The Reaction of Stock Market Returns to Unemployment[*]

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1

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ABSTRACT

We empirically investigate the short-run impact of *anticipated* and *unanticipated* unemployment rates on stock prices. We particularly examine the nonlinearity in the stock market's reaction to the unemployment rate and study the effect at each individual point (quantile) of the stock return distribution. Using *nonparametric* Granger causality and *quantile* regression-based tests, we find that *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 returns 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 stock market prices. For other quantiles, the impact is generally statistically insignificant. Thus, an increase in the anticipated unemployment rate is, in general, good news for stock prices. Finally, we offer a reasonable explanation for the reason, and manner in which, the unemployment rate affects stock market prices. Using the Fisher and Phillips curve equations, we show that a high unemployment rate is followed by monetary policy action of the Federal Reserve (Fed). When the unemployment rate is high, the Fed decreases the interest rate, which in turn increases the stock market prices.

1 Introduction

Stock market analysts argue that stock prices rebound after the announcement of an unemployment rate increase. However, there is no clear academic consensus in the literature on the impact of unemployment announcements on stock market returns. Most conclusions on the stock prices–unemployment rate causal relationship are based on *linear mean regression* analyses. In mean regression, dependence is due to only mean dependence, and therefore, studies based on regression analysis ignore the causal relationships that show up in conditional quantiles as well as higher-order conditional moments (such as volatilities, skewness, and kurtosis). This issue might have serious consequences on portfolio selection and risk assessment. Furthermore, many financial models suggest nonlinear causal relationships; for example, see Linton and Perron (2003), Dittmar (2002), and Bansal et al. (1993). The present study investigates nonlinearity in the stock market reaction to unemployment rates and examines the impact at different quantiles of the stock return distribution. We rigorously analyze the 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 for the reason, and manner in which, the unemployment rate affects stock prices.

Numerous papers have examined the links between stock market prices and the real economy. Given the importance of the issue for policy makers, researchers continue to be very interested in studying these relationships. Existing papers analyzed two directions of causality, one from stock market prices to the real economy, and the other from the real economy to stock market prices. In this study, we focus on the latter direction of causality. Our main difference with the existing literature is that we examine the reaction of both the *distribution function* and individual *quantiles* of stock market returns to the *anticipated* and *unanticipated* unemployment rates, but most existing papers consider only the conditional *linear mean* effect. They ignore the non-linear dependence and the dependence in the quantiles of the conditional stock market returns distribution. The unemployment rate is chosen to represent the real economy because, in addition to its accuracy, it gauges the economy's growth rate. It is one of the important indicators for the Federal Reserve (Fed) to determine the health of the economy when setting monetary policy.

Following Chen, Roll, and Ross (1986), several studies have shown reliable relationships between macroeconomic variables and security returns. Previous papers [see Bodie (1976), Fama (1981), Geske and Roll (1983), and Pearce and Roley (1983)] have shown that the aggregate stock returns are negatively related to inflation and money growth. According to Chen, Roll, and Ross (1986, pages 383-384), *"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, " *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) examined the impact of 17 macroeconomic variables, including unemployment rate, on the mean and volatility of stock returns. They estimated a daily equity returns GARCH model where the realized returns and their conditional volatility depend on the 17 macro series' announcements, to find the unemployment rate affecting not the mean, but the variance, of stock returns.

A recent paper by Boyd, Hu, and Jagannathan (2005) [hereafter BHJ (2005)] studied the impact of *unanticipated* unemployment rate on stock returns. This paper finds that an announcement of rising unemployment is generally good news for stocks during economic expansions and bad news during economic contractions. The main difference between BHJ (2005) and this paper can be summarized as follows: **(1)** BHJ (2005) focus *only* on the *conditional mean* effect using *linear* mean regression analysis, whereas we investigate the non-linear effect on the *conditional mean, conditional distribution*, and individual *quantiles* using a *nonparametric approach* as well as *conditional quantile* regression methods; **(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* the anticipated unemployment rate has a non-linear impact on the *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. *Nonparametric* causality tests allow for capturing the non-linearity and dependence in low- and high-order moments, whereas quantile regression-based tests help identify and examine the effect at each quantile of the distribution of stock returns. To the best of our knowledge, this is the first study to investigate the reaction of conditional distribution and quantiles of stock returns to anticipated and unanticipated unemployment rates. This is also the first study to use *nonparametric tests* to test for Granger non-causality in mean and distribution from anticipated and unanticipated unemployment rates to stock market returns.

Our study first follows the approach considered by Barro (1977, 1978), Barro and Rush (1980), Sheffrin (1979), and Makin (1982), among many others, and then decomposes the actual first log unemployment rate difference [hereafter growth rate] into its *"anticipated"* and *"unanticipated"* components. Barro (1977, 1978) used an autoregressive (AR) approximation to divide the observed money growth rate into anticipated and unanticipated components. Thus, our anticipated and unanticipated growth rate measures are taken from

AR approximation to the Wold decomposition of the weak stationary growth rate of unemployment. Thus, we ensure that the anticipated component is known at time t (containing only $t-1$ information) and the unanticipated component (news) is serially uncorrelated. Note that both these facts are not warranted in the approach developed by BHJ (2005).

Second, we investigate the stock market's reaction to anticipated and unanticipated unemployment rates through two nonparametric tests. The first one tests for Granger non-causality in mean, and the second one tests for general Granger non-causality in distribution. Both the tests do not require specification of the model that might link the two variables of interest and therefore avoid the misleading results due to model misspecification. Moreover, the two tests can detect both linear and nonlinear causal effects.

To test for Granger non-causality in mean, we use the nonparametric test recently proposed by Nishiyama, Hitomi, Kawasaki, and Jeong (2011) [hereafter NHKJ (2011)]. The test statistic is based on moment conditions. It can also test for the omitted variables in time series regression. To apply this test, we need a Nadaraya–Watson [see Nadaraya (1964) and Watson (1964)] nonparametric estimator for conditional moments. Using monthly data on the S&P 500 stock index and unemployment rate for the period 1950–2014, we find that only the time-lagged anticipated unemployment rate Granger causes the conditional mean of stock market returns. Thus, as shown later, the time-lagged anticipated unemployment rate has a *nonlinear* impact on stock market returns.

The test for the reaction of the *conditional distribution* of the stock market returns to anticipated and unanticipated unemployment rates is also based on the recent *nonparametric* Granger causality in distribution test statistic proposed by Bouezmarni and Taamouti (2014). This test detects the nonlinearity and dependence in low- and high-order moments as well as in quantiles. It is based on comparing the conditional distribution function estimators using an L_2 metric, where the distribution functions are estimated using the Nadaraya–Watson approach. Using monthly data, and contrary to the conventional t-statistic in a linear mean regression model, we find very convincing evidence that *anticipated* growth rate Granger causes the conditional distribution function of the S&P 500 stock returns. We also find that *unanticipated* growth rate does not affect the conditional distribution function of stock returns. Therefore, the unemployment rate affects the conditional distribution of stock market returns *only* through its anticipated component.

Third, the nonparametric general Granger non-causality in the distribution test discussed in the previous paragraph shows the impact of anticipated unemployment rate on stock return distribution. However, the rejection of Granger non-causality in the distribution hypothesis does not reveal the return distribution level(s) where causality exists. To overcome this problem, we consider conditional quantile regression-based tests to identify the unemployment rate components' impact on individual quantiles of the conditional stock returns distribution. This will produce a broader picture of the causality effect in various scenarios. With the same data used before, quantile regression analysis confirms our previous results and shows that only

the anticipated unemployment rate component affects stock return quantiles. The causal effect is usually heterogeneous across stock return quantiles. For the 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 generally represents good news for stock prices. For the lower quantiles $(0.05, 0.30)$, the effect is negative and statistically insignificant (even at the 10% significance level).

Finally, we offer a reasonable explanation for why and how the unemployment rate affects stock market prices. We use the monetary policy measure Federal funds rate to identify the possible channel of the impact of unemployment rate on stock prices. This channel can be summarized as follows: the unemployment rate affects the Federal funds rate, which in turn affects the stock market prices. We then use existing economic theory (Fisher and Phillips curve equations) to show that the Federal funds rate reacts negatively to unemployment rate. Numerous papers [see Rigobon and Sack (2002), Craine and Martin (2003), Bernanke and Kuttner (2005), and the references therein] show a negative impact of Federal funds rate on stock market returns. Thus, the signs in this channel 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 a decrease (increase) in stock market prices (returns).

This paper is organized as follows. Section 2 describes the data and discusses the methodology used to decompose the unemployment rate into its anticipated and unanticipated components. Section 3 uses nonparametric Granger causality tests to examine the statistical significance of the impact of anticipated and unanticipated unemployment rates on the conditional mean and distribution of stock returns. Section 4 examines the Granger causality at each quantile of stock market returns using the unemployment rate components. Section 5 identifies one possible channel that explains how unemployment rate affects stock prices based on the Fed's monetary policy action. Finally, Section 6 concludes the paper.

2 Data and Methodology

2.1 Monthly unemployment announcements

This section describes the data used and discusses the methodology followed to decompose the unemployment rate announced by the Bureau of Labor Statistics (BLS) into its anticipated and unanticipated components. On the first Friday of each month, the BLS of the U.S. Department of Labor announces the employment and unemployment rates of the United States for the previous month along with various worker characteristics (gender, age, color, origin, education, etc.) The unemployment rate represents the number of unemployed persons as a percent of the labor force. According to the 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." The government collects the data on unemployment through a monthly sample survey called the Current Population Survey (CPS) to measure the extent of unemployment in the country. The CPS has been conducted every month since 1940 in the United States. It has been expanded and modified several times since then. The U.S. Department of Labor releases revisions of its unemployment announcements for the previous three months, and thereafter the announcement becomes final. BLS offers a long and accurately dated time series on the unemployment rate.

We chose the unemployment rate data from among many other macroeconomic variables because, besides its accuracy, it gauges the economy's growth rate. It is one of the important indicators for the Fed to determine the health of the economy when setting monetary policies and for investors who use the unemployment statistics to look for sectors that are losing jobs faster.

The sample used here contains monthly seasonally adjusted unemployment rates and covers the period from January 1950 to September 2014, for a total of 777 observations. The summary statistics (not reported, but available upon request) for log unemployment rate $\log(ur_t)$ and its first difference $g_{u,t} = \log(ur_t) - \log(ur_{t-1})$, show that the unconditional distributions of monthly $\log(ur_t)$ and $g_{u,t}$ exhibit excess kurtosis and positive skewness as expected. [1] The sample mean of the growth rate is almost zero, the value of the sample skewness is also close to zero, but the sample kurtosis is greater than the normal distribution value of three. The zero p-value of the Jarque–Bera test for $g_{u,t}$, the growth rate of unemployment, indicates that this variable cannot be normally distributed.

We also perform an Augmented Dickey–Fuller test (hereafter ADF-test) for nonstationarity of log (unemployment rate) and its first difference, $g_{u,t}$. Using an ADF-test with only an intercept and a test with both an intercept and a trend, the null of the unit root is not rejected at the 5% level [p-values equal to 0.08 and 0.26 respectively]. We apply the same test to the first difference of log (unemployment), to find the null clearly rejected [p-values equal to zero in both cases]. Therefore, our analyses in the next sections are based on $g_{u,t}$.

2.2   Measuring anticipated and unanticipated unemployment rates

This section examines the reaction of stock market returns to anticipated and unanticipated growth rates of unemployment. We follow the approach of Barro (1977, 1978), Barro and Rush (1980), Sheffrin (1979), and Makin (1982), among others, to decompose the actual growth rate of unemployment into "*anticipated*" and "*unanticipated*" components. Barro (1977, 1978) uses AR approximation to divide the observed money

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[1]We use $\log(ur_t)$ instead of ur_t in order to work with the same transformation for the dependent variable (stock prices) and independent variable (unemployment rate). This makes it easier to interpret the results without having to change the main conclusion. Note that the returns are defined as the first difference of the log (stock prices). From a statistical perspective, the log transformation applied to ur_t reduces the skewness and eliminates certain types of heteroscedasticity. For the results obtained when using $ur_t - ur_{t-1}$ instead of $g_{u,t}$, see the appendix.

growth rate into anticipated and unanticipated components. The anticipated and unanticipated unemployment rates we consider are from the AR approximation to the MA (∞) Wold decomposition of weakly stationary process, the growth rate of unemployment ($g_{u,t}$). In comparison to many other linear and nonlinear processes, as argued by van Dijk, Teräsvirta and Franses (2002) and Deschamps (2008), AR processes are appropriate to model the unemployment rate.

The equation to decompose an observed growth rate into its anticipated and unanticipated components is

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

where $g_{u,t}$ is the growth rate of unemployment at time t, $(\mu, \beta_1, ..., \beta_p)'$ is the vector of parameters to estimate, and u_t is an error term. The number of lags, p, is based on the Akaike information criteria (AIC). Using the data described earlier, $p = 15$ (over a maximum of 30 lags). Further, the AR(15) model estimation results can be summarized by the following equation:

$$
\begin{aligned}
\hat{g}_{u,t} \;=\; & \underset{(0.434)}{8.35\ 10^{-4}} + \underset{(2.317)}{0.084}\ g_{u,t-1} + \underset{(4.393)}{0.160}\ g_{u,t-2} + \underset{(3.171)}{0.117}\ g_{u,t-3} + \underset{(2.150)}{0.078}\ g_{u,t-4} \\[2mm]
& + \underset{(2.189)}{0.079}\ g_{u,t-5} + \underset{(0.357)}{0.012} g_{u,t-6} + \underset{(0.153)}{0.005} g_{u,t-7} + \underset{(1.123)}{0.040} g_{u,t-8} - \underset{(-0.244)}{0.008}\ g_{u,t-9} \underset{(-3.146)}{-0.113}\ g_{u,t-10} \\[2mm]
& + \underset{(1.937)}{0.070}\ g_{u,t-11} \underset{(-4.041)}{-0.146}\ g_{u,t-12} \underset{(-0.538)}{-0.019}\ g_{u,t-13} \underset{(-1.024)}{-0.036}\ g_{u,t-14} \underset{(1.421)}{+0.050}\ g_{u,t-15}, \tag{2} \\[2mm]
R^2 \;=\; & 14.45\%,\ \textbf{F}\text{-statistic} = 8.392.
\end{aligned}
$$

To validate the estimated model, we consider an AR residual Portmanteau test for the existence of autocorrelations; the results (not reported, but available upon request) suggest that the estimated AR(15) model is adequate in that the residuals do not contain any correlation.

Finally, we use the estimated equation in (2) to decompose the observed growth rate $g_{u,t}$ into its anticipated component $g_{u,t}^e$, and unanticipated component $g_{u,t}^u$. Obviously, the anticipated component is the fitted values $g_{u,t}^e = E_{t-1}(g_{u,t}) \simeq \hat{g}_{u,t}$ and the "unanticipated" growth rate is the residuals $\hat{u}_t = g_{u,t} - g_{u,t}^e$. The anticipated and unanticipated components are shown in Figure 1. We find the anticipated component smoother than the unanticipated one, and the average values of the two components almost equal to zero [see Table 1].

2.3   Monthly stock return

The stock market data comprise the monthly S&P 500 indices including dividends, which are available from Yahoo Finance. As for unemployment rate, the sample covers the period from January 1950 to September 2014 for a total of 777 observations. Stock returns are computed using the standard continuous compounding

Table 1: Descriptive statistics of anticipated and unanticipated growth rates

	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera (Prob.)
g_u^e	0.00084	0.00007	0.01346	0.96285	7.81353	0.000
g_u^u	-0.0000	-0.00144	0.03274	0.49032	5.60806	0.000

Note: *This table reports the descriptive statistics of anticipated (g_u^e) and unanticipated (g_u^u) growth rates of unemployment rate. The sample covers the period from January 1950 to September 2014.*
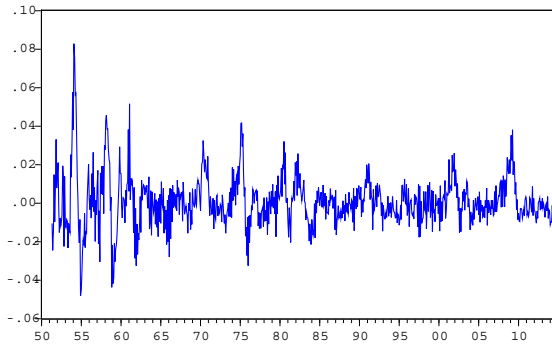
(a) Anticipated Growth Rate
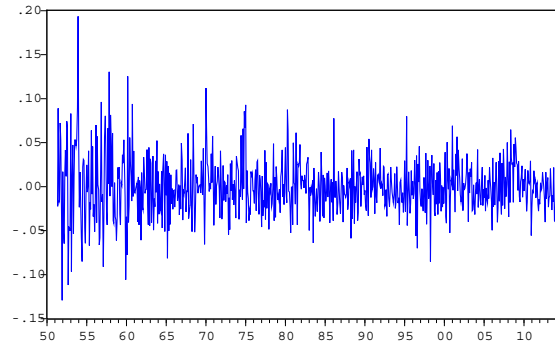
(b) Unanticipated Growth Rate

Figure 1: *This figure illustrates the time series of anticipated (g_u^e) and unanticipated (g_u^u) growth rates of unemployment rate. The sample covers the period from January 1950 to September 2014.*

formula. If we denote the time t logarithmic price of the stock market by p_t, the continuously compounded stock return from time $t-1$ to time t is defined by $r_t = p_t - p_{t-1}$. The stock returns summary statistics (not reported, but available upon request) show the S&P 500 price movements exhibiting the expected excess kurtosis and negative skewness. The sample kurtosis is greater than the normal distribution value of three. The p-value of the Jarque–Bera test statistic suggests that stock returns cannot be normally distributed. Finally, we perform ADF-tests for nonstationarity of the S&P 500 stock returns. The results of the ADF-test with only an intercept and with an intercept and a trend show that the S&P 500 stock return is stationary, thus validating the asymptotic distribution theory of the test statistics; we consider these in the following sections.

3   Stock market reaction: Nonparametric analysis

We begin by testing whether stock market returns react to anticipated and unanticipated unemployment rates in a broad framework so that the specification of the underlying model is left free. Nonparametric tests are well suited for that. They do not impose any restriction on the model linking the dependent variable to independent variables.

Most of the empirical studies on the stock price–unemployment rate relationship focus only on the traditional linear Granger causality tests based on conditional *linear* mean regression analysis; see BHJ(2005), Flannery and Protopapadakis (2002), and the references therein. Although these tests can easily detect linear causal relations, they find it hard to detect nonlinear causal relations [see Baek and Brock (1992), Hiemstra and Jones (1993), Bouezmarni and Taamouti (2014), and Bouezmarni, Rombouts, and Taamouti (2012)]. Therefore, traditional linear Granger causality tests might overlook the significant nonlinear relation between stock returns and unemployment rate.

In this section, we first test for Granger non-causality in mean and then check for 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 the mean. A comparison with the results obtained from linear regression tests will help us see the nature (linear or nonlinear) of the impact if any of the components of unemployment rate on the conditional mean of stock returns. Thereafter, we test for general Granger non-causality in distribution, again without assuming any parametric model for the conditional distribution of stock returns. This second test is to see whether the unemployment rate components affect other levels (apart from the mean) of the distribution of stock returns.

3.1 Nonparametric Granger Causality in Mean

To test for Granger non-causality in mean, we use the nonparametric test recently proposed by NHKJ (2011). The test statistic is based on moment conditions. To apply this test, we need the Nadaraya–Watson nonparametric estimator of moments. Before seeing how the test works, let us assume that $\{(r_t, \ z_t)'\}_{t=1}^{T}$ is a sample of T observations of 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 component or unanticipated component of $g_{u,t}$. Suppose we are testing the Granger non-causality in mean from z_{t-1} to r_t. This is to test the null hypothesis

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

against the alternative hypothesis

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

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

$$H_0^m : \Pr\left\{ E\left[v_t f\left(r_{t-1} \right) q(X_{t-1}) \right] = 0 \right\} = 1, \quad \text{for } \forall q\left(x \right) \in s_r^{\perp} \tag{3}$$

against the alternative hypothesis

$$H_1^m : \Pr\left\{ E\left[v_t f\left(r_{t-1} \right) q(X_{t-1}) \right] = 0 \right\} < 1, \text{ for some } q\left(x \right) \in s_r^{\perp}, \tag{4}$$

where $q\left(x \right)$ is any function in the Hilbert space $s_r^{\perp}$ orthogonal to the Hilbert L_2 space

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

Since $E\left[v_t f\left(r_{t-1} \right) q(X_{t-1}) \right]$ is unknown, we use a nonparametric approach to estimate it. Following NHKJ (2011), we use the Nadaraya–Watson method to estimate this expectation. To test the null hypothesis (3) against the alternative hypothesis (4), NHKJ (2011) suggest the test statistic

$$\hat{S}_T = \sum_{i=1}^{k_T} w_i \hat{a}_i^2, \tag{5}$$

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

Obviously, the test statistic $\hat{S}_T$ depends on the sample size. According to NHKJ (2011), 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 ε_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 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 $N(0,1)$ random variables. An advantage of this test is that its simulation is very simple and the critical values do not dependent on the data.

NHKJ (2011) further show that their test has nontrivial power against $\sqrt{T}$-local alternatives. They argue that previously proposed tests [see Bierens and Ploberger (1997) and Bierens (2004) among others] can be rewritten as special cases of their test statistic, and that the latter has an advantage over the earlier ones in that it can easily control the power properties directly. Finally, they use the weighting function $w_i = 0.9^i$ in simulation and show that their test has reasonably good empirical size and power for a variety of linear and nonlinear models. Their power section also discusses how sequence $\{w_i\}$ can be chosen to maximize power.

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 as equality between the distribution of stock returns conditional on its own past and the past (present) changes in the anticipated or unanticipated unemployment rate, and the distribution of stock returns conditional only on its own past, almost everywhere. This corresponds to testing the conditional independence of stock returns and the past (present) changes in the anticipated or unanticipated unemployment rate conditional on the past stock return. It tests the Granger non-causality in distribution, as opposed to the existing regression-based tests examining only Granger non-causality in mean. In the mean regression, the dependence is only due to the mean dependence; thus, the dependence described by high-order moments and quantiles is ignored.

Granger causality tests provide useful information on whether the knowledge of past (present) changes in the anticipated and unanticipated components of the unemployment rate improves the short-run forecasts of current and future movements in stock returns. The test considered here [hereafter non-linear Granger causality test, or nonparametric Granger causality test] can detect linear and non-linear Granger causality at any level (quantile) of the conditional distribution of stock returns.

We consider a new nonparametric test statistic proposed recently by Bouezmarni and Taamouti (2014) [hereafter BT (2014)]. This test is based on comparing the conditional distribution functions using an L_2 metric. Suppose we have to test the Granger non-causality in *distribution* from z_{t-1} (z_t) to r_t. This is done by testing

$$H_0^D : \Pr\left\{F\left(r_t \mid r_{t-1}, z_{t-1}(\text{or } z_t)\right) = F\left(r_t \mid r_{t-1}\right)\right\} = 1 \tag{6}$$

against the alternative hypothesis

$$H_1^D : \Pr\{F(r_t \mid r_{t-1}, z_{t-1}(\text{or } z_t)) = F(r_t \mid r_{t-1})\} < 1. \tag{7}$$

Note that due to the lack of persistence in the returns, in the above hypothesis we consider only one lag for the unemployment rate components (z) and stock returns (r).

Since the conditional distribution functions $F(r_t \mid r_{t-1}, z_{t-1}(\text{or } z_t))$ and $F(r_t \mid r_{t-1})$ are unknown, we consider a nonparametric approach to estimate them. Following BT (2014), we consider the Nadaraya–Watson approach, as proposed by Nadaraya (1964) and Watson (1964). For expositional simplicity, we focus our discussion on testing the time-lagged impact of g_u^u and g_u^e on stock market returns. The test can be defined similarly to that for testing contemporaneous (instantaneous) effects. Denoting $\bar{x} = (r, z)'$ and remembering that $X_{t-1} = (r_{t-1}, z_{t-1})' \in \mathbb{R}^2$ for $z = g_u^e, g_u^u$, the Nadaraya–Watson estimator of the conditional distribution function of r_t, given z_{t-1} and r_{t-1}, can be defined by

$$\hat{F}_{h_1}(r_t \mid \bar{x}) = \frac{\sum_{t=2}^{T+1} K_{h_1}(\bar{x} - X_{t-1}) \, \mathrm{I}_{A_{r_t}}(r_t)}{\sum_{t=2}^{T+1} K_{h_1}(\bar{x} - X_{t-1})}, \tag{8}$$

where $K_{h_1}(.) = h_1^{-2} K(./h_1)$, for $K(.)$ is 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}, can be defined as

$$\hat{F}_{h_2}(r_t \mid r) = \frac{\sum_{t=2}^{T+1} K_{h_2}^*(r - r_{t-1}) \, \mathrm{I}_{A_{r_t}}(r_t)}{\sum_{t=2}^{T+1} K_{h_2}^*(r - r_{t-1})}, \tag{9}$$

where $K_{h_2}^*(.) = h_2^{-1} K^*(./h_2)$, for $K^*(.)$ is a different kernel function and $h_2 = h_{2,T}$ is a different bandwidth parameter. Note that the Nadaraya–Watson estimators of conditional distribution functions are positive and monotone.

To test the null hypothesis (6) against the alternative hypothesis (7), we follow BT (2014) and use the following test statistic:

$$\hat{\Gamma} = \frac{1}{T} \sum_{t=2}^{T+1} \left\{ \hat{F}_{h_1}(r_t \mid X_{t-1}) - \hat{F}_{h_2}(r_t \mid r_{t-1}) \right\}^2 w(\overline{V}_{t-1}), \tag{10}$$

where $w(.)$ is a nonnegative weighting function of the data X_{t-1}, for $2 \leq t \leq T$. Obviously, the test statistic $\hat{\Gamma}$ depends on the sample size. It is close to zero if conditional on r_{t-1}, variables r_t and z_{t-1} are independent and it diverges in the opposite case. BT (2014) establish the asymptotic distribution of the nonparametric test statistic in (10). 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 valid asymptotically, for finite samples they suggest standardized data and the local bootstrap version of the test statistic. In a finite sample, an asymptotic normal distribution generally does not provide a satisfactory approximation of the exact distribution of a nonparametric test statistic. Further, a simple resampling from the empirical distribution

will not conserve the existing conditional dependence structure of the data. This shows the importance of using the local smoothed bootstrap as suggested by Paparoditis and Politis (2000). The latter improves considerably the finite sample properties (size and power) of the test.

BT (2014) report the results of their Monte Carlo experiment to illustrate the size and power of their test based on a local smoothed bootstrap. The simulation study considers two groups of data-generating processes (DGPs), corresponding 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 of the test. They also considered two different reasonable sample sizes, $T = 200$ and $T = 300$. For each DGP and sample size, they generated 500 independent realizations, and for each realization they obtained 500 bootstrapped samples. Since optimal bandwidths are not available, they 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 $c_2 = 0.7$), corresponding to the values commonly used in practice. These bandwidths satisfy the assumptions needed to derive the asymptotic distribution of the test statistic. From 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 the level $\alpha = 10\%$. Globally, the size of the test is fairly well controlled for even with a series of length $T = 200$. At 5%, all the rejection frequencies are within two standard errors. However, at 10%, three rejection frequencies are between two and three 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 has the greatest power when $c_1 = c_2 = 1$.

3.3 Empirical results: linear versus non-linear causality

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

$$r_t = \omega_r + \alpha_1 \ g^e_{u,t} + \alpha_2 \ g^e_{u,t-1} + \alpha_3 \ g^u_{u,t} + \alpha_4 \ g^u_{u,t-1} + \alpha_5 \ r_{t-1} + e_t, \tag{11}$$

where e_t is assumed to be an error term with conditional mean equal to zero. The parameters in equation (11) are unknown and can be estimated through ordinary least squares (OLS). The anticipated (resp. unanticipated) changes in unemployment rate $g^e_{u,t}$ (resp. $g^u_{u,t}$) do not instantaneously Granger cause stock market returns r_t if the null hypothesis $H_0 : \alpha_1 = 0$ (resp. $H_0 : \alpha_3 = 0$) holds. Similarly, $g^e_{u,t-1}$ (resp. $g^u_{u,t-1}$) does not Granger cause stock market returns r_t if the null hypothesis $H_0 : \alpha_2 = 0$ (resp. $H_0 : \alpha_4 = 0$) is not rejected.

Since the dependent variable in equation (11) is given by stock returns r_t, the error term e_t is very likely heteroscedastic. To avoid the effect of heteroscedasticity on inference, we consider a robust HAC t-statistic. The estimation and inference results obtained with the data described in section 2 are presented in Table

Table 2: Linear Granger causality in mean tests

r_t	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Const.	0.0056 (0.000)	0.0056 (0.000)	0.0056 (0.000)	0.0055 (0.001)	0.0056 (0.000)	0.0055 (0.001)
$g^e_{u,t}$	−0.0303 (0.813)		−0.0304 (0.814)			
$g^e_{u,t-1}$				0.1431 (0.236)		0.1431 (0.235)
$g^u_{u,t}$		−0.0288 (0.470)	−0.0288 (0.471)			
$g^u_{u,t-1}$					0.0093 (0.840)	0.0093 (0.839)
r_{t-1}	0.0501 (0.259)	0.0483 (0.272)	0.0482 (0.271)	0.0519 (0.247)	0.0517 (0.243)	0.0521 (0.244)
$R^2(\%)$	0.261	0.302	0.311	0.476	0.271	0.482

Note: *This table reports the estimation results that correspond to the linear mean regressions in (11). The p-values are given in parentheses. The sample covers the period from January 1950 to September 2014.*

2. The table shows that the constant terms in all linear mean regressions are positive and statistically significance at the 5% and 1% significance levels. We also find that the immediate effects of the anticipated and unanticipated components of unemployment growth on the conditional mean of stock market returns are negative whereas the time-lagged effects are positive. However, none of the coefficients of immediate and time-lagged effects is statistically significant at the 5% and 10% significance levels. The highest R^2 is obtained in the regression with time-lagged anticipated and unanticipated unemployment rates.

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

We apply the nonparametric test statistic given in (5) to test for *nonlinear* Granger non-causality in mean from g^e_u (resp. g^u_u) to stock market returns. Following NHKJ (2011), we choose as weighting function $w_i = 0.9^i$. We also considered many other weighting functions such as $w_i = 0.5^i$, 0.6^i, 0.7^i, and 0.8^i. For all the weighting functions considered, we found a negligible change in 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 again followed NHKJ (2011) in choosing the bandwidth $h = cT^{-0.3}$ for various values of $c : c = 1, 2.5, 5, 7.3$.

The results from testing the nonlinear time-lagged Granger non-causality in mean are presented in Table 3. The table reports the test statistics and the corresponding 5% critical values. For all the considered weighting functions and bandwidths, only the time-lagged anticipated unemployment rate (g^e_u) Granger

causes the conditional mean of stock market returns. Given the results of linear regression analysis [see table 2], this suggests that the time-lagged anticipated unemployment rate has a nonlinear effect on stock market returns.

We now test for general Granger non-causality in distribution from the anticipated and unanticipated components of $g_{u,t}$ to stock market returns. For this, we test the null hypothesis (6) against the alternative hypothesis (7) using the nonparametric test statistic given in (10). The results are presented in Table 4. The table reports the *p-values* computed using local smoothed bootstrap. Contrary to the linear mean regression-based tests, we find strong evidence at the 5% significance level of the *time-lagged* anticipated growth rate of unemployment rate Granger causing the conditional distribution function of stock market returns. Further, we find very weak evidence of an instantaneous causality between anticipated unemployment rate and stock market returns. Moreover, we also find convincing evidence of no instantaneous and time-lagged Granger causality from the unanticipated component of growth rate of unemployment to stock returns even at the 10% significance level. Thus, we conclude that the unemployment rate affects the distribution of stock market returns *only* through its anticipated component. This could imply that the *time-lagged* anticipated unemployment rate affects other levels (other than the mean) of the conditional distribution of stock market returns.

The rejection of Granger non-causality in the distribution hypothesis from the anticipated component of the unemployment rate to stock market returns does not indicate the quantiles of stock return distribution where causality may exist. To overcome this problem, in the next section, we use quantile regression analysis to identity the effect at each quantile of the stock return distribution.

4   Quantile analysis

While a large majority of regression models focus on examining the conditional mean of a dependent variable, we find an increasing interest in methods to model other aspects of the conditional distribution. One important and popular approach is quantile regression, which models the quantiles of the dependent variable given a set of conditioning variables. Originally developed by Koenker and Bassett (1978), the quantile regression model estimates the 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, the model describes how the median, or the 10th or 90th quantile of the response variable, can be affected by regressor variables. Moreover, quantile regression does not require strong distributional assumptions; it is robust against outliers compared to mean regression and can thus be estimated with greater precision than the conventional moments regression [see Harvey and Siddique (2000)].

Table 3: Nonparametric test (expression (5)) for nonlinear Granger causality in mean

Test statistic / H_0	From Time-lagged g_u^e to r	From Time-lagged g_u^u to r
Bandwidths: $h = cT^{-0.3}$	**Panel A**: $w_i=0.5^i$, Critical Value=2.60	
$c = 1$	3.27	0.805
$c = 2.5$	3.61	0.711
$c = 5$	3.61	0.707
$c = 7.3$	3.61	0.702
	Panel B: $w_i=0.6^i$, Critical Value=3.57	
$c = 1$	8.29	1.961
$c = 2.5$	8.15	1.933
$c = 5$	8.16	1.925
$c = 7.3$	8.15	1.923
	Panel C: $w_i=0.7^i$, Critical Value=5.01	
$c = 1$	19.12	3.01
$c = 2.5$	19.21	2.93
$c = 5$	19.23	2.92
$c = 7.3$	19.23	2.91
	Panel D: $w_i=0.8^i$, Critical Value=7.58	
$c = 1$	42.93	4.41
$c = 2.5$	42.35	4.37
$c = 5$	42.35	4.33
$c = 7.3$	42.34	4.31
	Panel E: $w_i=0.9^i$, Critical Value=14.38	
$c = 1$	79.55	5.27
$c = 2.5$	79.14	5.21
$c = 5$	79.18	5.12
$c = 7.3$	79.14	5.12

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 the anticipated component (g_u^e) and unanticipated component (g_u^u) of unemployment rate (g_u) to stock market returns (r). h_1 and w_i are the bandwidth parameter and weighting function in the test statistic (5). The sample covers the period from January 1950 to September 2014.*

Table 4: Nonparametric test (expression (10)) for nonlinear Granger causality in distribution

Test statistic / H_0	From g_u^e to r	From g_u^u to r
Bandwidths: $h_1 = c_1 T^{-1/4.75}$, $h_2 = c_2 T^{-1/4.25}$ **Panel A**: *Instantaneous Effect*		
$c_1 = c_2 = 2$	0.049	0.384
$c_1 = c_2 = 1.5$	0.061	0.402
$c_1 = c_2 = 1$	0.070	0.367
$c_1 = 0.8$, $c_2 = 0.7$	0.081	0.327
Panel B: *Time-lagged Effect*		
$c_1 = c_2 = 2$	0.000	0.392
$c_1 = c_2 = 1.5$	0.000	0.459
$c_1 = c_2 = 1$	0.000	0.436
$c_1 = 0.8$, $c_2 = 0.7$	0.000	0.365

Note: *This table reports the p-values of the nonparametric test for testing nonlinear instantaneous and time-lagged Granger non-causality in distribution from the anticipated (g_u^e) and unanticipated (g_u^u) components of unemployment rate (g_u) to stock market returns (r). h_1 and h_2 are the bandwidth parameters in test statistic (10). The sample covers the period from January 1950 to September 2014.*

To examine the estimation and inference of quantile regressions, we first denote the αth quantile of the conditional distribution of stock returns by $Q_\alpha(r_t \mid I_{t-1})$, where I_{t-1} is an information set containing past (present) covariates. Note that the null hypothesis in (6) is equivalent to

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

If H_0^Q holds for all α in $(0,1)$, the changes in components of the unemployment rate do not Granger cause the distribution of stock market returns. In other words, Granger non-causality in the 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 causality might exist. The null hypothesis for testing Granger non-causality at a given αth quantile of the stock return distribution is

$$H_0^{Q_\alpha} : Q_\alpha(r_t \mid r_{t-1}, z_{t-1}(\text{or } z_t)) = Q_\alpha(r_t \mid r_{t-1}), \text{ for a given } \alpha \in (0,1). \tag{13}$$

If $H_0^{Q_\alpha}$ holds, changes in the components of the unemployment rate do not Granger cause the αth quantile of the stock market returns.

Note that the null hypotheses H_0^Q and $H_0^{Q_\alpha}$ are general hypotheses in that they do not specify the functional form of conditional quantiles that might be linear or nonlinear. However, because nonparametric quantile regression is not yet well developed, we follow the literature and propose a linear quantile regression

as approximation to the possible non-linear quantile regression specification as follows:

$$r_t = \theta(\alpha)' w_{t-1} + \varepsilon_t^{(\alpha)}, \text{ for a given } \alpha \in (0,1), \tag{14}$$

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

$$Q_\alpha \left(\varepsilon_t^{(\alpha)} \mid r_{t-1}, z_{t-1} \right) = 0, \text{ for } \alpha \in (0,1); \tag{15}$$

that is, the conditional αth quantile of the error term is equal to zero. Note that for the purposes of estimation and inference, the i.i.d. errors assumption is not needed.

From the quantile regression in (14), the time-lagged anticipated and unanticipated components of unemployment rate do not Granger cause the αth *quantile* of stock market returns if $H_{lin,0}^{Q_\alpha} : \beta_1(\alpha) = 0$ holds. We can similarly define an *instantaneous* Granger non-causality in the αth quantile between the components of unemployment rate and stock returns by replacing in equation (14) z_{t-1} for z_t.

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

$$\hat{\theta}(\alpha) = \arg\min_{\theta(\alpha)} \left(\sum_{t:r_t > \theta(\alpha)' w_{t-1}} \alpha \mid r_t - \theta(\alpha)' w_{t-1} \mid + \sum_{t:r_t < \theta(\alpha)' w_{t-1}} (1-\alpha) \mid r_t - \theta(\alpha)' w_{t-1} \mid \right). \tag{16}$$

Estimator $\hat{\theta}(\alpha)$ minimizes the 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 median regression and asymmetric otherwise. This estimator can be used to solve the linear programming problem. Several algorithms to solve 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, estimator $\hat{\theta}(\alpha)$ is asymptotically normally distributed [see Koenker (2005)]

$$\sqrt{T} \left(\hat{\theta}(\alpha) - \theta(\alpha) \right) \overset{d}{\sim} \mathcal{N}(0, \Sigma_\alpha). \tag{17}$$

Here, "$\overset{d}{\sim}$" denotes convergence in distribution, Σ_α 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 the Normal distribution.

The computation of an estimator of covariance matrix Σ_α is very important in quantile regression analysis. Generally, we distinguish between three classes of estimators: **(1)** methods for estimating Σ_α in i.i.d. settings; **(2)** methods for estimating Σ_α for independent but non-identically distributed settings; and **(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 more efficient in small samples is based on the design matrix

bootstrap [see Buchinsky (1995)]. The design matrix bootstrap estimator of Σ_α was initially suggested by Efron (1979, 1982); it is given by

$$\hat{\Sigma}_\alpha^* = \frac{T}{B} \sum_{j=1}^{B} \left(\hat{\theta}_j^* \left(\alpha \right) - \hat{\theta} \left(\alpha \right) \right) \left(\hat{\theta}_j^* \left(\alpha \right) - \hat{\theta} \left(\alpha \right) \right)', \tag{18}$$

where $\hat{\theta}_j^* \left(\alpha \right)$ is the quantile regression estimator based on the jth bootstrap sample for $j = 1, ..., B$. Bootstrap samples $\left\{ \left(r_t^*, z_t^* \right)' \right\}_{t=1}^{T}$ are drawn from the empirical joint distribution of r and z. The design matrix bootstrap is the most natural form of bootstrap resampling; it is valid in settings where the error terms $\varepsilon_t^{(\alpha)}$ and regressors $\left(z_{t-1}, r_{t-1} \right)'$ are not independent. Using Monte Carlo simulations, Buchinsky (1995) examined six different estimation procedures of the asymptotic covariance matrix Σ_α: design matrix bootstrap, error bootstrapping, order statistic, sigma bootstrap, homoscedastic kernel, and heteroscedastic kernel. He draws Monte Carlo samples from real data sets and evaluates the estimators under various realistic scenarios. His results favor the design bootstrap estimation of Σ_α for a general case. Consequently, in our empirical application, we use a t-statistic based on the standard errors obtained from the design matrix bootstrap estimator.

4.1   Empirical Results

Nonparametric analysis has shown that the 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 nonparametric Granger non-causality tests have shown that only the *time-lagged* unemployment rate components can explain stock market returns, we concentrate on testing the time-lagged effects using the quantile regression specification as follows:

$$r_t = \eta_r^{(\alpha)} + \lambda_1^{(\alpha)} \, g_{u,t-1}^e + \lambda_2^{(\alpha)} \, g_{u,t-1}^u + \lambda_3^{(\alpha)} r_{t-1} + \varepsilon_t^{(\alpha)}, \text{ for } \alpha \in (0,1), \tag{19}$$

with $Q_\alpha \left(\varepsilon_t^{(\alpha)} \mid g_{u,t-1}^e, \, g_{u,t-1}^u, r_{t-1} \right) = 0$. For the estimation of parameters $\eta_r^{(\alpha)}, \lambda_1^{(\alpha)}, \lambda_2^{(\alpha)}$, and $\lambda_3^{(\alpha)}$ and to test their statistical significance, we use the techniques discussed in section 4.

The estimation and inference results for the coefficients of the anticipated and unanticipated components of the unemployment rate in equation (19) are reported in Figures 2 and 3, respectively. The figures show that the point estimates of the coefficient of impact of the time-lagged anticipated unemployment rate are negative for the quantile range (0.05, 0.30) whereas the estimates are positive for the quantile range (0.30, 0.95) [see Figure 2-(a)]. Thus, during a bear market, the point estimates of the 20% lowest quantiles are negative whereas during a bull market, the estimates are positive for 75% of the upper quantiles of the stock market returns distribution. From Figure 2-(b), the effect is statistically significant both at the 5% and 1% significance levels for quantile range (0.35, 0.80), but it is not significant for lower and upper quantiles.
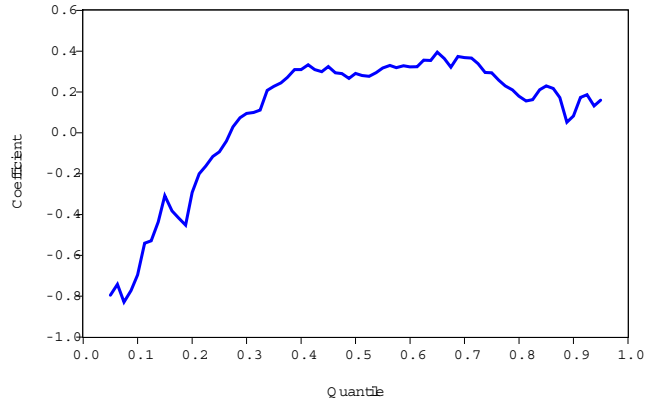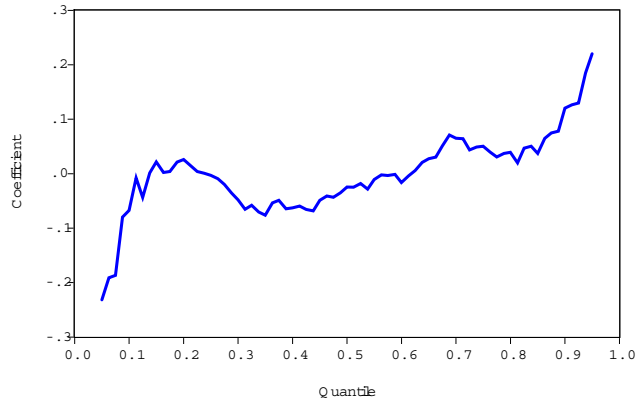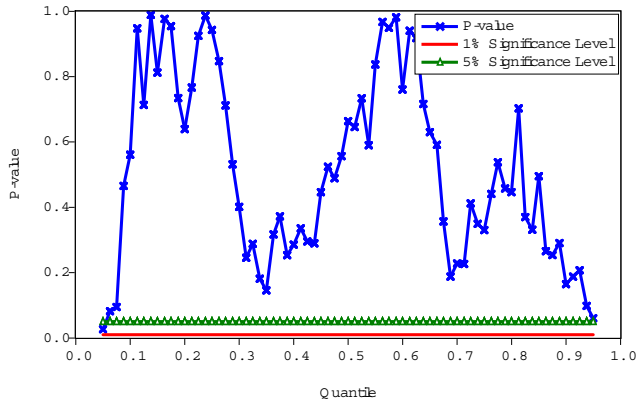
(a) Coefficient
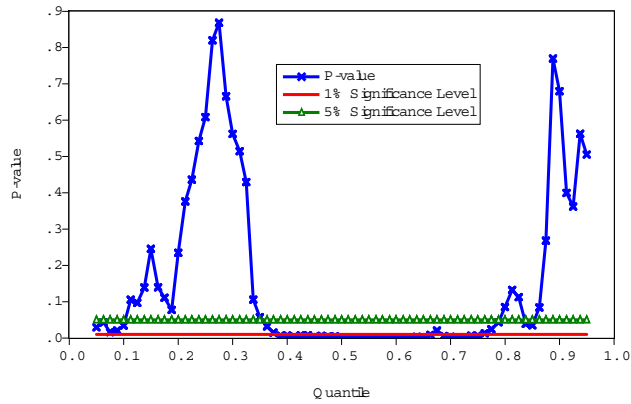
(b) P-value

Figure 2: *This figure illustrates the coefficient estimates and p-values for the statistical significance of the causal impact of the anticipated component (g_u^e) of the growth rate of unemployment(g_u) on the quantiles of stock market returns. The results correspond to the quantile regressions in (19). The sample covers the period from January* 1950 *to September* 2014.

(a) Coefficient

(b) P-value

Figure 3: *This figure illustrates the coefficient estimates and p-values for the statistical significance of the causal impact of the unanticipated component (g_u^u) of the growth rate of unemployment (g_u) on the quantiles of stock market returns. The results correspond to the quantile regressions in (19). The sample covers the period from January* 1950 *to September* 2014.

Thus, most of the time, an increase in time-lagged anticipated growth rate leads to a statistically significant increase in stock market returns. This may be linked to the results in Table 4. In particular, the coefficients for the quantile range of (0.35, 0.80) are roughly equal to 0.25 on average, meaning that an anticipated increase in unemployment growth rate of 1% raises the monthly stock returns by 0.25%. [2]

Moreover, from Figure 3-(a), contrary to the anticipated unemployment rate, the sign of the impact of the unanticipated rate on stock market returns is not clear: the sign changes across quantiles, indicating that its effect is not statistically significant. This is confirmed in Figure 3-(b), where the effect is statistically insignificant both at the 1% and 5% significant levels for all the stock market return quantiles. This result is also as expected from the analysis of causality in distribution in Table 4. In fact, Table 4 indicated that there will be no causal relationship between the unanticipated component, g_u^u, of the unemployment rate and stock returns.

Again, quantile regression analysis confirms that only the anticipated component, g_u^e, of the unemployment rate affects the stock market returns. This is both economically and statistically significant. It provides empirical evidence that we can learn more about the stock market through studying the joint dynamics of stock prices and unemployment rate. Thus, quantile analysis provides stylized facts on how the monthly aggregate stock prices and unemployment rate are intertemporally related.[3]

Finally, we checked the robustness of our results by repeating the previous nonparametric (for mean and distribution) and parametric (for mean and quantile) analyses using the *changes* in the unemployment rate $(ur_t - ur_{t-1})$ instead of the growth rate of unemployment $(log(ur_t) - log(ur_{t-1}))$. To save space, we report only the main results that correspond to our quantile analysis; see Figures 7–9 in the appendix. From the figures, the results from using the new transformation of the unemployment rate are quite similar to those obtained previously, thus confirming our conclusions.

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[2]Note that we are looking at a percentage, not a percentage point. A better way to interpret these numbers is to convert them into annual rates. Thus, when in a month the unemployment rate goes from 5.00% to 5.05%, in annual terms this represents an increase from 5.00% to 5.63%. Therefore, if investors anticipate such an annual increase in the unemployment rate, this will cause an annual increase in stock returns of 3.4% (0.25% monthly). This roughly represents half the annual average of the stock returns, which is not very large, given that it has been caused by a no minor increase in the annual unemployment rate.

[3]To check the robustness of our earlier results, we considered an alternative statistical procedure based on the Markov Chain Marginal Bootstrap (MCMB) method [see He and Hu (2002) and Kocherginsky, He, and Mu (2005)] for testing the statistical significance of the impact of the anticipated unemployment rate on stock market returns. Both the design bootstrap and MCMB methods yielded similar results. Finally, we tried several other specifications to separate unanticipated and anticipated unemployment. For example, we considered a specification where we had to add some nonlinearity: dummy variable for the 2008 financial crisis and the square of the lagged growth rate. Both the nonparametric and parametric results (for mean and quantile) are very similar to those obtained in the present paper. The results are available upon request.

5   Explaining the stock market reaction to unemployment rate

In this section, we identify one possible channel through which stock market prices react to the unemployment rate. We follow the argument of Bernanke and Blinder (1992) that any measure of monetary policy "*should respond to the Federal Reserve's perception of the state of the economy*". We believe that this can explain the movements in monetary policy measures (Federal funds rate) in terms of movements in unemployment rate. This function quantifies the reaction of such measures to changes in the unemployment rate. To complete the channel, stock market prices must react to the monetary policy measure Federal funds rate. One possible channel is given by the following scheme:

$$\text{Unemployment Rate} \quad \longrightarrow \quad \text{Federal funds rate} \quad \longrightarrow \quad \text{Stock Market prices;}$$

this suggests that the unemployment rate affects the Federal funds rate, which in turn affects the stock market prices. Evidence of a causal effect from the Federal funds rate to stock market prices (returns) can be found in the literature. Several studies have investigated the impact of the Federal funds rate on stock market prices, the most recent ones being Rigobon and Sack (2002) and Bernanke and Kuttner (2005), which found a negative impact of the Federal funds rate on stock market returns. Since the latter causal effect is well established in the literature, we next focus on analyzing the causal impact of unemployment rate on the Federal funds rate. We will also briefly examine the causal effect of the Federal funds rate on stock market returns.

We start with the following simple observation based on real data. Figure 4 plots the monthly U.S. unemployment rate and Federal funds rate. The data on the effective Federal Funds Rate are from the Federal Reserve Bank of St Louis and date back to July 1954. From the figure, the two variables move generally in opposite directions, with some lag: a decrease (increase) in unemployment rate is always followed by an increase (decrease) in the Federal funds rate. This could reveal the important relationship between unemployment rate and the Federal Funds Rate.

We now explore the existing economic theories to investigate the reaction of the Federal funds rate to the unemployment rate. We consider the well-known Fisher and Phillips curve equations. Let $i_{n,t}$, $i_{r,t}$, π_t, and ur_t, be the nominal interest rate, realized real interest rate, actual rate of inflation, and the unemployment rate at time t, respectively. From the Fisher equation, the following identity holds:

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

The difference between the nominal interest rate $i_{n,t}$ and realized real interest rate $i_{r,t}$ gives by the actual inflation rate π_t. Further, from a simple version of the Phillips curve equation, we have
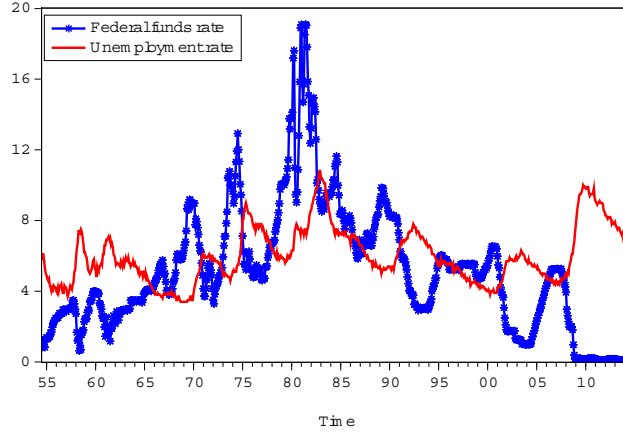
$$\pi_t = \pi^e + v - \alpha ur_t, \tag{21}$$

Figure 4: *This figure illustrates the time series of unemployment rate and the Federal funds rate. The sample covers the period from July* 1954 *to September* 2014.

where π^e is the expected inflation, v represents exogenous economic shocks, and α is a positive constant. For expositional simplicity, we assume that the expected inflation and economic shocks are constant, at least in the short run. Considering random variables π^e and v 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 have a tool to control inflation, and if they are willing to raise inflation, they can achieve a lower unemployment level. By plugging the Fisher equation into the Phillips curve equation, we obtain

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

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

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

Thus, from equations (22) and (23), we find that

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

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

To confirm the previous theoretical result of negative impact of unemployment rate on the Federal funds rate, we first consider a mean regression of the growth of the Federal funds rate on the constant and time-lagged growth rate of unemployment $(g_{u,t})$. We find that the coefficient estimate of the unemployment rate impact is negative and equal to -0.896. The latter is statistically significant with a robust t-statistic equal to -4.428. We also applied quantile regressions; the results shown in Figure 5 confirm the strong negative and statistically significant unemployment rate impact on the Federal funds rate.

(a) Coefficient	(b) P-value
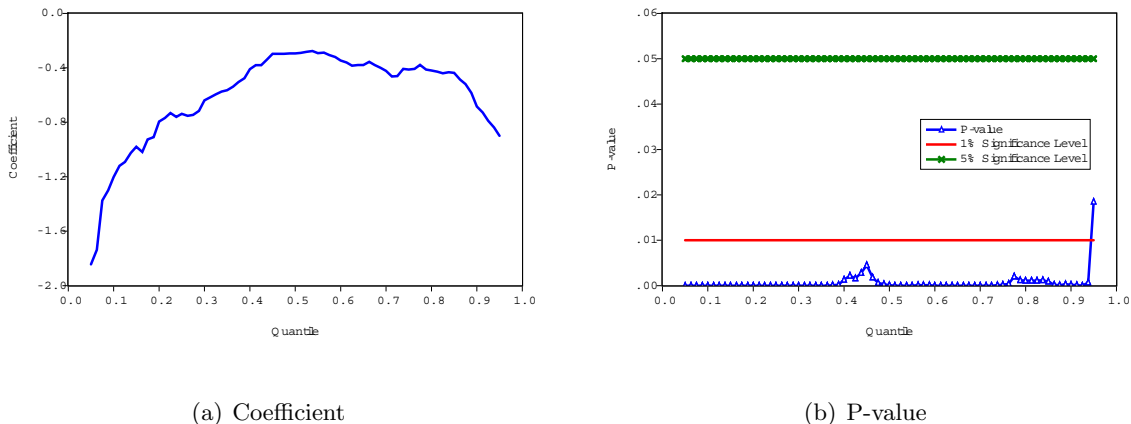
Figure 5: *This figure illustrates the coefficient estimates and the p-values for the statistical significance of the causal impact of the growth rate of unemployment on the Federal funds rate. The sample covers the period from July* 1954 *to September* 2014.

Finally, we briefly examine the causal impact of the Federal funds rate on stock market returns. We use quantile regressions to identify the sign of the impact of the Federal funds rate, say ffr_t, on S&P 500 stock returns:

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

Figures (6)-(a) and 6-(b) report the coefficient estimates and p-values for statistical significance of those coefficients, respectively. The stock market returns react immediately to the Federal funds rate. From these figures, the Federal funds rate has a negative and statistically significant impact on the quantile range $[0.788, 0.95]$. Bernanke and Kuttner (2005) also find a negative Federal funds rate impact on the mean stock returns.

The signs of the various causal links in the channel through the Federal funds rate can be summarized as follows: a decrease (increase) in unemployment rate is followed by an increase (decrease) in the Federal funds rate, which in turn leads to an immediate decrease (increase) in stock market prices. This confirms our finding in section 4 that a decrease (increase) in unemployment rate is followed by a statistically significant decrease (increase) in stock market prices.

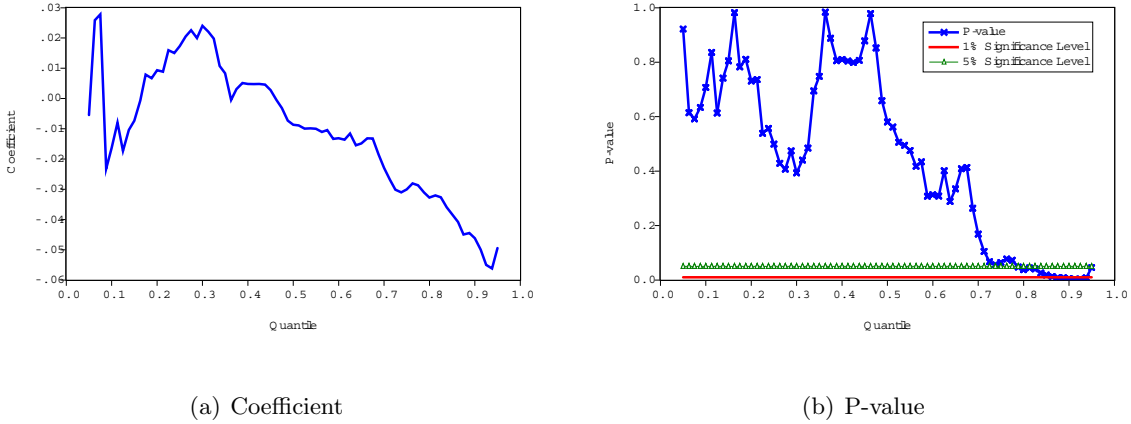|	
(a) Coefficient	(b) P-value

Figure 6: *This figure illustrates the coefficient estimates and the p-values for the statistical significance of the immediate causal impact of the Federal funds rate on stock returns. The sample covers the period from July 1954 to September 2014.*

6 Conclusion

We examined the nonlinearity in the stock price–unemployment rate relationship. We conducted a rigorous analysis of the impact of the 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* the *anticipated* unemployment rate has a *strong* impact on stock prices.

From quantile regression analysis, the causal effects of the anticipated unemployment rate on stock returns are usually heterogeneous across quantiles. For the quantile range (0.30, 0.80), an increase in the anticipated growth rate of the unemployment rate leads to an increase in stock market prices. For other quantiles, the impact is statistically insignificant. Thus, an increase in the anticipated unemployment rate is good news for stock market prices.

Finally, we offer a reasonable explanation for why and how the unemployment rate affects stock market prices. Using the Fisher and Phillips curve equations, we show that a high unemployment rate is followed by monetary policy action of the Fed. When the unemployment rate is high, the Fed decreases the interest rate, which in turn increases the stock market prices.

A Appendix: Additional empirical results of using changes in unemployment rate
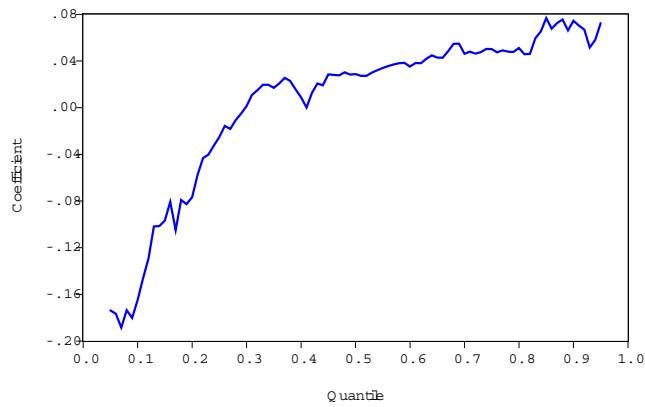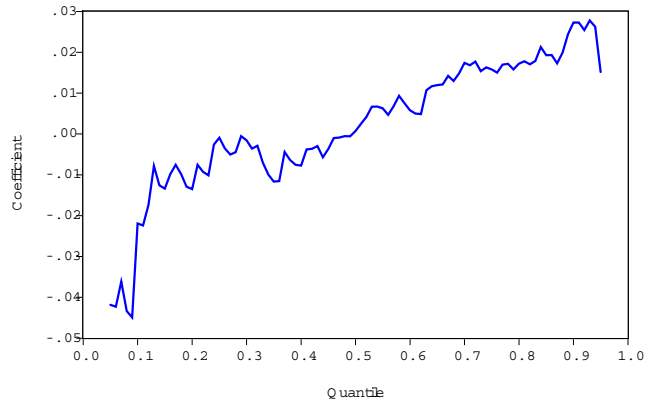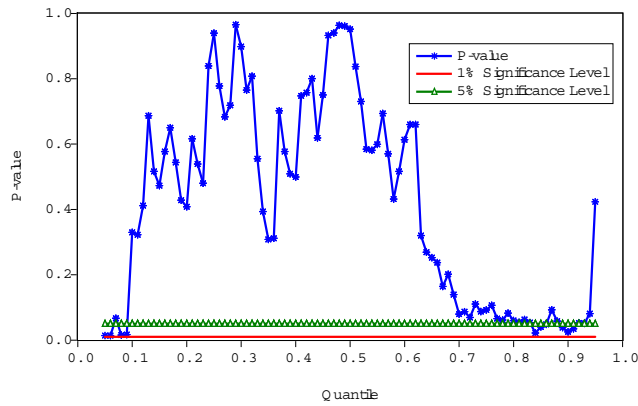
(a) Coefficient
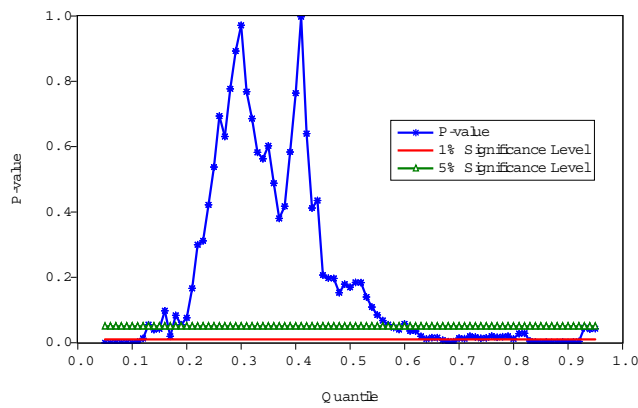
(b) P-value

Figure 7: *This figure illustrates the coefficient estimates and p-values for the statistical significance of the causal impact of the anticipated component of changes in unemployment rate on the quantiles of stock market returns. The results correspond to the quantile regressions in (19), but the growth rate of unemployment is replaced by the changes in unemployment rate. The sample covers the period from January* 1950 *to September* 2014*.*

(a) Coefficient

(b) P-value

Figure 8: *This figure illustrates the coefficient estimates and p-values for the statistical significance of the causal impact of the unanticipated component of changes in unemployment rate on the quantiles of stock market returns. The results correspond to the quantile regressions in (19), but the growth rate of unemployment is replaced by the changes in unemployment rate. The sample covers the period from January* 1950 *to September* 2014.
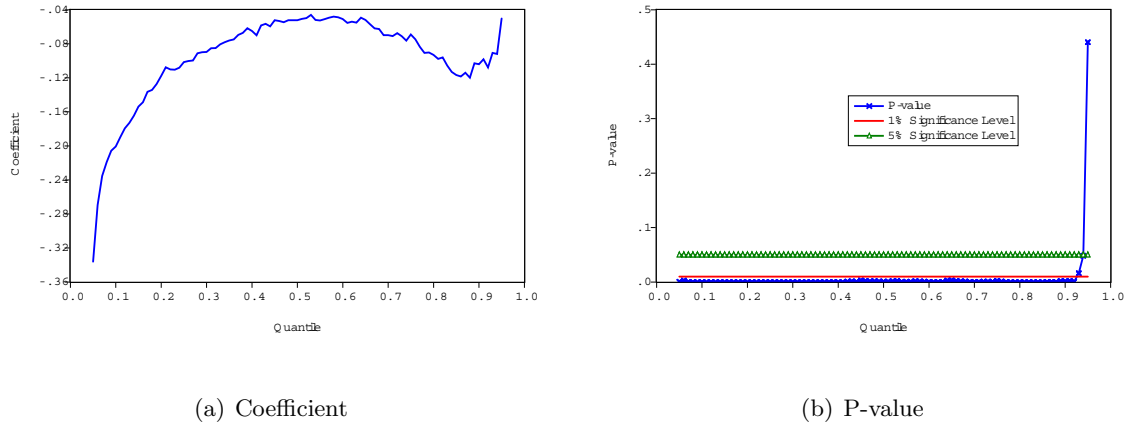
(a) Coefficient   (b) P-value

Figure 9: *This figure illustrates the coefficient estimates and p-values for the statistical significance of the causal impact of changes in unemployment rate on the Federal funds rate. The sample covers the period from July* 1954 *to September* 2014.

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