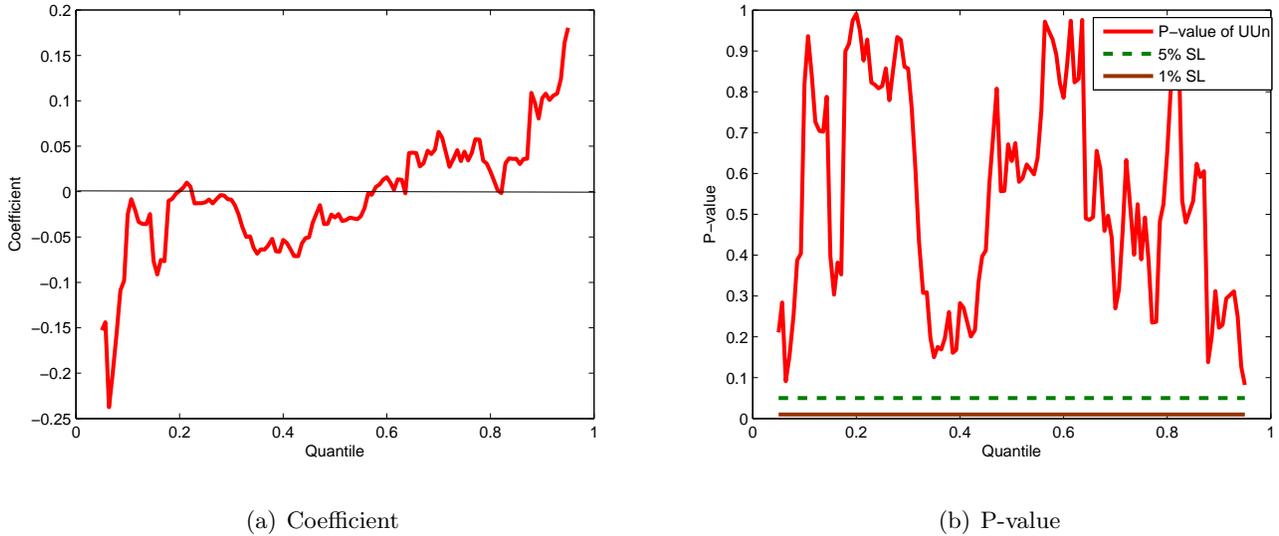


Figure 3: Causal effect of unanticipated growth rate on quantiles of stock market return

Figure 2-(b) shows that the effect is statistically significant both at 5% and 1% significance levels for quantile range (0.35, 0.80), except for very extreme lower and upper quantiles. We conclude that for most of the time an increase in time-lagged anticipated growth rate leads to a statistically significant increase in stock market return.

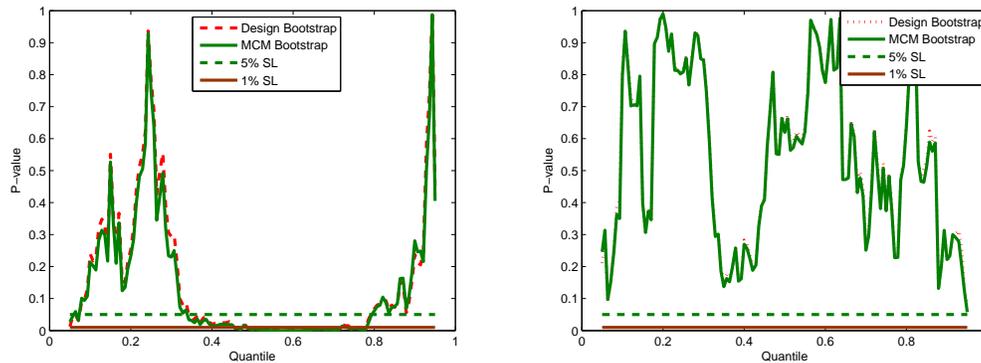
Moreover, Figure 3-(a) shows that, contrary to the anticipated unemployment rate, unanticipated rate has no impact on stock market return: the sign of the effect changes continuously across the quantiles. This is confirmed by Figure 3-(b) where we see that the effect is statistically insignificant both at 1% and 5% significant levels and at all quantiles of stock market return.

Again quantile regression analysis confirms that unemployment rate affects stock market return only through its anticipated component. This effect is both economically and statistically significant. 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.

## 4.2 Robustness

To check the robustness of the results found before, here we consider an alternative statistical procedure given by Markov Chain Marginal Bootstrap (MCMB) method for testing the statistical significance of the impact of anticipated unemployment rate on stock market returns. 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) Causal effect of anticipated unemployment growth rate on quantiles of stock market return (b) Causal effect of unanticipated unemployment growth rate on quantiles of stock market return

Figure 4: P-values using design bootstrap versus modified Markov chain marginal bootstrap

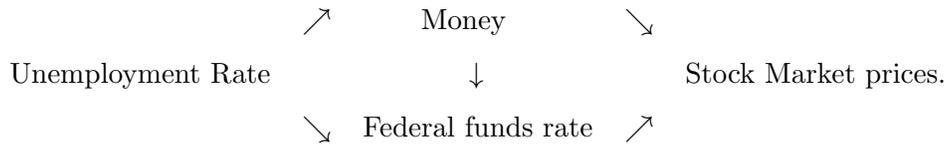
We apply MCMB autocorrelation algorithm to double check the statistical significance of the impact of anticipated and unanticipated components of unemployment rate on the conditional quantiles of stock market return. We particularly compare the results using the design bootstrap and the modified MCMB of KHM(2005). The empirical results are presented in Figure 4 which compares the p-values from the design bootstrap, used in the previous subsection, and the modified MCMB of the impact of anticipated and unanticipated unemployment growth rates on quantiles of stock market returns. We find that both methods yield to similar results, which confirms our previous conclusions.

Finally, we should also mention that similar results hold for quarterly data. The results are available upon request.

## 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



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.

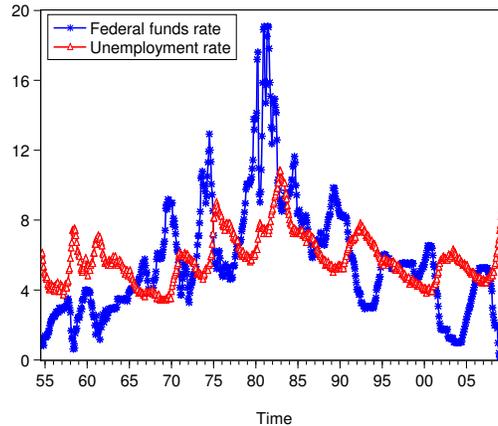


Figure 5: Unemployment rate and Federal funds rate.

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  $i_{n,t}$ ,  $i_{r,t}$ ,  $\pi_t$ , and  $u_t$ , 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:

$$i_{n,t} = i_{r,t} + \pi_t. \tag{19}$$

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  $\pi_t$ . Further, from the simple version of Phillips curve equation, we have

$$\pi_t = \pi^e + v - \alpha u_t, \tag{20}$$

where  $\pi^e$  is the expected inflation,  $v$  represents exogenous economic shocks, and  $\alpha$  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  $\pi^e$  and  $v$  random variables will not affect our analysis. Thus, Equation (20) implies that a rise in unemployment rate lowers inflation by the amount  $\alpha$ . 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

$$i_{n,t} = \pi^e + v - \alpha u_t + i_{r,t}. \tag{21}$$

Equation (21) 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:

$$\frac{di_{n,t}}{du_t} \Big|_{di_{r,t}=0} \cdot \quad (22)$$

Thus, based on equations (21) and (22), we show that:

$$\frac{di_{n,t}}{du_t} \Big|_{di_{r,t}=0} = -\alpha. \quad (23)$$

Since  $\alpha$  is a positive value, the marginal effect of unemployment rate on nominal interest rate must be negative  $\frac{di_{n,t}}{du_t} \Big|_{di_{r,t}=0} < 0$ . 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 time-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.

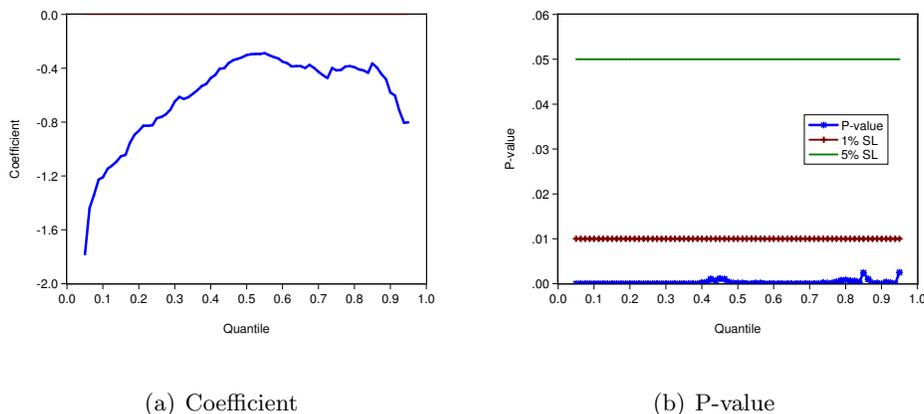


Figure 6: Impact of growth rate of the unemployment rate on Federal funds rate.

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:

$$r_t = \pi_0^{(\alpha)} + \pi_1^{(\alpha)} ffr_t + \pi_2^{(\alpha)} ffr_{t-1} + \pi_3^{(\alpha)} r_{t-1} + \tilde{e}_t^\alpha, \text{ for } \alpha \in [0.05, 0.95]. \quad (24)$$

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.

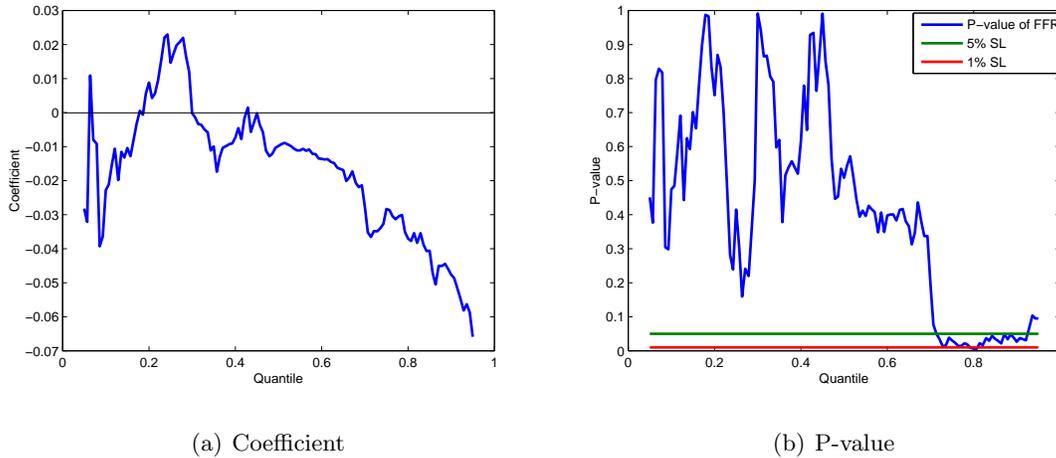


Figure 7: Immediate impact of Federal funds rate on stock returns.

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 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.<sup>1</sup> Figure 8 shows that the stock market prices move the same way as the ratio of money supply to unemployment rate. 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 non-parametric tests to formally investigate the relationship between anticipated/unanticipated unemployment rate and money supply.

<sup>1</sup>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.

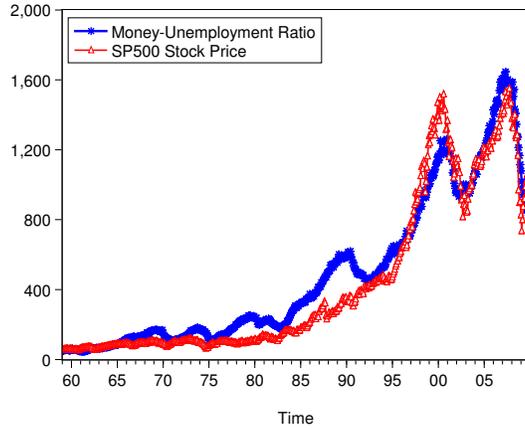


Figure 8: Money-Unemployment rate ratio and SP 500 stock price.

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

$$H_0^D : \Pr \{F(m_{s_t} | m_{s_{t-1}}, z_{t-1}(z_t)) = F(m_{s_t} | m_{s_{t-1}})\} = 1, \quad (25)$$

against the alternative hypothesis

$$H_1^D : \Pr \{F(m_{s_t} | m_{s_{t-1}}, z_{t-1}(z_t)) = F(m_{s_t} | m_{s_{t-1}})\} < 1, \quad (26)$$

where  $z_{t-1}$  (resp.  $z_t$ ) =  $g_{u,t-1}^e, g_{u,t-1}^u$  (resp.  $g_{u,t}^e, g_{u,t}^u$ ) and  $m_{s_t}$  is the money supply growth rate at time  $t$ . The latter is defined as:  $m_{s_t} = \log(MS_t) - \log(MS_{t-1})$ , where  $MS_t$  is the money supply a time  $t$ . The results of nonparametric tests are presented in Table 5. The latter reports the *p-values* for testing the instantaneous (**Panel A**) and time-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, and weak evidence of time-lagged effect. Consequently, the distribution function of money supply growth rate reacts to changes in the unemployment growth rate. Interestingly, we also find that only anticipated unemployment rate affects money supply. This might 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,

$$m_{s_t} = \delta_{ms} + \rho_1 g_{u,t}^e + \rho_2 g_{u,t-1}^e + \rho_3 g_{u,t}^u + \rho_4 g_{u,t-1}^u + \rho_5 m_{s_{t-1}} + \epsilon_t. \quad (27)$$

The estimation results reported in Table 6 confirm the results obtained using nonparametric test: only anticipated unemployment rate affects immediately money supply growth rate. We find that the impact is

Table 5: Nonparametric test (expression (9)) for nonlinear Granger Causality in distribution, money supply

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

**Note:** This table reports the  $p$ -values of nonparametric test for testing nonlinear instantaneous and time-lagged Granger non-causality in distribution from anticipated and unanticipated unemployment growth rates to money supply growth rate.

Table 6: Conditional Mean Regressions: Estimation and Inference

Mean	Model 1	Model 2	Model 3
<i>Const.</i>	0.00099 (0.000)	0.00098 (0.000)	0.00097 (0.000)
$g_{u,t}$			
$g_{u,t-1}$			
$g_{u,t}^e$	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)
$ms_{t-1}$	0.5802 (0.000)	0.5910 (0.000)	0.5881 (0.000)
$R^2(\%)$	36.214	35.214	36.535

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

$$ms_t = \theta_{ms}^{(\alpha)} + \xi_1^{(\alpha)} g_{u,t}^e + \xi_2^{(\alpha)} g_{u,t}^u + \xi_3^{(\alpha)} ms_{t-1} + \epsilon_t^\alpha, \text{ for } \alpha \in [0.05, 0.95] \quad (28)$$

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.

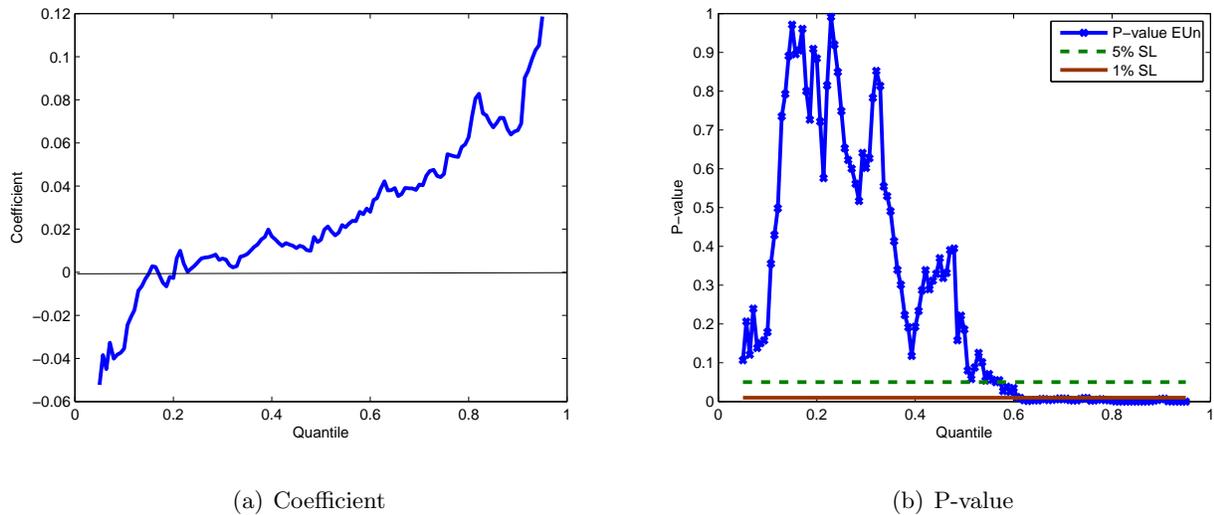
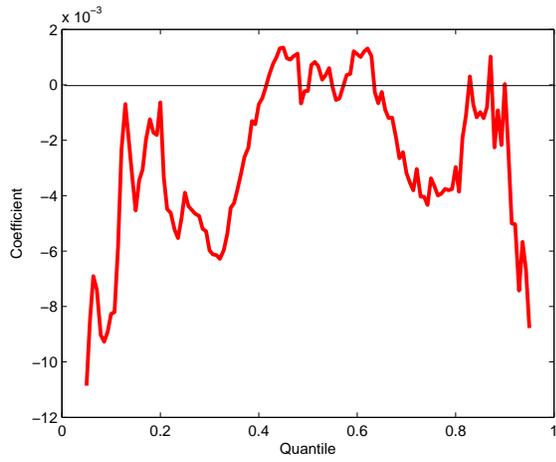


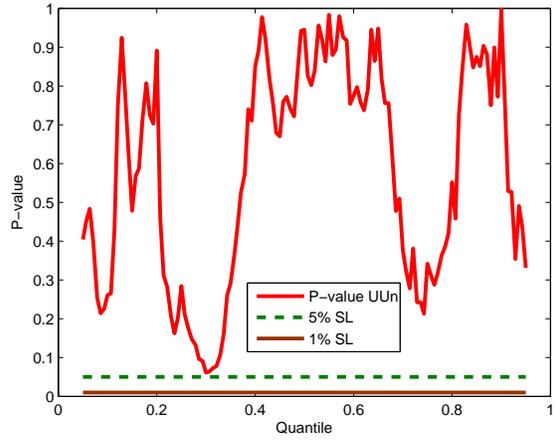
Figure 9: Impact of anticipated growth rate of the unemployment rate on money supply growth rate.

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).

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

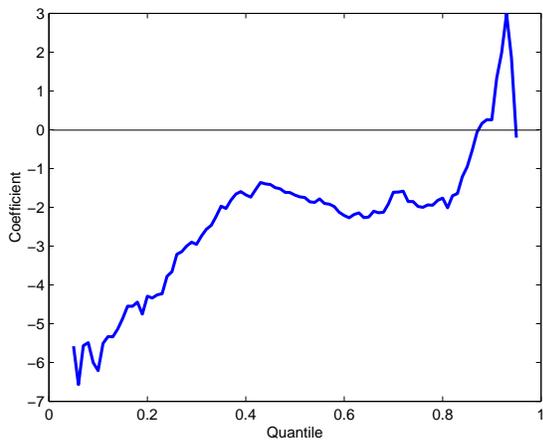


(a) Coefficient

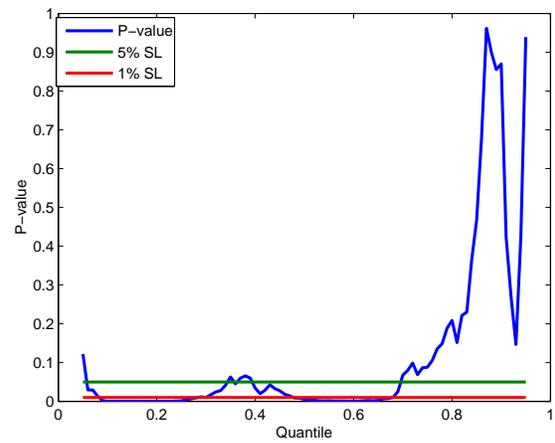


(b) P-value

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



(a) Coefficient



(b) P-value

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

exactly to the positive impact that we found in section 4.1. Finally, using the same data as the one in the present paper, Taamouti (2012) found a direct impact of money supply on stock prices.

## 6 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. 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] Barnes, M.L. and Hughes, A.W., (2002). "A Quantile Regression Analysis of the Cross Section of Stock Market Returns," *Federal Reserve Bank of Boston Working Paper*.
- [4] Barro, R.J. (1977), "Unanticipated money growth and unemployment in the United States," *American Economic Review*, vol. 67, pp. 101-115.
- [5] Barro, R.J. (1978), "Unanticipated money, output and the price level in the United States," *Journal of Political Economy*, vol 86, pp. 549-80.

- [6] 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.
- [7] 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.
- [8] Bernanke, B. and Blinder, A. (1992) “The Federal funds rate and the channels of monetary transmission,” *American Economic Review*, vol. 82, pp. 901-21.
- [9] 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.
- [10] Birz, G. and Lott Jr., J.R. (2011), “The effect of macroeconomic news on stock returns: New evidence from newspaper coverage,” *Journal of Banking & Finance*, vol. 35, pp. 2791-2800.
- [11] Bodie, Z. (1976), “Common stocks as a hedge against inflation,” *Journal of Finance*, vol. 31, pp. 459-470.
- [12] Bouezmarni, T., Roy, R. and Taamouti, A. (2011), “Nonparametric tests for conditional independence using conditional distribution,” *Working paper*, Université de Montreal and Universidad Carlos III de Madrid.
- [13] Bouezmarni, T., Rombouts, J. and Taamouti, A. (2012). “A Nonparametric Copula Based Test for Conditional Independence with Applications to Granger Causality,” *forthcoming in Journal of Business and Economic Statistics*.
- [14] 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.
- [15] Buchinsky, M. (1995), “Estimating the asymptotic covariance matrix for quantile regression models: A Monte Carlo study,” *Journal of Econometrics*, vol. 68, pp. 303-38.
- [16] Copper, R. (1974), “Efficient capital markets and the quantity theory of money”, *Journal of Finance*, vol. 19, pp. 887-908.
- [17] 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.
- [18] 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.
- [19] Chen, N.F., Roll, R. and Ross, S. (1986), “Economic forces and the stock market,” *Journal of Business*, vol. 59, pp. 383-403.

- [20] Craine, R. and Martin, V. (2003), "Monetary policy shocks and security market responses," University of California at Berkeley, Working Paper.
- [21] Chuang, C-C., Kuan, C-M. and Lin, H-Y., (2009). "Causality in quantiles and dynamic stock return-volume relations," *Journal of Banking & Finance*, Vol 33, pp. 1351-1360.
- [22] Deschamps, P.J. (2008), "Comparing smooth transition and Markov switching autoregressive models of US unemployment," *Journal of Applied Econometrics*, vol. 23, pp. 435-462.
- [23] Ding, Z., Granger, C.W.J. and Engle, R.F. , (1993). "A long memory property of stock market returns and a new model," *Journal of Empirical Finance*, vol. 1, pp. 83-106.
- [24] 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.
- [25] Efron, B. (1979), "Bootstrap methods: Another look at the jackknife," *Annals of Statistics* vol. 7, pp. 1-26.
- [26] Efron, B. (1982), "The jackknife, the bootstrap and other resampling plans," *Society for Industrial and Applied Mathematics, Philadelphia, PA*.
- [27] Fama, E.F. (1981), "Stock returns, real activity, inflation, and money," *American Economic Review*, vol. 71, pp. 545-565.
- [28] 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.
- [29] Geske, R. and Roll, R. (1983), "The fiscal and monetary linkage between stock returns and inflation," *Journal of Finance*, vol. 38, pp. 1-34.
- [30] Hamburger, J.M., and Kochin A.L. (1972), "Money and stock prices: The channels of influence", *The Journal of Finance*, vol. 27, pp. 231-249.
- [31] Harvey, C. and Siddique, A. (2000), "Conditional skewness in asset pricing tests," *The Journal of Finance*, vol. 55, pp. 1263-1295.
- [32] He, X. and Hu, F. (2002), "Markov chain marginal bootstrap," *Journal of the American Statistical Association*, vol 97, pp. 783-795.
- [33] 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.

- [34] Homa, K.E., and Jaffee, D.W. (1971), "The supply of money and common stock prices", *Journal of Finance*, vol. 27, pp. 1045-1066.
- [35] Kang, J., Kim, S.T, Lee, C. and Min, B-K. (2011), "Macroeconomic risk and the cross-section of stock returns," *Journal of Banking & Finance*, vol. 35, pp. 3158-3173
- [36] 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.
- [37] Koenker, R. and Bassett, G. (1978), "Regression quantiles," *Econometrica*, vol. 46, pp. 33-50.
- [38] Koenker, R. and D'Orey, V. (1987), "Algorithm AS 229: Computing regression quantiles," *Applied Statistics*, vol. 36, pp. 383-393.
- [39] Koenker, R., and Hallock, K.F. (2001), "Quantile regression," *Journal of Economic Perspectives*, vol. 15, pp. 143-156.
- [40] Koenker, R. (2005), *Quantile regression*. New York: Cambridge University Press.
- [41] Lee, T-H. and Yang, W. (2006). "Money-Income Granger-Causality in Quantiles," *University of California, Riverside Working Paper*.
- [42] Makin, J.H. (1982), "Anticipated money, inflation uncertainty and real economic activity," *The Review of Economics and Statistics*, vol. 64, pp. 126-134.
- [43] Nadaraya, E. A. (1964), "On estimating regression," *Theory of Probability and its Applications*, vol. 9, pp. 141-142.
- [44] Nishiyama, Y., Hitomi, K., Kawasaki, Y., and Jeong, K. (2011). "A consistent nonparametric test for nonlinear causality-Specification in time series regression," *Journal of Econometrics*, 165, pp. 112-127.
- [45] Nowak, S., Andritzky, J., Jobst, A. and Tamirisa, N. (2011), "Macroeconomic fundamentals, price discovery, and volatility dynamics in emerging bond markets," *Journal of Banking & Finance*, vol. 35, pp. 2584-2597.
- [46] Palmer, M. (1970), "Money supply, portfolio adjustments and stock prices", *Financial Analysts Journal*, vol. 26, pp. 19-22.
- [47] 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.
- [48] 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.

- [49] 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.
- [50] Rigobon, R. and Sack, B. (2002). “The Impact of monetary policy on asset prices,” NBER Working Paper No. 8794.
- [51] 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.
- [52] Sheffrin, S.M. (1979), “Unanticipated money growth and output fluctuations,” *Economic Inquiry*, vol. 17, pp. 1-13.
- [53] Taamouti, A. (2012), “Stock market’s reaction to money supply: Nonparametric Analysis,” Universidad Carlos III de Madrid Working paper.
- [54] Thorbecke, W. (1997), “On stock market returns and monetary policy” *The Journal of Finance*, vol. 52, pp. 635-654.
- [55] Thornton, J. (1993), “Money, output and stock prices in the UK: Evidence on some (non) relationships”, *Applied Financial Economics*, vol. 3, pp. 335-338.
- [56] Watson, G. (1964), “Smooth regression analysis,” *Sankhya*, vol. 26, pp. 359-372.