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Can federal reserve policy deviation explain response patterns of financial markets over time?

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CORE

DISCUSSION PAPER

Can federal reserve policy deviation explain response patterns of financial markets over time?

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Abstract

Yes. By using real-time structure break monitoring techniques we find evidence against monotonic response pattern, specifically three response structures of US stock market to the federal monetary policy actions based on a sample from 1989-2010. We re-estimate the market response in each of the three structures and find results stronger than previously documented especially in 2001-2008. We propose a "FedGap" variable which measures the deviation of Fed policy from the "Taylor Rule" in explanation and find it to be significant with economic meaning. We conclude that market responses proportionally to the size of the FedGap and it thus serves as a new "macro-state" factor which can explain the dynamic response patterns of financial markets. We also examine the issue from the bond market, and find similar results.

Keywords: real-time structure breaks, dynamic market response, monetary policy, Taylor Rule, FedGap.

JEL Classification: E44, G12, G14, G28

1. Introduction

Monetary policy action is defined by the response of the markets and both industry and regulators seek a deeper understanding of this relationship[2]. A vast literature on the theories and econometric methods used to describe the relationship between monetary policy actions and financial market reactions, especially in the stock markets, is established. A standard event study methodology, such as the Bernanke and Kuttner (2005) method[3], requires the collection of every single Federal funds rate announcement or action of the Federal Open Market Committee (FOMC) with their corresponding stock market reactions, then performing a linear regression to quantitatively analyze monetary policy's impact on the stock market. An implicit assumption in this approach is that responses in the sample are homogeneous. However, this assumption of homogeneity is hard to be satisfied for long duration samples as there would have structural changes in the response pattern due to time-varying economic and market conditions. As a consequence, any examination of market responses to policy actions should account for possible "pattern breaks" to allow for multiple structures instead of a single pattern. This is the first motivation of this study.

Despite the importance, very few researches have considered this issue before. Among those few works, Guo (2004) documents a state-dependent effect of monetary policy on stock prices of different firm sizes. Small stocks were found to be more sensitive to the Federal Reserve's monetary policy than big stocks in the sample of late 1970s, but this relationship disappeared in the sample of 1990s.[4] Demiralp and Jordà (2004), who perform the Bai and Perron (1998) test for structural breaks on the regression in Kuttner (2001) to examine possible changes in response patterns in the bond markets. From February 4th, 1994, the Federal Reserve changed their practice to one of publicly announcing federal funds rate changes immediately after every FOMC meeting, possibly leading to a change in the market response pattern. Their results supported the hypothesis that there is a structural break around February 4th, 1994 and that the FOMC schedules allow markets to better anticipate the timing and the nature of future policy moves since then.

Although the work of Demiralp and Jordà (2004) is in the same spirit of our motivation, their test is retrospective as the Bai and Perron (1998) test for structural breaks is a one-off

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[2]For example, regulators must consider potential market responses when setting monetary policy, and then monitor the market response to the policy in real time, measuring the effects of the policy action and preparing for any needed modification. Good regulation practice requires that policy action be accurate and effective while also considering such details as the wording and timing of the announcement. Gukaynak et al. (2005) study the role of FOMC statements wording and find that it could effectively affect public expectation.

[3]Bernanke and Kuttner (2005) conclude that an unexpected 25-basis-point rate cut would typically lead to an increase in stock prices of around 1%. By including the policy surprise variable in the framework of Campbell and Ammer (1993), they find that the impact of monetary policy surprises on stock prices comes either through expected future excess returns or expected future dividends.

[4]This is attributed to the credit channel of monetary transmission and the corresponding fact that in the late 1970s, the business conditions were typically bad, and in the 1990s, the business conditions were typically good. A more direct reason was that firms relied more on debt in the late 1970s than in the 1990s.

historical test for structural change. As we seek to pin down the time-varying structure of market responses in real time, we employ the real-time structural change monitoring technique proposed by Chu et al. (1996) in the current study. Compared with traditional retrospective tests, it overcomes the problem noted by Robbins (1970) that repeated usage of retrospective tests as new observations arise makes the probability of rejecting a true null hypothesis of no change approaching one, and has a very promising size control performance. Further, with a real-time monitoring technique, we can obtain information regarding market reactions in real time rather than retrospectively. It is important for the timely evaluation of every policy action. This is the second motivation of this study.

By focusing on Bernanke and Kuttner (2005), we apply the real time monitoring methodology of Chu et al. (1996) in examining the relationship between monetary policy actions and financial market responses with an updated sample period from June 5th, 1989 to December 31st, 2009, covering 189 events of FOMC announcements or actions. The monitoring procedure reports that the events at April 18th, 2001 and January 22nd, 2008 are 2 break points. Therefore, they naturally divide the total data set into 3 sub-samples. The results clearly show that there exists different response patterns which are confirmative to our intuitions. We re-estimate the response relationship in the 3 sub-samples respectively and find that compared to the results in other two sub-samples as well as Bernanke and Kuttner (2005), the stock market responses to the monetary policy extremely significant in the second sub-sample (April 18th, 2001 to January 22nd, 2008).

To interpret the possible factors which could explain the changing patterns of market responses, we follow the methodologies of two recent works, Basistha and Kurov (2008) for the business cycle, and Jansen and Tsai (2010) for bull or bear market conditions. By replicating their approaches with our extended sample, we find that the conclusions of the two works are no longer valid. We find that the response pattern or structure identified in our study can span both bullish and bearish market conditions and we argue that this indicates that the market response pattern may not be totally subject to market conditions. Although this sounds counterintuitive, we further argue that the underlying explanation is that during the extended sample period, the Fed dramatically deviated from its former policy rules and that this could affect the originally valid response pattern. As discussed by Calomiris (2009), with respect to monetary policy, the Fed has a "dual mandate" and should vary the supply of its liabilities to achieve a balance between its two ultimate objectives: maximizing price stability and minimizing cyclical fluctuations in unemployment. One way to balance these two objectives is described by the classical "Taylor Rule". However, the Fed departed dramatically from the Taylor Rule from 2001 to 2008. Calomiris (2009) argues that subsequently the Fed's objectives with respect to price stability and unemployment are hard to discern or characterize through any rule as everything seems to have taken a back seat to the immediate objective of limiting short-term financial sector fallout by setting the Fed funds rate to zero and announcing various guarantees or quantitative targets for the purchase or support of various categories of private securities. This makes it extremely hard to predict monetary policy, or to hold the Fed accountable to achieving its unannounced and hence, unobservable goals. This may provide evidence that the Fed changed and altered people's

belief toward it.

We supply evidence by empirical examination with a constructed new explanation variable, "FedGap" (a measure we proposed of how much Fed deviates from the classical Taylor Rule), which is significant in the explanation of the change of market response patterns. Such results indicate that in addition to those factors discussed in the literature, the change of Fed's goal is also a factor which can have dramatic impact on the response pattern of financial markets to policy actions. We also apply the same procedure to the U.S. Bond market and find similar results.

The contributions of our work are manifold. First, this paper re-examines the relationship between monetary policy actions and markets' responses with an updated larger sample. The results show that structural breaks exist, implying that the estimation results of some previous research are biased with homogeneous assumptions. We identify the structural break points in real time and obtain a greater understanding of the interaction. Second, we demonstrate that a real-time monitoring technique is a valuable tool for studies of financial market regulation. Finally, we document some new evidence which sheds light on the re-thinking of the determination of the market response pattern as well as the role of the Fed in any response structural change.

We organize the paper as follows: Section 2 discusses the real-time monitoring methodology and data processing procedure; Section 3 presents empirical results obtained from an examination of the stock market; Section 4 provides further interpretation of the results; Section 5 discusses these results based on an examination of the U.S. Treasury bond market; and we conclude the paper in Section 6.

2. Methodology and Data

2.1. Real-time monitoring methodology

To avoid the intrinsic problem of retrospective monitoring tests as mentioned before, we propose the real-time monitoring procedure/methodology introduced by Chu et al. (1996). Most tests for structural breaks are retrospective tests, i.e., given a set of observations, those tests decide if a break has occurred within the time span of the data[5]. Repeated applications of retrospective test could lead to rejection probability of the null hypothesis of no break approaching one ,even there is no break, when new observations become available and grow (Robbins 1970). Therefore, in contrast to the classical one-shot tests to detect a structural break within the data span, Chu et al. (1996) suggest an online procedure to monitor structural breaks that has the actual size close to the nominal size. The basic framework of the real time monitoring procedure are as follows. As described in Chu et al. (1996), given an initial fixed training sample of size m, the monitoring scheme needs a stopping device, determined by a detecting statistics (detector), Z_n, and a boundary function, $g(n/m)$, to monitor

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[5]See e.g., Andrews (1993), Incln and Tiao (1994).

whether the breaks occur after the data being increased to $n(n \geq m)$. More precisely, under the null hypothesis of no break, Z_n may cross a boundary function $g(n/m)$, for some $n \geq m$, with certain probability, say 0.05 or 0.10. On the other hand, if a break indeed occurs, we expect Z_n to cross $g(n/m)$ with a large probability. Operationally, the null hypothesis is rejected when $Z_n \geq g(n/m)$ for some $n \geq m$. Otherwise, the monitoring process keeps on running until a break is observed.

As a matter of fact, two detectors are considered in Chu et al. (1996), the cumulative sum(CUSUM) of recursive residuals and the parameter fluctuations (FL). Since the CUMSUM of recursive residuals detector could lead to the weakness of power((Ploberger et al. (1989)), we only consider FL detector in our paper. Suppose the regression as $Y_t = X_t' \beta_t + \varepsilon_t$, Chu et al. (1996) define a fluctuation detector by $\hat{Z}_n = n D_m^{-1/2} (\hat{\beta}_n - \hat{\beta}_m)$, where $D_m = M_m^{-1} V_0 M_m^{-1}$, M_m is $O(1)$, and uniformly positive definite such that $m^{-1} \sum_{t=1}^{m} X_t X_t' - M_m \xrightarrow{p} 0$. The crucial idea of this FL detector is the deviation of the updated parameter estimate $\hat{\beta}_n$ from the historical parameter estimate $\hat{\beta}_m$. Chu et al. (1996) also assume that the following multivariate FCLT (Functional Central Limit Theorem) holds:

$$x_\lambda^m = m^{-1/2} D_m^{-1/2} \Big(\sum_{t=1}^{[m\lambda]} x_t x_t' / [m\lambda] \Big)^{-1} \sum_{t=1}^{[m\lambda]} X_t \varepsilon_t \Rightarrow w(\lambda), \quad \lambda \in [1, \infty) \qquad (1)$$

Where

(i) $\{X_t \varepsilon_t\}$ obeys a FCLT with $V_0 = \lim_{m \to \infty} m^{-1} E \Big[\big(\sum_{t=1}^{m} X_t \varepsilon_t \big) \big(\sum_{t=1}^{m} X_t \varepsilon_t \big)' \Big]$ positively definite;

(ii) $m^{-1/2} \bar{Z}_{[m\lambda]} \Rightarrow \overline{w}(x) - \lambda \overline{w}(1) = \overline{W}^0(\lambda)$, $\lambda \in [1, \infty)$.

$\overline{W}^0(\lambda)$ is a K-dimensional Brownian Bridge. They further suggest the following stopping boundary:

$$g(n/m) = m^{-1/2} \Big(\frac{n-m}{m} \Big) \Big[\big(\frac{n}{n-m} \big) \big[a^2 + \ln \big(\frac{n}{n-m} \big) \big] \Big]^{1/2} \qquad (2)$$

And the parameter a^2 controls the crossing probability of the FL detector under the null hypothesis of no break (H_0). For example, when $a^2 = 7.78$ and 6.25, the preceding crossing probability is 0.05 and 0.10 respectively. As shown previously, H_0 is rejected when $|\hat{Z}_n| \geq g(n/m)$ for some $n > m$, otherwise, the monitoring process keeps running until the opposite is observed. On the other hand, once a break has been detected, we rerun the monitoring procedure for the rest samples to detect possible second break point. The whole process stops when the size of the left samples is smaller than that of the training sample, say m.

2.2. Data processing procedure

A full understanding of market reactions requires us to determine to what degree a policy is anticipated by the market, that is, to quantify the expected and unexpected component of each action. Kuttner (2001) proposes a market-based technique to solve this problem. By utilizing the Fed funds futures, the unexpected component of every policy action can be

constructed from the change in the futures contract price on the announcement day relative to one day prior. Specifically,

$$\Delta i_t^u = \frac{D}{D-d}(f_{t,d}^0 - f_{t,d-1}^0) \tag{3}$$

Where Δi^u is the unexpected target rate change. Suppose there is a FOMC policy action on day d of month t. $f_{t,d}^0$ is the futures rate, which equals to 100 minus the current-month "30-day Fed Funds Futures" contract settlement price. The superscript 0 means the contract is the one will expire at the end of month m, and 1 represents the one that will expire in the next month, analogically. There is a scaling factor in the formula, $\frac{D}{D-d}$ in which D is the number of days in month t. This is necessary because the official specification of the "30-day Fed Funds Futures" contract's daily settlement is based on the average daily Fed Funds overnight rate for the delivery month, rather than the rate on any specific day. If the event happens on the first day of month m, then $f_{t-1,d}^1$ is used instead of $f_{t,d-1}^0$. If the event happens on one of the last 3 days of month t, the formula $\Delta i^u = f_{t,d}^1 - f_{t,d-1}^1$ is used, so that the effect of any month-end noise in the effective Federal funds rate is minimized[6].

Thus, the expected component can be derived as actual rate change minus surprise as in Equation (4).

$$\Delta i_t^e = \Delta i_t - \Delta i_t^u \tag{4}$$

Besides separating the FOMC Fed funds rate , event window selection is also important for capturing the picture of a policy shock to financial markets. In February 1994, the Federal Reserve started the practice of an explicit announcement of the Fed funds rate decision after FOMC meetings. Usually, the announcement is at 2:15 p.m. EST, when the Fed funds futures market in the CBOT and the stock markets are not yet closed. Therefore, the policy action is reflected in the closing prices of futures contracts and the CRSP broad index. The date of event is simply the date of the policy announcement. However, before February 1994 there was no explicit announcement so the new Fed funds target rate was only known by investors when the Fed funds market opened the next day. Following Bernanke and Kuttner (2005), we solve this problem by assigning most dates of events as the day following policy decisions[7].

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[6]See Kuttner (2001) for more details.

[7]There are three exceptions. The first is December 18th, 1990, when the Fed announced a 50 basis points cut in the discount rate at 3:30 p.m., after the close of the futures market. This was correctly inferred as a 25 basis points cut in the Fed funds rate by the market. The difference between the closing futures rate on December 18th and the opening rate on December 19th is used to measure the surprise. The second is October 15th , 1998, when a 25 basis points cut was announced at 3:15 p.m. The difference between the closing futures rate on October 15th and the opening rate on October 16th is used to measure surprise. The last one occurred on October 8th , 2008, when a joint statement by Federal Reserve and other seven central banks around the globe was issued at 7:00 a.m. EST. We do not make any adjustment because there is no time mismatching between the stock markets and the futures market and the 1 day price differences of the two markets adequately catches the policy shock.

Based on an event-study perspective, we collect FOMC Fed funds rate decisions and the corresponding 1 day broad stock index returns of those dates (CRSP value weighted). For the purpose of this paper, the events are defined as scheduled FOMC meetings (no matter whether there is a target rate change or not) and unscheduled FOMC meetings with target rate change decisions. The full sample ranges from June 1989 through to December 2009. As the CBOT launched the market of 30-day Fed funds futures in 1989, the first observation is on June 5th,1989. Altogether, the sample contains 189 observations. Studies like Bernanke and Kuttner (2005) and Boyd et al. (2005) show that the 1-day market response to monetary policy announcements is contaminated if the unemployment report of the BLS is released on the same day. Since we aim at detecting possible structure breaks in response patterns, and such multiple news releases may contribute to market response, we keep them in the sample to reflect the maximum observations for study. Our subsequent findings are qualitatively indifferent, even when excluding them. Table 1 presents the descriptive statistics for our sample.

Table 1: Descriptive Statistics for Main Variables

	All	1st	2nd	3rd
Obs.	189	116	55	18
μ_{R_t}	0.368	0.256	0.341	0.357
σ_{R_t}	1.179	0.902	1.328	1.834
$\mu_{\Delta i_t^e}$	-0.015	0.004	-0.013	-0.141
$\sigma_{\Delta i_t^e}$	0.197	0.153	0.225	0.295
$\mu_{\Delta i_t^u}$	-0.031	-0.033	-0.017	-0.061
$\sigma_{\Delta i_t^u}$	0.103	0.093	0.086	0.183
μ_{FedGap}	-0.933	-0.177	-2.096	-1.931
σ_{FedGap}	1.646	1.113	1.332	2.524

Note: μ denotes the mean value and is in percentage, σ denotes the standard deviation. R_t refers to event-day response, Δi_t^e and Δi_t^u refers to the expected and unexpected component of the Fed policy action, respectively. 1st refers to the first subsample period from 1989 - 2001, 2nd refers to sample period 2001-2008, 3rd covers sample period from 2008-2010. FedGap refers to the deviation of Federal monetary policies from the Taylor Rule, which is a proxy proposed in the current study for measuring role change of the Fed.

3. Empirical Results

3.1. Real-time Structure Break Testing for Stock Market Reaction

We use the real time monitoring test to detect the potential structural change of the regression relationship of monetary policy announcement and market response described by Bernanke and Kuttner (2005)'s specification. H_t is the 1-day return of CRSP value weighted index on event days. Δi_t^e and Δi_t^u are the same as symbols in the methodology description.

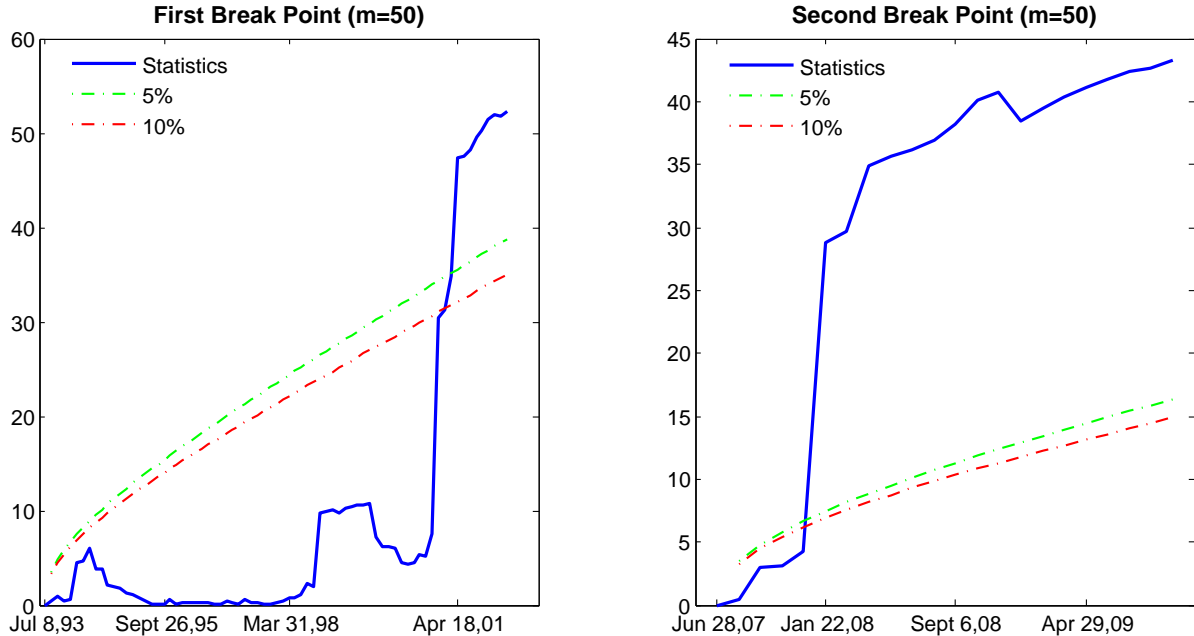$$H_t = a + b^e \Delta i_t^e + b^u \Delta i_t^u + \varepsilon_t \tag{5}$$

Figure 1: Real-Time Structure Break Tests for CRSP Value Weighted Index's Responses to FOMC Announcements (1989-2010) (m=50)

Note: In this figure, the solid line represents the real time response detector and the dashed line and dot line represent 5% and 10% significance level of the boundary functions which is established for real time monitoring of the structure change. The horizontal-axis represents the time points after the training window (m=50 here) and the vertical-axis represents the FL detector statistics.

The result is presented in Figure 1.

In Figure 1, the solid line represents the real-time response detector and the dashed line and dot line represent 5% and 10% significance levels of the boundary functions which is established for real time monitoring of the structure change. The results clearly demonstrate that there is a historical period that the detector cross the boundary and the break point is at the event of April 18th, 2001. After the first break point has been detected, we rerun the same procedure by using another 50 observations since April 18th, 2001 as the training sample, and the second point is detected at January 22nd, 2008. The whole sample is then naturally divided into three subsamples. Hence, there are two new relationships between Federal Reserve policy actions and market responses in contrast with the historical relationship of 1989-2001. We conclude that more than one response pattern exists and that, as far as we know, this is the first time a study has documented the exact structure changing periods.
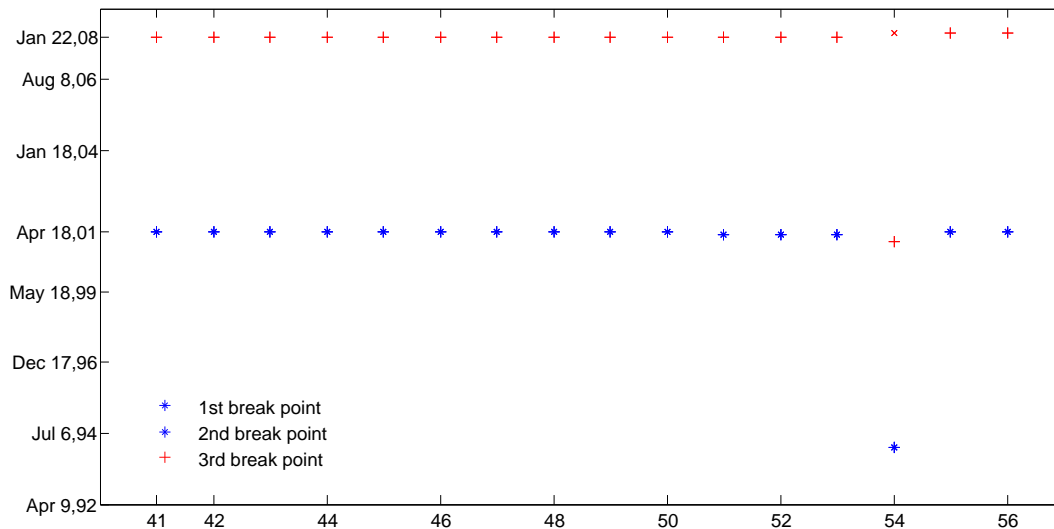
Figure 2: Distribution of Structure Break Points with Setting of Training Sample Size

Note: This figure describes the distribution of break points detected with the different setting of m, which ranges from 41 to 56. The horizontal axis in the figure is m, the vertical axis is the location of the detected break.

Reassuringly, the evidence of structural change is very robust. It remains regardless of the m value or whether the estimation method of V_0 is either Robinson (1998)'s long term variance method or OLS. Figure 2 presents a more complete view of the full spectrum of detection results. It describes the distribution of break points detected with the different setting of m, the training sample size, which ranges from 41 to 56. The horizontal axis in the figure is m, the vertical axis is the location of the detected break. From Figure 2, it is clear that the location of the first break point is robust, and only when m equals 51, 52 or 53, the break locates one event earlier (Mar 20th, 2001). Further, the location detected for the second point (January 22nd, 2008) is even more robust compared to the first break point. We also believe the result of $m = 54$ is an outlier. Thus, we take the points detected at April 18th, 2001 and January 22nd, 2008 as the robust locations of response patterns switching.

The events that the unemployment report of BLS release in the same day (as the FOMC announcement) are mainly distributed in the training periods (first 50 observations). As we mentioned before, there is a probability that our break-detecting results are potentially biased by the contamination of the impact to markets from the unemployment report releases. We therefore kick out all the events that unemployment report is released at the same day as the Fed announcements and run this monitoring procedure again. And we can obtain almost identical result as before, which leads us to believe unemployment report release does not

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adversely impact our finding[8].

3.2. Stock Market Response in Different Structures

Using the break points detected above, we can re-estimate the stock market responses within each subsample. Following previous literature, we present our empirical results estimated by OLS with White's heteroskedasticity-consistent estimates of the standard errors together with the WLS method.

Table 2: Stock Market Responses to FOMC Announcements in Different Subsamples (structures)

Sample	Obs	Est.	Intercept	Expected	Surprise	$\bar{R}^2$
all	189	OLSW	0.30***	-0.57	-2.06	0.036
			(0.08)	(0.75)	(1.61)	
1st	116	OLSW	0.14*	1.25**	-3.78**	0.135
			(0.09)	(0.54)	(1.75)	
2nd	55	OLSW	0.20	0.18	-8.85***	0.321
			(0.13)	(0.30)	(1.21)	
3rd	18	OLSW	0.94**	-2.82*	3.02**	0.257
			(0.40)	(1.52)	(1.06)	
B&K(2005)	131	OLSW	0.12	1.04**	-4.68***	0.171
			(0.09)	(0.48)	(1.57)	

Note: OLSW refers to OLS with White's heteroskedasticity-consistent estimates of the standard errors. Standard errors are reported in the parentheses. *, **, *** indicate that the coefficient is statistically significant at 10%, 5%, and 1% levels, respectively.

It is clearly shown in Table 2 that the coefficients estimated is quite different across subsamples. On the factor of surprise, the coefficient in the 1st subsample is -3.78, but changes to -8.85 in the 2nd subsample, which is more than doubled with even significant t-statistics. That means, the market response is more significant, and the investors are more "responsive to Feds monetary policy announcements and policy actions. It is also notable that the coefficient of the expected term is significant in the first sample period whereas insignificant in the second one. Meanwhile, the adjusted R^2 is much larger in the second sub-sample than that in the 1st sub-sample. As there is a break point within the sample period in Bernanke and Kuttner (2005), our results suggest that their model has more powerful explanatory ability and more consistent with the theory in the second period. In the 3rd subsample, the coefficient of surprise is positive and not statistically significant. We believe that this is due to the randomness caused by small sample problem, since there is only 18 events in that period. Because of there exists three different patterns, the explanation power of the Bernanke and Kuttner (2005) in regression including all the observations has been weakened, further indicating that the structural breaks need to be considered. The findings clearly show that there exists multiple response patterns, which confirms our intuition and argument before.

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[8]Results are available from the authors upon request.

Table 3: Estimating Responses with Pattern Dummy Variables

Est.	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	$\bar{R}^2$
OLSW	0.30***	-0.57	-2.06		-	-	-	-	-	0.036
	(0.08)	(0.75)	(1.61)							
OLSW	0.13	1.30	-4.51***	0.07	0.85**	-1.13	-3.49**	-4.12**	7.90***	0.200
	(0.09)	(0.54)	(1.66)	(0.16)	(0.40)	(0.82)	(1.67)	(3.38)	(2.04)	

Note: Standard errors are reported in the parentheses. *, **, *** indicate that the coefficient is statistically significant at 10%, 5%, and 1% levels, respectively.

In order to further illustrate the response patterns, we run the explanatory regression again by differentiating subsamples using dummy variables as following:

$$
\begin{aligned}
R_t =& \alpha + \beta_1 \Delta i_t^e + \beta_2 \Delta i_t^u + \beta_3 D_t^1 + \beta_4 D_t^2 + \beta_5 \Delta i_t^e D_t^1 \\
&+ \beta_6 \Delta i_t^e D_t^2 + \beta_7 \Delta i_t^u D_t^1 + \beta_8 \Delta i_t^u D_t^2 + \varepsilon_t
\end{aligned}
\tag{6}
$$

Where D_t^1 is set to be 1 when the event is in the 2nd subsample and 0 otherwise. Analogically, $D_t^2 = 1$ when the event is in the 3rd subsample. $\Delta i_t^u D_t^2 = \Delta i_t^u \times D_t^2$ is the cross term proposed with the aim to capture potential structural change in the market reaction to surprise. $\Delta i_t^e D_t^2 = \Delta i_t^e \times D_t^2$ is also included in the regression in case there exists breaks in the market reaction to expected target rate change. We report the regression results in Table 3.

The significance of the coefficients from the regressions vividly characterize the dynamic of the multiple response patterns in the historical period. We can see once controlling for the patterns with dummy variables, the coefficient before the surprise term (β_2) is significant. In the period of the second subsample, the coefficient is about 2 times of the first subsample in terms of magnitude(-4.51 plus -4.12, compared with -4.51). We can also obtain that the insignificance of the coefficient on the surprise target rate change as shown in Table 2 for the whole sample is mainly contributed by the observations in the 3rd subsample, since it is significant with a positive coefficient while it is negative in 1st and 2nd subsample. In addition, the adjusted R^2 improves a lot, more than 16%.

Generally speaking, the U.S. and the world economies enjoyed relatively stable growth during our sample period before the sub-prime crisis. Beneath this peaceful surface, one may wonder, what could produce the detected three structural changes in financial market reaction? Why are the break points located on April 18th, 2001 and January 22th, 2008? And why does the market become more sensitive during the 2nd subsample?

The answers are complicated by the CRSP Value Weighted Index having both a significant response and a relatively weak response to the FOMC announcements, which are defined by the structural break points detected above. One natural explanation would be that the market changes the way it processes information. But rational expectation theories demand that decision making be based on available information. This kind of response structure

switching can also be attributed to external factors other than the market itself or possibly the market's own time-varying properties. In other words, there exists possibility that the information itself has changed in nature leading to the structure shifting as a result of the interaction between two-way information traffic instead of, as most previous studies perceive, one-way traffic.

Explanations with economic insights by comparing and contrasting the market responses under different visible conditions were the preferred results of the literature. Indeed, there are many factors that may change the fundamental aspects of a financial market, such as the business cycle, bull or bear market conditions, and the status of monetary policy. However, most relevant economic interpretation provided by previous studies fails to explain our findings[9]. For the remainder of this paper, we attribute the cause of the multiple response patterns to "the Federal Reserve's role change" and present the logic behind this assertion and the corresponding evidence. There is rare literature on this topic. Taylor (2009) shows that the actual interest rate set fell well below what the Taylor rule would suggest policy should be. Between the end of 2001 and late 2007, U.S. monetary policy greatly deviated from the Taylor rule. There has been no greater or more persistent deviation of actual Fed policy since the turbulent days of the 1970s. The structural changes we detected and the deviation between the target Fed funds rate decisions and the rates the Taylor rule suggests are almost coincident in location. This inspires us to explore further.
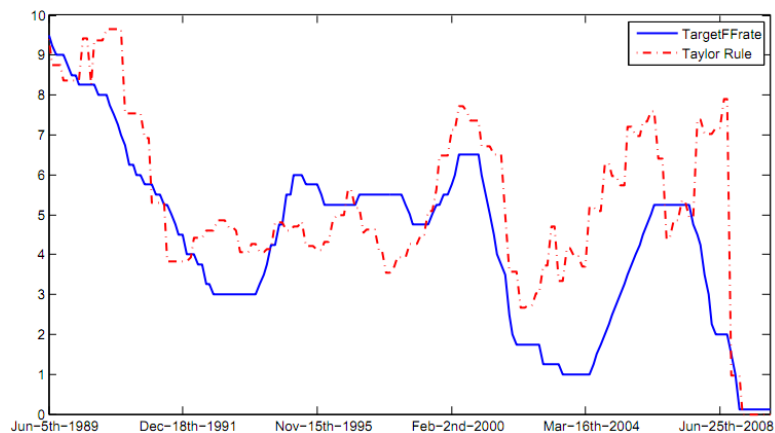

Figure 3: Taylor Rule and Federal Fund Target Rates: 1989-2010

Note: This figure depicts the deviations of Federal Reserve monetary policy from the Taylor Rule over the entire sample period of our study from 1989-2010.

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[9]We delay the presentation of these results in the next subsection.

Figure 3 clearly depicts the deviations of Federal Reserve monetary policy from the Taylor Rule over the entire sample period i.e., 1989-2010. We follow Taylor (1993) in calculating the Taylor Rule value of interest rates. Specifically, the Taylor Rule used in the paper is in its classic form:

$$i = 2 + \pi + 1/2(\pi - 2) + 1/2(q - q*) \tag{7}$$

Where π denotes the inflation rate, and the inflation target is set as 2%. q denotes the real output while q* denotes the potential real output. We use the change in CPI in the last quarter and potential GDP as the measure of the inflation rate and the output target, respectively. The data are obtained from the FRED. Clearly, the Fed monetary policy dramatically deviated from the Taylor Rule from 2001 with the gap maintained until around the end of 2007. Compared to Figures 1 and 2, where we identify the structure breaks in financial market reactions, it is obvious that the break points we identified with real-time monitoring techniques coincide with the deviation over time of monetary policy.

We thus believe that the role of the Federal Reserve during 2001 to 2008 was not the same as in the preceding period; it underwent a role change. The Federal Reserve Act regulated three key objectives: maximum employment, stable prices, and moderate long-term interest rates. The Taylor rule is a simple, and probably a very effective monetary policy rule that guides a central bank to fulfill these objectives. If we assume that the Taylor rule is how central banks realize their objectives, then the Fed's monetary policy deviation from the Taylor rule means that the Fed's role as protector of a stable economy changes[10], also changing the market's perception of the Fed. Taking the case of the 2001 to 2008 period, for example, where the U.S. economy is almost completely driven by Fed policy, monetary decisions were unusually important to the market participants, inducing the market's automatic response, even though markets better anticipate policy changes[11]. This is supported by the current study, which is based on a real-time monitoring procedure.

To quantify the role deviation of the Federal Reserve, we propose a simple empirical measurement, the "FedGap". Specifically, the FedGap is the Fed funds target rate set by the Fed minus the Fed funds rate as the Taylor Rule suggests. The frequency of the FedGap is quarterly as we wish to have one observation of this measurement for each of the events in our sample. Thus, we assign the last value of FedGap before the date of that event to the event. Actually, during the 2008 financial crisis period of our sample, there are some observations where the Fed funds rate Taylor Rule suggests to be negative however the Fed funds rate target set by the Fed is in the range of [0, 0.25%]. For expediency, we set them as zero, and consequently the corresponding FedGap is also equal to zero. This variable is simple but it is enough to reveal something influential in this study.

In the following section, we show that our reasoning helps explain why the conclusions of Bernanke and Kuttner (2005) and Jansen and Tsai (2010) on the relationship between the

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[10]See also the discussions in Calomiris (2009).
[11]see Demiralp and Jordà (2004) for related discussions.

market response to Fed announcements and business cycle or bull/bear conditions is invalidated with our sample. This demonstrates the importance in relationship descriptions of the proposed factor.

3.3. Explanation for Pattern Changes

3.3.1. Business Cycle

One natural question following our findings above is how to explain the different response patterns of structures of the stock market to Federal policy actions. Basistha and Kurov (2008) study cyclical variations in the effect of Fed policy on the stock market. Based on 3 indicators of the business cycle -NBER announcement, XRIC and CFNAI- they find that S&P 500 index returns show a much stronger response to unexpected changes in the Federal funds target rate in the recession and tight credit market conditions of 1990 to 2004. However, with our updated dataset, we find that their conclusion no longer holds, based on their original methodology[12]. We investigate this by applying an explanatory regression with similar specifications to Basistha and Kurov (2008), or

$$R_t = \alpha + \beta_1 \Delta i_t^u RM_t + \beta_2 \Delta i_t^u (1 - RM_t) + \varepsilon_t \tag{8}$$

where RM_t is the NBER recession dummy. It equals 1 when the observation is in the recession period announced by the NBER Business Cycle Committee, and is 0 otherwise. $\Delta i_t^u RM_t = \Delta i_t^u \times RM_t$ is the cross-term which captures the responses in the recession period.

Table 4: Explain S&P 500 Index Response Patterns to Monetary Policy Changes with Business Cycle

Sample	Obs	Est.	Intercept	Recession(β_1)	Expansion(β_2)	$\beta_1 - \beta_2$	R^2
Current study	189	OLSW	0.29***	-0.41	-3.96***	3.55	0.063
			(-0.09)	(2.02)	(1.74)	(2.61)	
Basistha & Kurov (2008)	130	OLSW	0.19**	-6.69***	-5.01**	-1.68	0.188
			(0.09)	(1.59)	(2.00)	(2.50)	

Note: Standard errors are reported in the parentheses. OLSW is ordinary least square method with White heteroskedasticity consistent standard errors. *, **, *** indicate that the coefficient is statistically significant at 10%, 5%, and 1% levels, respectively.

The regression results are reported in Table 4. From the table, the estimated responses, as using OLSW, in expansion periods is about 10 times as much as those in recession periods and β_1 is no longer statistically significant. This is in opposite of the conclusion of Basistha and Kurov (2008) that markets respond more in recession periods than in expansion periods. This also challenges our intuition. After further consideration, we believe this result

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[12]Intuitively, our 2nd subsample period of 2001-2008 covers a complete business cycle with most of the period in expansion

is due to the existence of multiple response patterns over our full sample period and that the responses in the 2nd subsample are significantly larger whereas the majority of the 2nd subsample is in a period of expansion. Thus this increases the responses of the expansionary period of the whole sample. To testify this, we classify the recession periods and expansion periods in the 3 subsamples by utilizing a dummy variables regression

$$R_t = \alpha_0 + \beta_0 \Delta i_t^u + \sum_{i=2}^{3} \left\{ \alpha_i^e e_{i,t} + \beta_i^e \Delta i_t^u e_{i,t} \right\} + \sum_{j=1}^{3} \left\{ \alpha_j^r + \beta_j^r \Delta i_t^u r_{j,t} \right\} + \varepsilon_t \qquad (9)$$

We also take possible changes of the intercepts into account. $e_{i,t}$ is set to be 1 if the event belongs to the expansion period of the i th subsample and 0 otherwise. $r_{j,t}$ analogically indicates every event in the recession period of j-th subsample, $\Delta i_t^u r_{j,t} = \Delta i_t^u \times r_{j,t}$ represents the cross term of surprise and dummy variable, to capture the response patterns in the recession of j-th subsample. $\Delta i_t^u e_{i,t} = \Delta i_t^u \times e_{i,t}$ considers breaks in the expansion period of the i-th subsample. We take the expansion period of the first subsample as the benchmark. We report the regression results in Table 5.

Table 5: Estimating Responses in Different Structure Regimes with Dummies for Business Cycles

Est.	α_0	β_0	β_2^e	α_1^r	α_2^r	β_2^r	α_3^r	β_3^r	$\bar{R}^2$
OLSW	0.26***	-2.15**	-8.99***	-0.72**	-1.13***	-9.85***	1.59***	6.69***	0.328
	(0.08)	(0.99)	(2.17)	(0.31)	(0.40)	(2.56)	(0.30)	(1.64)	

Note: OLSW is ordinary least square method with White heteroskedasticity consistent standard errors. Standard errors are reported in the parentheses. *, **, *** indicate that the coefficient is statistically significant at 10%, 5%, and 1% levels, respectively.

In economic terms, the insignificance of all the dummy variables can be interpreted as the response patterns in those periods statistically indifferent from that in the expansion period of the first subsample. The scenario in the recession of 1st subsample belongs to this group. However, compared with α_0, α_1^r and α_2^r reveals intercepts of -0.46 and -0.87 in the recession of 1st and 2nd subsample, respectively. Given the same negative(positive) surprise, they will deliver smaller rise(bigger fall) in stock index, even the response patterns in recessions is statistically indifferent from those in expansions. The different intercept reflects the asymmetric properties, which is consistent with the multiple response structure observation. In the 2nd subsample, the coefficient of the monetary surprise in expansion is $\beta_0 + \beta_2^e$, which equals to -11.14. That means a hypothetical 1% unexpected Fed Funds rate cut will lead to about 11% increase in the stock market index. On the other hand, the coefficient of the monetary surprise in recession is $\beta_0 + \beta_2^r$ equals to -12, which is a little bit larger than the expansion period. This implies Bernanke and Kuttner (2005)'s empirical conclusions are marginal valid here. Given the results from Table 4, we can argue that their original conclusions can not help in explaining our findings based on the full sample analysis. But once one accounts for

multiple response structures the inconsistency can be reasonably explained. The coefficients for the recession period of the 3rd sample α_3^r and β_3^r are positive, it is counter-intuitive but it is confirmative with our re-estimation result in the 3rd subsample from Table 2. We also attribute this to the small sample problem.

3.3.2. Bull/Bear Market

Asymmetries exist widely in financial markets. For example, agents' behavior in a bull market may be different from those in a bear market, and the "good news, bad news" stylized fact is broadly confirmed in every financial market. The general finding is that the market reaction is more pronounced in a bear market. Jansen and Tsai (2010) examine asymmetries in the impact of monetary policy surprises on the stock returns of bull and bear markets during 1994 and 2005. They concluded that the impact of a surprise policy action in a bear market, for most industries, is significantly greater than the impact of a surprise monetary policy in a bull market. They use the technique from Pagan and Sossounov (2003) for separating bull and bear markets. We follow this approach, use monthly data to identify the turning points and then switch to daily data to accurately locate the turning points at the daily level[13].

Following the specification of Jansen and Tsai (2010), we examine the relationship between market response patterns and the bull/bear market states. With the dummy variable identifying events in the bull market, we then have

$$R_t = \beta_0 + \beta_1 \Delta f_t^u + \beta_2 \Delta f_t^u \times \text{Bull}_t + \varepsilon_t \tag{10}$$

where Δf_t^u is the unexpected target rate change, and Bull_t is the dummy variable that labels all the events in bull markets with value 1 and labels 0 otherwise. The results of this regression appear in Table 6 and exhibit a different story to those of Jansen and Tsai (2010).

Table 6: S&P 500 Index Responses in Bull/Bear Market Conditions from 1989-2010

Sample	Obs.	Est.	β_1	$\beta_1 + \beta_2$
Current Study	189	OLSW	-2.99	-1.41
			(3.16)	(1.18)
Jansen and Tsai (2010)	100	OLSW	-7.7***	-1.4
			(1.7)	(1.6)

Note: Standard errors are reported in the parentheses. WLS is weighted least square method. OLSW is ordinary least square method with White heteroskedasticity consistent standard errors. *, **, *** indicate that the coefficient is statistically significant at 10%, 5%, and 1% levels, respectively.

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[13]The testing results show that the market turns bearish between June 4th, 1990 and October 11th, 1990; February 2nd, 1994 and June 24th, 1994; September 1st, 2000 and October 9th, 2002; and October 10th, 2007 and March 9th, 2009.

From Table 6, neither beta is statistically significant, implying that the conclusion of Jansen and Tsai (2010) does not hold in the updated longer sample. This finding might also relate to the structural change or multiple response patterns we documented over the long sample. This can be illustrated more clearly by going one step further and dividing the bull and bear markets into 3 subsamples using dummy variables. We propose a dummy variable regression model as follows:

$$R_t = \phi_0 + \theta_0 \Delta f_t^u + \sum_{i=2}^{3} \left\{ \phi_i^{\text{Bear}} \text{Bear}_{i,t} + \theta_i^{\text{Bear}} \Delta f_t^u \text{Bear}_{i,t} \right\}$$
$$+ \sum_{j=1}^{3} \left\{ \phi_j^{\text{Bull}} \text{Bull}_{j,t} + \theta_j^{\text{Bull}} \Delta f_t^u \text{Bull}_{j,t} \right\} \tag{11}$$

Where, $\text{Bear}_{i,t} = 1$ if the event is in the bear market of i-th subsample and 0 otherwise. At the same time, $\text{Bull}_{i,t} = 1$ analogically labels events in the bull market of j-th subsample with value 1 and 0 otherwise, $\Delta f_t^u \text{Bear}_{i,t} = \Delta f_t^u \times \text{Bear}_{i,t}$, is the cross term of surprise and dummy variable,to capture the response patterns in the bear market of i-th subsample.$\Delta f_t^u \text{Bull}_{i,t} = \Delta f_t^u \times \text{Bull}_{i,t}$ considers the bull period of the j-th subsample. In this specification, the bear market of the first subsample is the benchmark.

We report the refined dummy variable regression result in Table 7.

Table 7: Explaining Responses in Different Structure Regimes with Dummies for Bull/Bear Conditions

ϕ_0	θ_0	ϕ_1^{Bull}	ϕ_2^{Bull}	θ_2^{Bear}	ϕ_3^{Bull}	ϕ_3^{Bear}	θ_3^{Bear}	$\bar{R}^2$
-0.54***	-1.58	0.84***	0.95***	-11.84***	1.41***	2.28***	5.96***	0.23
(0.19)	(0.96)	(0.22)	(0.24)	(1.97)	(0.41)	(0.37)	(1.63)	

Note: Results obtained using OLSW. Standard errors are reported in the parentheses. *, **, *** indicate that the coefficient is statistically significant at 10%, 5%, and 1% levels, respectively.

The result shows that the response is the same in the bear market of 1st subsample and the bull market in the whole sample. The response in the bear market of the 2nd subsample is negative, large and highly statistically significant and θ_0 (the response in the bear market of the 1st subsample, which also represents 3rd subsample), has a higher value of t-statistics than β_1 in Table 6. It means that Table 7's result is closer to Jansen and Tsai (2010)'s original conclusion, though θ_0 is still not significant. Furthermore, the market does react more to "good news" (negative surprise, i.e., more rate cut than expected) and less for "bad news" in bull markets, since ϕ_1^{Bull}, ϕ_2^{Bull} and ϕ_3^{Bull} are all positive and highly significant. This is consistent with Jansen and Tsai (2010)'s conclusion that the impact of a monetary policy surprise in a bull market is smaller in magnitude than the impact in a bear market, and is generally statistically insignificant. This implies Jansen and Tsai (2010)'s empirical results may probably still holds after the time varying response structure considered and controlled for.

3.3.3. Monetary Stance

Monetary policy stance is another possible answer for explaining market responses. Simply put, easing cycle and contraction cycle are the two main status of the monetary policy. The period of the 2nd subsample in our study is neatly a complete easing cycle plus a contraction cycle. Thus, the monetary policy status can not provide enough explanation for our findings[14].

4. Further Interpretation

So far, we have illustrated that the explanation for invalidation of previous empirical explanations for market response based on business cycle and bull/bear markets in our extended sample lies on the observation of the response patterns switching across three structures. But what is the deeper mechanism beneath?

We attribute it to the role change of the Federal Reserve, i.e. it is the Federal Reserve's role change induces the structure breaks which in turn leads to "counterintuitive response" observations documented in the extended sample. More specifically, we want to determine whether our FedGap variable proposed can provide any help in explaining the invalidation of previous conclusions about business cycle and bull/bear. Naturally, we tried to add FedGap into the specification of Basistha and Kurov (2008) as well as Jansen and Tsai (2010), hoping to bring the results of the extended sample back to original conclusions. However, the result shows there is no strong evidence that taking FedGap into account can reanimate Basistha and Kurov (2008) as well as Jansen and Tsai (2010)'s conclusions[15]. Actually, this is understandable as FedGap can only help explain the difference between periods when there's large variation of the variable itself. But, in our 2nd subsample, the FedGap is relatively stable while there is a recession period and a expansion period, as well as a bearish market and a bullish market in sequence. FedGap can not help in characterizing the different response patterns based on existence of both of market conditions in the same structure[16].

How then, are we to interpret the influence of the Fed's role change? We believe that the FedGap is a state variable that underlies the whole relationship. Just like the response patterns, the Fed's role change should also be a variable describing a fundamental state in which such response pattern studies should be based on. It is reasonable to argue that

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[14]Besides, in Jansen and Tsai (2010), policy announcements are divided into 3 groups: "positive rate change", "no rate change" and "rate cut". The corresponding regression shows a similar result, only "no rate change" has explanation power. The results of the insignificant coefficients of "positive rate change" and "rate cut" indicate that the market response pattern in the monetary policy easing cycle is indifferent from that in the monetary policy contraction cycle.

[15] The results are available from the authors upon request.

[16]Obviously, why previous conclusions fail in our sample is not an omitted variable problem. So, the right solution is to classify every event in the expansion period (bull market) into 2 groups: events in the expansion(bull market) of the 2nd subsample and events in the expansion(bull market) of non-2nd subsample, to isolate the strong response change caused by the Fed role change. This is what we do in the previous 2 subsections.

different role states determine different response patterns and it is also consistent with our intuition discussed in the introduction.

In order to show the validity of our arguments, we perform an ordered probit regression with the specification

$$y_t = \beta \times \text{FedGap}_t + \varepsilon_t \tag{12}$$

Where

$$\begin{cases} y_t = 0, & \text{if } 1^{st} \text{ subsample} \\ y_t = 1, & \text{if } 2^{nd} \text{ subsample} \\ y_t = 2, & \text{if } 3^{rd} \text{ subsample} \end{cases} \tag{13}$$

The results are presented in Table 8.

Table 8: Ordered Probit Regression for Examining "FedGap" in Explaining CRSP Value Weighted Index's Response Pattern Changes

β	$\bar{R}^2$
-0.42***	0.158
(-6.91)	

Note: Z-statistics are shown in parentheses. *** indicate that the coefficient is statistically significant at 1% levels.

The statistically significant coefficient provides evidence that FedGap matters. β is negative because the value of FedGap is negative for most of our sample. Given the evidence that the Fed's role change has an effect on response patterns, we propose that the Fed's role change probably affects the intensity or elasticity of the market responses which is measured by the coefficient of responses. The regression below provides some supporting evidence for this proposal. The sensitivity measurement of the market response patterns, g_t, is constructed by dividing the event-day CRSP returns (responses) by the magnitude of the corresponding surprises[17], and we regress it on the FedGap in (14). We exclude these observations with zero surprises in the examination. Table 9 reports the results.

$$g_t = \alpha + \beta \times \text{FedGap}_t + \varepsilon_t \tag{14}$$

The significant positive coefficient of beta is consistent with economic logic (under OLSW, it is also positive but less significant), as the value of FedGap is negative for most of the time in our sample while the coefficient of surprise in Bernanke and Kuttner (2005) is also negative. The results suggest FedGap is closely related to the surprise-adjusted market response and directly explains why the market reacts more significantly to the surprise in our 2nd subsample, in which the magnitudes of FedGap are larger than those in the first

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[17]We define g_t to be a surprise-adjusted responses, which is also an empirical proxy for the variation of response elasticity.

Table 9: Surprise-adjusted Market Response Patterns and the FedGap

Est.	α	β	$\bar{R}^2$
OLSW	12.03***	5.98**	0.033
	(4.60)	(3.01)	

Note: OLSW is OLS with White's heteroskedasticity-consistent estimates of the standard errors. Standard errors are reported in the parentheses. *, **, *** indicate that the coefficient is statistically significant at 10%, 5%, and 1% levels, respectively.

subsample[18].

5. Bond Market Responses Structure Changes

We also study U.S. bond markets and compare and contrast the results with those from the stock market in order to see whether the findings are consistent. The same monitoring procedure is applied on 1 year treasury bond securities with the maturity of 1 year. The results[19] show that January 3rd, 2001 is the robust first break point which is insensitive to the choice of m in a reasonable range, which is close to the first break point we detected the stock market. This clearly suggests that the bond market shares some common reaction patterns to monetary news with the stock market. This is understandable as bonds have long been regarded by stock market investors as the best tool for hedging adverse shifts of economic-wide conditions. In the detection for the second point, the results are not as robust as the first break point. For m equals and greater than 50, the second point is located around March 18th, 2008, while for m smaller than 50, there is no break detected. We can thus conclude that January 3rd , 2001 is a robust structural break point and that March 18th, 2008 is a break which is relative weakly identified. Given the results, we re-estimate the regression in the two subsamples divided by the break points of January 3rd, 2001.

From Table 10, we see that the bond market has multiple response patterns too. The explanation power of the original Bernanke and Kuttner (2005) model in the first sample is stronger than that of the second sample. This clearly indicates it is necessary to consider structure changes when examining financial market responses to macroeconomic policy changes and further confirms that monotonically structured responses patterns should be rejected and that our real-time techniques for structure break monitoring work effectively in financial markets. As our work focuses on stock market responses, so we leave discussion of the effect of any role change of the Federal Reserve in the bond markets as a separate topic for future work.

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[18]The results in the third subsample is incomparable as there are only 18 observations.

[19]All the results are available from the authors upon request.

Table 10: Structure Based 1 Year Treasury Bond Market Responses to the Monetary Policy Changes, 1989-2010

Sample	Obs	Est.	Intercept	Expected	Surprise	$\bar{R}^2$
all	189	OLSW	-0.11	0.82	16.27***	0.231
			(0.25)	(2.68)	(3.23)	
1st	113	OLSW	-0.03	-0.01	10.76***	0.388
			(0.12)	(0.86)	(2.14)	
2nd	76	OLSW	-0.31	1.43	22.00***	0.235
			(0.49)	(3.77)	(5.32)	

Note: OLSW is OLS with White's heteroskedasticity-consistent estimates of the standard errors. Standard errors are reported in the parentheses. *, **, *** indicate that the coefficient is statistically significant at 10%, 5%, and 1% levels, respectively.

6. Concluding Remarks

Financial market response to macroeconomic news announcements has been a very important topic of research in finance for long. Generations of researchers have endeavored to provide theories and empirical evidences for monitoring, explaining and predicting patterns of reactions and channels of interactions between markets and regulations. Motivated by the Bernanke and Kuttner (2005) work, we extend their classical event study methodology by going one step further to discuss real time structure changes of the stock market response to the FOMC announcements based on an extended sample from 1989-2010. By using real-time structure break monitoring techniques, we find evidence against monotonic response pattern, specifically three response structures of US stock market to the federal monetary policy actions. We then re-estimate the market response in each of the three structures and find results stronger than previously documented especially in 2001-2008. We propose a "FedGap" variable which measures the deviation of Fed policy from the "Taylor Rule" in explanation and find it to be significant with economic meaning. This FedGap can also explain why previous conclusions on market response to Fed announcements and business cycle or bull/bear conditions fail in the current study. We further conclude that the FedGap serves as a new "macro-state" factor which can explain the dynamic response patterns of financial markets. Similar results are also obtained from the bond markets.

We would like to end this paper with a word from Taylor (2000):

"*In macroeconomics there is never only one accepted explanation for any big event— whether the Great Depression, the Great Inflation, or the Long Boom. By debating alternative explanations we learn and hopefully improve policy in the future.*"

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