The Asymmetric Effects of Monetary Policy on Stock Market

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Abstract

This paper investigates the asymmetric effects of monetary policy on the U.S. stock market across different monetary policy regimes and different stock market phases. It uses a Markov-switching dynamic factor model to date the turning points of each bear market and bull market, and to generate a new composite measure that represents the overall stock market movements. A time-varying parameter analysis, which is undertaken in the framework of a state space model and estimated via Kalman Filter, is then used to study the contemporaneous and lead-lag effects of monetary policy on stock returns. The results provide evidence that changes in monetary policy regimes and stock market conditions shape the time-varying relationship between monetary policy and stock returns. It is observed that the monetary policy of changing monetary aggregates has fewer impacts in bear markets than bull markets, but changes in federal funds rate can be more influential in bear markets. The results also indicate that increases in monetary aggregates or reductions in the federal funds rate have positive contemporary impacts on stocks only during the periods in which they are used as the monetary policy target by the Federal Reserve.

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1 Introduction

The Federal Reserve has two ultimate objectives for its monetary policy: to support maximum sustainable output and employment, and to maintain stable price level. These two goals are explicitly announced in the 1977 amendment to the Federal Reserve Act. It is stated by mounting literatures on the transmission of monetary policy that the Federal Reserve affects real economy through the financial markets and especially the stock market. For instance, as Bernanke and Kuttner (2005) state, the effects of monetary policy on macroeconomic objectives are at best indirect and lagged, and the most direct and immediate influence of monetary policy is on the stock market. Many other studies also support the view that monetary policy has an instantaneous and significant impact on stock market (see, for example, Thorbecke, 1997; Patelis, 1997; Lastrapes 1998; Rigobon and Sack, 2004; Farka 2009, among others). The commonly accepted wisdom is that expansionary monetary policy measures should have a positive effect on the stock performance.

Given the fact that monetary policy has significant influence on stock market, several cross-section studies have sought to investigate if monetary policy has asymmetric impacts on stock performance according to different firm characteristics such as its size and capital intensity. For example, Ehrmann and Fratzscher (2004) concluded that capital-intensive firms and financial-constraint firms are more strongly affected by monetary policy.

Several time-series studies (Durham 2001, 2003) showed that the relationship between monetary policy and stock market return is historically unstable and time-varying. However, there is not much done in the literature analyzing how and why the relationship varies over time. Is it possible that the time-varying response of stock return to monetary policy depends on drastic changes in monetary regimes or the phases of the stock market being in a bull or bear market?

The aim of this paper is to explore whether the effects of monetary policy on stocks are asymmetric over time depending on the stock market phases and the monetary policy regimes from 1970s to present. This topic has gained popularity in the current scenario of expansionary monetary policy and historically high stock price level in the U.S.

Understanding the responsiveness of stock market to changes in monetary policy shed light on the transmission mechanism of monetary policy, since stock market performance plays an important role on real activities through many channels.

Investigating the impact of monetary policy across different stock market phases and monetary policy regimes naturally requires identifying the beginning and the end of these phases and regimes. The periods of monetary policy regimes can be defined using the dates on which monetary policy intermediate targets changed, which is well-documented in the Federal Reserve's history. Yet, agreement on the dates of stock market turning points between bull and bear market regimes is far from unanimous. Moreover, there is even no commonly accepted formal definition of bear and bull markets in academic literatures.

National Bureau of Economic Research (NBER) provides business cycle dates that are regarded as official. This dating is obtained by examining the comovement in the switch of several major economic variables. This paper uses the NBER's principle together with Chauvet (1998/1999) classification method to define the bull and bear markets by employing a Markov-switching dynamic factor model to date their turning points. The framework is cast in a state space model, and estimated via Kalman Filter (1960) and Hamilton Filter (1989). The dynamic factor model captures the clustering of shifts between upward and downward tendency of a variety of popular stock indices. The Markov-switching feature reflects the asymmetry of stock movements in terms of growth rate and volatility, and is able to statistically identify the date of turning points through the smoothed probabilities.

The results show that the model successfully captures all bear markets and bull markets. Moreover, the model also produces a new composite index that represents the stock market price movements more precisely and broadly. The new composite measure has advantages over existing stock indices, given that they are criticized for their limitation on the coverage of certain types of stocks and stock exchanges. The Markov-switching dynamic factor model also calculates the average durations of bear and bull markets, and the probability of bear and bull market at every time point. These results help investors and policy makers understand in which state the stock market is and where the stock market moves towards.

In the next step, this paper uses the proposed new stock market movement index into a time-varying parameter model to explore the dynamic interrelationship between monetary policy and stock performance across different monetary policy regimes and stock market phases. Monetary policy is represented not only by short-term policy interest rate and but also by monetary aggregates to reflect the fact that these two variables have been used as the monetary targets in the Federal Reserve's history. The lead-lag relationship and contemporaneous relationship are analyzed in two separate time-varying parameter models, which are represented in the state space models, and estimated through the Kalman Filter and maximum likelihood estimation method. To the best of my knowledge, this article is the first to study this topic in the framework of Markov-switching dynamic factor model and time-varying parameter model. It can unveil features of their relationship that have not been captured previously.

The results show that the influence of monetary policy on stock return is different across monetary policy regimes which are classified by the monetary policy target changes. The contemporary signaling effect of federal funds rate changes impact the stock market only during periods in which the federal funds rate is used as monetary policy target by the Federal Reserve. This is also the case for monetary aggregates. That is, monetary aggregates affects stock market positively only during periods in which they are used as monetary policy targets in 1970s and 1980s.

This paper also provides evidence of the asymmetric response of stock return to monetary policy during bear and bull markets. In fact, there is a sharp drop in the correlation between monetary aggregate and stock returns in every bear market, indicating that the influence of expansionary monetary policy through increases of monetary aggregate is much weaker in bear markets, and can even have a negative effect on the stock market. However, an expansionary monetary policy through reduction in federal funds rate is influential in improving stock returns in bear markets.

The remainder of the paper is organized as follows. The next section discusses the studies conducted in the past literature. Section 3 describes the theoretic framework of the relationship between monetary policy and stock movements. The data are described in the fourth section. Section 5 illustrates the Markov-switching dynamic factor model and time-varying parameter model, which are the empirical models applied in this study. Section 6 presents the empirical results. This paper is concluded in the seventh section with some discussion of additional issues. Estimation procedures are discussed in the Appendix.

2 Literature Review

2.1 Literatures on the U.S. stock market regimes

The fundamental understanding of a bull market is a period of substantial and continuous increase of stock prices, and a bear market is a period of substantial and continuous reduction in stock prices. Stock market commentators often define a bull market as a 20% or 25% stock price rise, and a bear market as a 20% or 25% stock price decline. Some financial analysts identify the beginning of a bear market when the 50-day moving average line crosses the 200-day moving average line from the above, and holds below. However, in the academic area, the finance and economics literatures have no commonly accepted definition of bull market and bear market. Several studies provided their own definitions of bull and bear markets, such as Chauvet and Potter (2000), Pagan and Sossounov (2003), and Chen (2007). For example, Chen (2007) used a simple Markov-switching model on S&P 500 stock returns to estimate the probabilities of bear market and bull market, and it found that the correlation between the bull market probability and the bull market binary variable constructed by using 20% cutoff line is round 0.7.

2.2 Literatures on the U.S. monetary policy regimes

According to Meulendyke (2003) and Mishkin (2006), the Federal Reserve’s monetary policy experienced substantial changes over the past four decades. In 1970, Arthur Burns was appointed chairman of Board of Governors of the Federal Reserve, and the Federal Reserve started to use monetary aggregates as intermediate target and federal funds rate as operating target to fight inflation, which was caused by the procyclical monetary policy. However, this monetary target policy was unsuccessful in controlling inflation, due to the fact that monetary aggregate target and federal funds rate may conflict with each other. In 1979, Paul Volcker became the Federal Reserve chairman. The Federal Reserve's monetary policy has shifted into a new regime in 1980s. The main goal in this era is to change interest rate to fight serious inflation. The operating target was switched from federal funds rate into nonborrowed reserve and borrowed reserve sequentially. Monetary aggregate still served as the intermediate monetary target. A predetermined target path for nonborrowed reserve and borrowed reserve was based on the objective for the monetary aggregate.

When Alan Greenspan was elected as Federal Reserve's chairman in 1987, the Federal Reserve announced that it would no longer use monetary aggregate as its target. Abandoning monetary aggregates as the guide for its monetary policy, the Federal Reserve has restarted to target federal funds rate since early 1990s. Periods in 1990s and 2000s were featured by the clear monetary policy goal in terms of macroeconomic variables, clear operating target which is federal funds rate, without an explicit intermediate target. By actively and timely changing federal funds rate, the Federal Reserve tried to keep the economy and financial market on track. Ben Bernanke began his tenure in early 2006. The same monetary strategy continued until 2007, when a more complicated problem came up. Since 2008, a sufficient injection of bank reserves has brought the federal funds rate fundamentally close to zero, so that the zero lower bound rules out further policy interest rate reduction. The Federal Reserve has to seek alternative monetary policy tools, known as quantitative easing and forward guidance.

2.3 Literatures on general responsiveness of stock to monetary policy

The responsiveness of stock movements to monetary policy has been a matter of increased concern. For most of these studies, monetary policy is divided into two main streams: changing the monetary aggregate and changing the policy interest rates. The effects of expansionary monetary policy, such as increasing money supply and reducing policy interest rates, on the stock return are claimed to be positive in these empirical researches. Thorbecke (1997) employed a monthly VAR model for the period from 1967 to 1990 to analyze the link and used the federal funds rate to measure monetary policy. He found that the response of stock returns to a negative one standard deviation shock to the federal funds rate is 0.8%. This empirical finding that a positive relationship between the expansionary monetary policy of reducing policy interest rate and stock return has been confirmed by Patelis (1997), Lastrapes (1998) and many others. In a more recent study, Rigobon and Sack (2004) used the policy shocks that take place on certain dates such as the days of FOMC to examine this topic, and documented a positive linkage between expansionary monetary policy and stock movements. In a similar vein, Bernanke and Kuttner (2005) took a more traditional event-study approach, while controlling directly for certain kinds of information jointly influencing monetary policy and stock return. They applied ordinary least squares regressions in an event study, and found that an unexpected 25 basis points decrease in the federal funds target rate is associated with a one percent increase in the stock prices.

But there is not yet a consensus on this conclusion, as several articles provide counter examples on the direction of effects. Cornell (1983) found the link between money supply announcement and asset prices can be either positive or negative, depending on the underlying assumption and hypothesis. He discussed three hypotheses (expected inflation hypothesis, Keynesian hypothesis, and real activity hypothesis) suggested in the previous literature as well as the risk premium hypothesis that he proposed. Lee (1997) applied rolling regressions to measure the relationship between short-term interest rate and stock prices, also indicating an unstable linkage. There is some dissent on the response of stock market to the monetary policy among the existing literature. The direction of the reaction is impossible to determine ahead. Possible explanations for this dissent are provided in the theoretical analysis section of this paper.

2.4 Literatures on the asymmetric effects of monetary policy on stock return

Chen (2007) studied the monetary policy's asymmetric effects on stock returns in different stock market conditions, and found that monetary policy has a larger effect in less booming stock markets and stagnant stock markets. His finding indicated that a contracting monetary policy is more likely to cause a weak stock market. Jansen and Tsai (2010) investigated the asymmetric impact of monetary policy on stock return in bull and bear market during the time period from 1994 to 2005, and showed that the monetary policy shocks in bear market is large, negative, and statistically significant. Kurov (2010) analyzed the stock returns on Federal Open Market Committee (FOMC) announcement days, and found that monetary policy shocks have strong influence on market participants' sentiment, and this impact is even stronger in a bear stock market. Laopodis (2013) examined the dynamic relationship between monetary policy and stock market during the three distinct monetary policy regimes of Burns, Volcker and Greenspan since 1970s. It found there was a very weak relationship between monetary policy action via federal funds rate and stock return in 1990s. His paper provides evidence for asymmetric effects of monetary policy on stock in different regimes of monetary policy and different stock market conditions.

3 Theoretical Analysis

The most popular theory for the stock price valuation is the present value model or discounted cash flow model. This model is well explained by Crowder (2006) and many other studies. The intrinsic stock price is valued as the present value of future expected dividends cash flows of the company and terminal stock price at the last period of holding horizon. The intrinsic stock price is simultaneously determined by two parts: future cash flows and the discounting rate. Therefore, monetary policy can affect stock price through both future cash flows and discounting rate which is linked to interest rate.

The Federal Reserve has several monetary tools available, such as open market operations, discount loans, and required reserves. It also has the ability to set discount rate and federal funds rate target to affect the financial markets and real economic activities. It is widely accepted that all the monetary policy measures can be summarized into two major channels: changes in monetary aggregate and changes in short-term interest rate. These two measures are correlated most of the time, in that a rise of money supply in terms of bank reserves will put downward pressure on the short-term interest rate which clears the reserve market. However, this is correct only under the condition of fixed money demand. If money demand increases, an increase in money supply may not necessarily generate a drop in interest rate. Another exception arise in the scenario of current zero lower bound interest rate, which already rules out further policy interest rate reduction. Hence, it is appropriate to examine the effect of change in money supply and change in interest rate separately.

It is commonly believed that expansionary monetary policy, considered as a rise in money supply or a reduction in short-term policy interest rate, can drive up the stock price by increasing the future cash flow and decreasing discounting rate. However, the actual mechanism behind is much more complicated. The impacts of expansionary monetary policy on stock market can be either positive or negative. In addition, the effects through these two channels can reinforce or offset each other.

In general, the response of stock prices to the expansionary monetary policy of reducing interest rate is positive. That is why there exists a long tradition for the Federal Reserve to drop short-term policy interest rates in an attempt to promote the stock market condition. The detailed reasons for the positive linkage are presented as follows. First, a lower interest rate indicates a lower discounting rate, implying a higher present value of future cash flows and hence a higher stock price, given that the future cash flows are constant. Second, when interest rates decrease, saving in banks and investing in bonds or other interest related investment vehicles become less profitable and attractive. Financial market participants switch into stock investment, leading to a rise in the demand for stocks. Stock prices go up accordingly. Third, companies with high debt in their balance sheets will benefit when interest rates decrease, resulting in higher net income and higher stock prices. It is also less costly for firms to borrow new loans to fuel their business growth, which will be favorable for firms' financial situation and stock value growth. Fourth, with lower interest rates, consumers are more willing to borrow to finance big purchases. It largely affects certain industries such as real estate and automobiles, generating a boost in companies' revenues and stock prices.

However, there are several exceptions to the above situations, leading to a possible negative linkage between the expansionary monetary policy of reducing interest rate and the stock price movements. First, companies in the certain industries would suffer loss from the reduced interest rate. For example, a lower interest rate will generate a smaller net interest margin for banks. This will cause a decrease in profits and stock prices in banking industry, resulting in a negative relationship between the expansionary monetary policy of reducing interest rate and the stock price. Second, international capital makes its decision largely based on the interest rate of the target country. However, a lower interest rate is not attractive for international capital, and even causes domestic money to flow out, which is detrimental for the domestic stock market and stock prices. Third, as elucidated by Cornell (1983), money and stocks are considered as two of many assets in the portfolio of investors. A decrease in interest rate means the opportunity cost of holding money in the portfolio is lower, motivating investors to replace stocks with money. A lower demand for stocks reduces stock prices. The above positive and negative relationship between the expansionary monetary policy of reducing interest rate and stock prices may offset each other. In theory, the final relationship can be either positive or negative, depending on which force dominates the other.

More surprising is that the expansionary monetary policy of increasing money supply can also have either positive or negative impacts on stock price movements. The following reasons explain the positive effect of expansionary monetary policy of increasing money supply on stock prices. First, a higher money supply allows banks to have more cash for loans. Consumers are easier to borrow to make big purchases, which will contribute to the rise of firms' revenue and stock prices. At the same time, the firms are easier to get access to loans, which provide the fuel for business expansion and stock price growth. Second, in the real activity hypothesis discussed by Cornell (1983), one of the Federal Reserve's responsibilities is to balance the money demand and the money supply. An increase in money supply hints at a higher money demand anticipated by the Federal Reserve, caused by higher anticipated future output. Higher anticipated future output will raise firms' future revenue and cash flows, leading to higher stock prices. Besides, higher anticipated future output can also tremendously improve investors' sentiment, which is favorable for stock price growth. Therefore, changes in money supply display a positive relationship with stock price.

On the other hand, the expansionary monetary policy of a rise in money supply can also have negative impacts on stock prices. The stock market can perceive the increase in money supply as a reinforcement signal that the economy is entering difficult times and the Federal Reserve is taking measures to help the declining market, which generate a pessimistic sentiment and has a negative effect on market sentiment and stock performance. Additionally, under the Keynesian assumption of sticky price, an increase in money supply will cause the real money balances to rise. Interest rates must drop to produce an offsetting rise in money demand to clear money market. Since there is a possible positive relationship between interest rate and stock prices, which is illustrated above, the ultimate effect of an increase in money supply on stock prices is likely to be negative. Lastly, higher money supply will create a higher expected future inflation. Since stock return is considered to be negatively associated with inflation, which is claimed by existing studies (see Nelson, 1976; Fama and Schwert, 1977), stock prices will reduce accordingly due to the high inflation. Due to the above reasons, the effect of expansionary monetary policy on stock movements can't be determined ahead.

4 Data

The overall price level of stock market is measured by the stock index. The most popular and influential stock indices in the U.S stock market nowadays are Dow Jones Industry Average, Standard & Poor's 500, and NASDAQ Composite. Fortune (1998) shows that these stock indices display divergent movements, implying that different stock index represents different segments of the U.S. stock market and contributes different information about the stock market. Dow Jones Industry Average Index has the longest history and is the only price-weighted index. It only covers the largest 30 blue-chip stocks and all the stocks are listed in New York Stock Exchange. S&P 500 is a value-weighted stock index, representing 500 stocks traded in New York Stock Exchange, American Stock Exchange, and NASDAQ stock market. The market value of stocks included in the S&P500 range from large-capitalization to mid-capitalization. NASDAQ Composite covers more than 5000 stocks listed in the NASDAQ exchange. Most of these stocks are considered as technology stocks and small-capitalization stocks. As each stock index measures different stock market segments, it is reasonable to combine all three stock indices to study the overall movements of the U.S. stock market. A major contribution of this paper is developing a better and broader composite measure for stock market price movements by capturing the clustering in movement of different stock exchanges and stock sectors. This is very much distinguished from Chauvet (1998/1999), who uses stock fundamentals such as price earnings ratio and dividend yield to extract a stock market common factor to represent the fluctuations of stock market.

Interest rate and monetary aggregate are two main measures of the Federal Reserve's monetary policy. As mentioned in the literature review, both federal funds rate and different measures of monetary aggregates have been used as the monetary policy target in the Federal Reserve's history. This paper uses the federal funds rate to represent the short-term policy interest rate. The Federal Reserve directly controls two short-term policy interest rates, which are discount rate and federal funds rate. As a measurement of interest rate monetary policy, the federal funds rate is more favorable than discount rate. In 2003, the Federal Reserve reformed the discount lending system, and set the discount rate 100 basis point higher than the federal funds rate to penalize the discount borrowing. Discount loan is no longer used regularly by the depository institutions during the normal time. The choice of federal funds rate was also supported by Bernanke and Kuttner (2005), who claim that changes in federal funds rate has the most immediate effect on financial markets. On the other hand, this paper chooses Divisia M4 and M2 as the representative of monetary aggregate. Divisia M4 is a broad monetary aggregate, containing negotiable money market securities, such as commercial paper, negotiable CDs, and T-bills. Divisia M4's components are modernized to be consistent with current financial innovations and financial market facts.

The data is measured in monthly frequency and the sample period ranges from March 1971 to November 2012. The data is obtained from the websites of Federal Reserve Bank of St. Louis FRED database, Center for Financial Stability and Yahoo Finance.

5 Empirical Models

5.1 Empirical Model for the Identification of Bull and Bear Markets

Burns and Mitchell (1946) proposed and Diebold and Rudehusch (1996) stressed two important features for the business cycle of economy: the comovement of the macroeconomic variables and the asymmetry between expansions and recessions. This is also the principle that the National Bureau of Economic Research (NBER) uses to provide the official periods of business cycle and the dates at which the shift of economic phase take place in the United States. In order to date an economic peak, which is the turning points of the transition from an expansion to a recession, the National Bureau of Economic Research seeks for the comovement in the switch of several major economic variables from the upward growth into the decline. The economic trough, which is the turning point of the transition from an expansion phase to a recession phase, is dated by the National Bureau of Economic Research using the reversed method. The dates of business cycle turning points and its calculation method are widely accepted by the public. These two features – comovement and asymmetry – apply to the fluctuation cycle of stock market as well. First, there exists a comovement of stock prices among stocks in different sectors and different exchanges. The common dynamics of different stock prices can be represented by an unobserved common factor in a dynamic factor model, which reflects the overall movement of the stock market. The dynamic factor model, developed by Geweke (1977), Sargent and Sims (1977), and Stock and Watson (1989, 1991), successfully captures the common underlying source which generates comovements among different variables. The second feature demonstrates that stock market behaves differently during bull market regime versus bear market regime. It is possible that the growth rate or volatility is completely different in different regimes. However, a linear model is not capable to capture this asymmetry in the stock market price dynamics. Hamilton’s (1989) state-dependent Markov switching model is designed to characterize this nonlinearity feature as it allows for switching between different regimes.

Therefore, in order to apply the NBER’s principle to date the turning points of stock market regimes and study the two features inherent in the stock market, which are comovement and asymmetry, the dynamic factor model and the state-dependent Markov-switching model become the natural choice for my research. More specifically, one aim of this paper is to combine the dynamic factor model and the state-dependent Markov switching model, and construct a new composite stock market indicator to better represent the overall movements of the U.S. stock market. The Markov-switching dynamic factor model is undertaken in the framework of a state space model, and estimated via Kalman Filter (1960) and Hamilton Filter (1989). The dynamic factor model captures the clustering of shifts of a variety of popular stock indices between their upward tendency and downward tendency. The Markov-switching feature reflects the asymmetry of stock movements in growth and volatility, and is able to statistically identify the dates of turning points using transition probabilities.

Diebold and Rudebusch (1996) proposed a Markov-switching dynamic factor model which encompasses these two features in one model for the first time. However, they did not actually carry out the estimation due to the heavy computational burden. Kim and Yoo (1995) and Chauvet (1998) developed the Markov-switching dynamic factor model and actually undertook the estimation by using the maximum likelihood estimation method to estimate both the dynamic common factor and the regime-switching transition probabilities simultaneously. This paper follows Chauvet (1998) to assume that the intercept and variance of the common factor is Markov switching between different regimes. Kim and Nelson (1999) provided a detailed summary, and this paper uses their algorithm as the main reference.

Markov-switching dynamic factor model is carried out within state-space models. State-space model was originally developed by Kalman (1960), and was applied to solve dynamic problems that involve unobserved state variables. The unobserved dynamic common factor is just one component of the unobserved state vector. State-space models are made up of two equations, measurement equation and transition equation. Measurement equation shows the relationship between observed variables and unobserved state variables. Transition equation shows the dynamic relationship between the state variable and its own lagged terms.

The essence of a Markov-switching dynamic factor model is that one unobserved dynamic factor, f_t, captures the comovements of a vector of time-series observed variables,

Y_t, which have higher dimension. The unobserved dynamic factor, which follows an autoregression, has the mean and conditional volatility that are functions of a Markov state variable S_t, with the purpose of measuring the potential asymmetries across different stock market regimes in terms of growth rate and volatility. The random variable S_t takes the value of zero or one, and represents the regime of stock market, either bear or bull. The vector of time-series observed variables is also impacted by a vector of idiosyncratic disturbances, e_t. These idiosyncratic disturbances capture the special features that are specific to an individual observed variable. The latent factors also follow an autoregressive time series process, which can take the form of either AR(1) or AR(2).

In equations, the Markov-Switching dynamic factor model is presented as following,

$$\Delta Y_t = \gamma \Delta f_t + \Delta e_t$$

$$\Delta f_t = \mu_{S_t} + \phi \Delta f_{t-1} + w_t, \qquad w_t \sim i.i.d.N\left(0, \sigma^2_{w\_S_t}\right)$$

$$e_t = \varphi(L) e_{t-1} + \epsilon_t, \qquad \epsilon_t \sim i.i.d.N(0, \Omega)$$

$$\mu_{S_t} = \mu_0 S_t + \mu_1 (1 - S_t), \qquad S_t = 0,1$$

$$\sigma^2_{w\_S_t} = \sigma^2_{w\_0} S_t + \sigma^2_{w\_1} (1 - S_t), \quad S_t = 0,1$$

where L is the lag operator and $\Delta = 1 - L$; Δf_t is a unobserved common factor extracted from major stock indices; γ represents the vector of factor loadings that describes the contribution of each stock index; e_t denotes the vector idiosyncratic components representing the unique feature of each stock index, and follows a normal distribution.

In the setting of Markov switching dynamic factor model in this paper, observed time series are stock indices. This paper uses these three indices to construct the new composite measure of stock market movements. Let Y_t be a vector of 3 x 1 observed variables in their log form at time *t*, which consists of Dow Jones Industry Average Index, S&P 500 Index, and NASDAQ Index in order. Every variable can be decomposed into a common factor and a specific or idiosyncratic component. The common factor captures the simultaneous upward and downward fluctuations of stocks that are widespread in all the stock exchanges and sectors. In other words, a bear market occurs when all the three indices drop significantly at the same time and a bull market occurs when all the three indices increase simultaneously. If only one index drops and other indices increase or stay the same, this movement will be captured by the idiosyncratic term of that index, rather than by a common unobserved factor.

The Markov switching from one state to another is controlled by the transition probability matrix with element $P_{ij} = p(S_t = j|S_{t-1} = i)$, where $\sum_{j=0}^{1} P_{ij} = 1, i, j = 0,1$. Besides, Δe_t and w_t are assumed to be mutually independent at all lags and leads. $\varphi(L)$ and Ω are diagonal based on the setting of dynamic factor framework. The common factor f_t and idiosyncratic terms e_t are assumed to be uncorrelated at all lags and leads. The common factor and the idiosyncratic term follow a separate autoregressive process. For the dynamic factor model, it is widely accepted that the common factor follows a AR(1) process. However, the dynamics of the idiosyncratic terms have several possibilities. This paper estimates two most popular specifications, which are AR(1) and AR(2). The first Markov-switching dynamic factor model (MSDF-Model 1) uses AR(1) for the idiosyncratic terms and the second Markov-switching dynamic factor model (MSDF-Model 2) uses AR(2) for the idiosyncratic terms.

The specific state-space representations for the Markov-switching dynamic factor model 1 and Markov-switching dynamic factor model 2 are shown as following:

MSDF-Model 1:

Measurement equation: $\Delta Y_t = H\beta_t$

$$\begin{bmatrix} \Delta Y_{1t} \\ \Delta Y_{2t} \\ \Delta Y_{3t} \end{bmatrix} = \begin{bmatrix} \gamma_1 & 1 & 0 & 0 \\ \gamma_2 & 0 & 1 & 0 \\ \gamma_3 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta f_t \\ e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix}$$

Transition equation: $\beta_t = \mu_{S_t} + F\beta_{t-1} + v_t$

$$\begin{bmatrix} \Delta f_t \\ e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} = \begin{bmatrix} \mu_{S_t} \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \phi & 0 & 0 & 0 \\ 0 & \varphi_{11} & 0 & 0 \\ 0 & 0 & \varphi_{21} & 0 \\ 0 & 0 & 0 & \varphi_{31} \end{bmatrix} \begin{bmatrix} \Delta f_{t-1} \\ e_{1,t-1} \\ e_{2,t-1} \\ e_{3,t-1} \end{bmatrix} + \begin{bmatrix} w_t \\ \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \end{bmatrix}$$

$$v_t \sim i.i.d. N(0, Q)$$

$$Q = \begin{bmatrix} \sigma_{w\_S_t}^2 & 0 & 0 & 0 \\ 0 & {\sigma_1}^2 & 0 & 0 \\ 0 & 0 & {\sigma_2}^2 & 0 \\ 0 & 0 & 0 & {\sigma_3}^2 \end{bmatrix}$$

The models are estimated by using a combination of the dynamic factor model in the state-space representation and the Markov switching, as implemented by Kim (1994). He provided filtering and smoothing algorithms for the Markov-switching dynamic factor model, with a maximum likelihood estimation of unknown parameters and unobserved factors. Augmented Dickey-Fuller unit root tests (1979) are applied to each of index variable. The unit root test results show that each variable has a unit root. Johansen (1988) cointegration test is also conducted, indicating no cointegration relationship among these variables. According to Stock and Watson (1991), time series with unit root but without cointegration should enter the model in their first difference. All the log differenced variables are standardized by subtracting sample mean and dividing by sample standard deviation.

MSDF-Model 2:

Measurement equation: $\Delta Y_t = H\beta_t$

$$\begin{bmatrix} \Delta Y_{1t} \\ \Delta Y_{2t} \\ \Delta Y_{3t} \end{bmatrix} = \begin{bmatrix} \gamma_1 & 1 & 0 & 0 & 0 & 0 & 0 \\ \gamma_2 & 0 & 0 & 1 & 0 & 0 & 0 \\ \gamma_3 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \Delta f_t \\ e_{1t} \\ e_{1t-1} \\ e_{2t} \\ e_{2t-1} \\ e_{3t} \\ e_{3t-1} \end{bmatrix}$$

Transition equation: $\beta_t = \mu_{S_t} + F\beta_{t-1} + v_t$

$$\begin{bmatrix} \Delta f_t \\ e_{1t} \\ e_{1t-1} \\ e_{2t} \\ e_{2t-1} \\ e_{3t} \\ e_{3t-1} \end{bmatrix} = \begin{bmatrix} \mu_{S_t} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \phi & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \varphi_{11} & \varphi_{12} & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \varphi_{21} & \varphi_{22} & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \varphi_{31} & \varphi_{32} \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \Delta f_{t-1} \\ e_{1t-1} \\ e_{1t-2} \\ e_{2t-1} \\ e_{2t-2} \\ e_{3t-1} \\ e_{3t-2} \end{bmatrix} + \begin{bmatrix} w_t \\ \epsilon_{1t} \\ 0 \\ \epsilon_{2t} \\ 0 \\ \epsilon_{3t} \\ 0 \end{bmatrix}$$

$$v_t \sim i.i.d.N(0, Q)$$

$$Q = \begin{bmatrix} \sigma^2_{w\_S_t} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & {\sigma_1}^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & {\sigma_2}^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & {\sigma_3}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

For identification, it is necessary to standardize one of the factor loadings γ_i or factor variance $\sigma^2_{w\_S_t}$ to be one. In our model setting, the factor variance follows a

Markov-switching process to capture the asymmetry between bull and bear markets in volatility. We set second factor loading γ_2 to one. The estimation procedures are shown in the Appendix, which includes Kalman filter, Hamilton filter, smoothing, and approximations.

It is likely that the effects of monetary policy on stock performance can be different in bear market and bull market, which is the focus of this study. This paper provides the dates of each bear market and bull market to assist the analysis of effects of monetary policy on stock performance. In order to define the turning point of bear market and bull market, we need to define the procedure for identify these turns. The above Markov-switching dynamic factor model provides probabilities that can be used as the rule. During periods classified as good stock performance, smoothed probability of bear market regime $pr(S_t = 0|I_T)$ is mostly close to 0. This probability spikes upward sharply and remains high when stock market enters into a bear market. Although visual inspection is helpful to measure the time periods of bear markets and bull markets, a formal definition is needed to precisely date the turning points using probabilities. The commonly accepted method used by Hamilton (1989) and Chauvet and Piger (2003), a turning point is defined to take place when smoothed probability of bear market regime $pr(S_t = 0|I_T)$ moves across the 50 percent line, which separates the time periods when bear market is more likely from the time periods when bull markets is more likely. Therefore, the beginning date of the bear market is defined as the time point when smoothed probability of bear market regime $pr(S_t = 0|I_T)$ changes from below 50 percent into above 50 percent. The ending date of the bear market is similarly defined as the time point when smoothed probability of bear market regime $pr(S_t = 0|I_T)$ changes from above 50 percent into below 50 percent.

5.2 Empirical Model for the Analysis of Monetary Policy's Impact on Stock Market

The Markov-switching dynamic factor model also produces a composite index to represent the overall stock market price movements, and calculates the probability of bear market and bull market. Then this paper applies this stock price movement index into four time-varying parameter models to study the predictive and contemporaneous effect of monetary policy on stock market performance. Time-varying parameter model (see Kim and Nelson 1989) is chosen to study the effect of monetary policy on stock market for the following three reasons. First, the changing coefficients statistically measure the dynamic relationship between monetary policy and stock market in different time periods, which is also the focus of this study. Second, stock price reflect market participants' expectation of the future. Investors in the stock market revise their expectations when new information becomes available. The changing coefficients capture the expectation revision of investors and show how investors have been changing the view on stock market. Third, time-varying parameter model is undertaken within the environment of a state-space model, which is calculated through a Kalman filter and the maximum likelihood estimation. As Harrison and Stevens (1976) and Kim and Nelson (1999) argued, an investor's uncertainty about the future arises not only because of the uncertainty about future random disturbance, but also from the uncertainty about the accuracy of estimated parameter values of the model. The equation in the Kalman filter for the variance of forecast error fully captures this property. The specification of the time-varying parameter model is presented as following.

Time-Varying Parameter Model:

$$\Delta f_t = \beta_{0t} + \beta_{1t}\Delta M_t + \beta_{2t}\Delta i_t + u_t$$

$$\beta_{it} = \beta_{it-1} + \varepsilon_{it} \quad i = 0,1,2$$

Measurement equation: $\Delta f_t = x_t \beta_t + u_t$

$$\Delta f_t = \begin{bmatrix} I & \Delta M_t & \Delta i_t \end{bmatrix} \begin{bmatrix} \beta_{0t} \\ \beta_{1t} \\ \beta_{2t} \end{bmatrix} + u_t$$

Transition equation: $\beta_t = \beta_{t-1} + \varepsilon_t$

$$\begin{bmatrix} \beta_{0t} \\ \beta_{1t} \\ \beta_{2t} \end{bmatrix} = \begin{bmatrix} \beta_{0,t-1} \\ \beta_{1,t-1} \\ \beta_{2,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{0t} \\ \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

$$u_t \sim i.i.d.N(0, {\sigma_u}^2)$$

$$\varepsilon_t \sim i.i.d.N(0, Q)$$

$$Q = \begin{bmatrix} {\sigma_0}^2 & 0 & 0 \\ 0 & {\sigma_1}^2 & 0 \\ 0 & 0 & {\sigma_2}^2 \end{bmatrix}$$

where Δf_t is a unobserved common factor extracted from the three major stock indices in the previous dynamic factor model measuring the overall stock price movement; β_{it} is time-varying coefficient which measures the relationship between monetary policy and stock prices; ΔM_t is the difference of log broad monetary aggregate, which is measured by Divisia M4 in the first and second time-varying parameter model and by M2 in the third and fourth ones*;* Δi_t is the difference of log federal funds rate; u_t is the error term of the regression equation.

The first time-varying parameter model explores the contemporary relationship among M4, federal funds rate and stock market. This study also investigates lead-lag relationship among M4, federal funds rate and stock market in the time-varying parameter Model 2. As shown by Friedman (1988), monetary aggregate has different contemporary relationship and leading relationship with stock prices. Considering the fact that this paper uses monthly data and many studies documented that the effects of monetary policy action on stocks are immediate, the analysis on the relationship between monetary policy and stock return with one month lag is conducted. In the time-varying parameter model 3 and time-varying parameter model 4, this paper uses a narrower money supply measurement M2 to replace M4 for robustness check.

6 Empirical Results

The Maximum likelihood estimation results for the parameters of Markov-switching dynamic factor models are shown in the Table 1, with standard errors in the parentheses. Based on the estimation results, Markov-switching dynamic factor model 2 is more favorable than Markov-switching dynamic factor model 1. Markov-switching dynamic factor model 1 has an insignificant variance for the second idiosyncratic term σ_2, indicating that the common factor was dominated by the second variable S&P500 index and the contribution of the other two indices is trivial. But the value of the second idiosyncratic term is significant. Besides, model 2 has a higher log likelihood value than model 1. Therefore, this paper adopts model 2 as the Markov-switching dynamic factor model.

Table 1: The Estimation Results of Markov-Switching Dynamic Factor Models

Parameter	MSDF-Model 1	MSDF-Model 2
ϕ	0.213 (0.044)	0.216 (0.043)
φ_{11}	0.269 (0.043)	0.303 (0.046)
φ_{12}		-0.023 (0.007)
φ_{21}	0.108 (0.000)	-0.091 (0.082)
φ_{22}		-0.922 (0.051)
φ_{31}	0.345 (0.042)	0.373 (0.045)
φ_{32}		-0.035 (0.009)
σ_1	0.297 (0.009)	0.288 (0.010)
σ_2	0.0002 (0.007)	0.025 (0.011)
σ_3	0.453 (0.014)	0.452 (0.015)
σ_{w_1}	1.423 (0.106)	1.416 (0.106)
σ_{w_2}	0.622 (0.035)	0.616 (0.036)
γ_1	0.955 (0.014)	0.964 (0.014)
γ_3	0.855 (0.021)	0.859 (0.021)
μ_0	-0.376 (0.149)	-0.383 (0.149)
μ_1	0.140 (0.042)	0.143 (0.043)
P_{00}	0.829 (0.070)	0.822 (0.075)
P_{11}	0.927 (0.028)	0.924 (0.030)
likelihood	314.6	321.5

The factor loading measures the contribution of each stock index to the dynamic common factor. The estimates of factor loadings γ_i in the MSDF-Model 2 are all significantly positive, which means all the indices have positive contributions to the underlying common factor. The model allows the intercept and the variance of the common factor to follow Markov switching between two regimes, and they are all statistically significant and very different from its own counterpart. The intercept of bear market regime

μ_0 has expected negative sign while the intercept of bull market regime μ_1 has expected positive sign, implying that the underlying common factor has downward movements in bear markets but upward movements in bull markets. It is also shown by the estimation results that stock market is more volatile in bear market than bull market, given that σ_{w_1} is larger than σ_{w_2}. Moreover, the probability for the bear market to stay in the bear market is $P_{00} = p(S_t = 0|S_{t-1} = 0) =$ 82.96%. This shows that the expected duration of bear market is 5.6 months, which is calculated by using formula $1/(1 - P_{00})$. Similarly, the probability for the bull market to stay in the bull market is $P_{11} = p(S_t = 1|S_{t-1} = 1) =$ 92.4%. The expected duration of bull market is about 13.2 months, calculated by $1/(1 - P_{11})$.

Figure 1 plots the smoothed probability of the bear market in the Markov-switching dynamic factor model. The reason for presenting the smoothed probability rather than the filtered probability lies in the fact that the filtered probability is based on information available up to currently available time *t*, but the smoothing is based on all the information through all time periods *T*. Therefore, the smoothed probability has more information available than the filtered probability, and provides a more accurate inference on the unobserved state vector and its covariance matrix.

Figure 1: The Smoothed Probability of Bear Market for the U.S. Stock Market

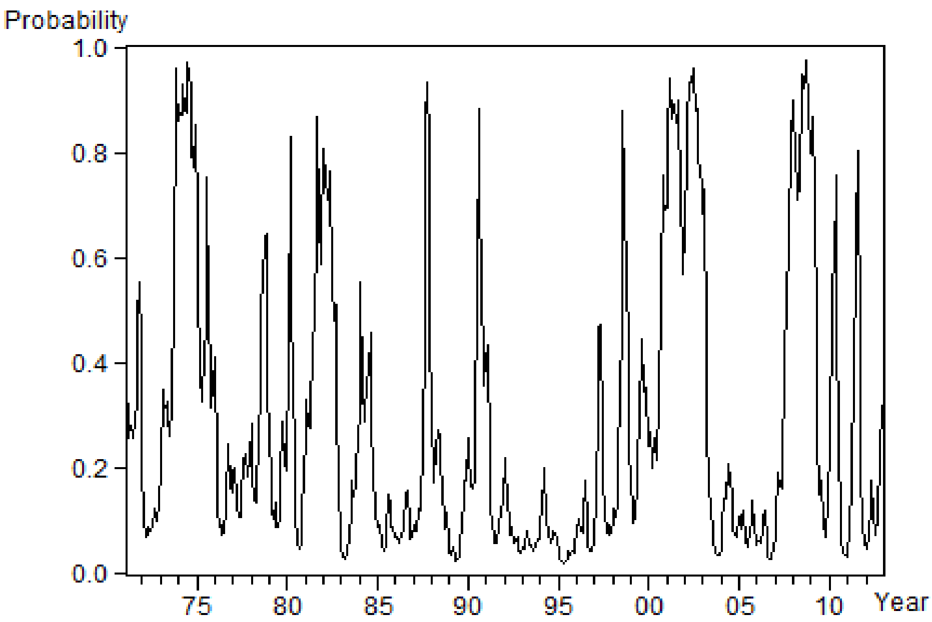


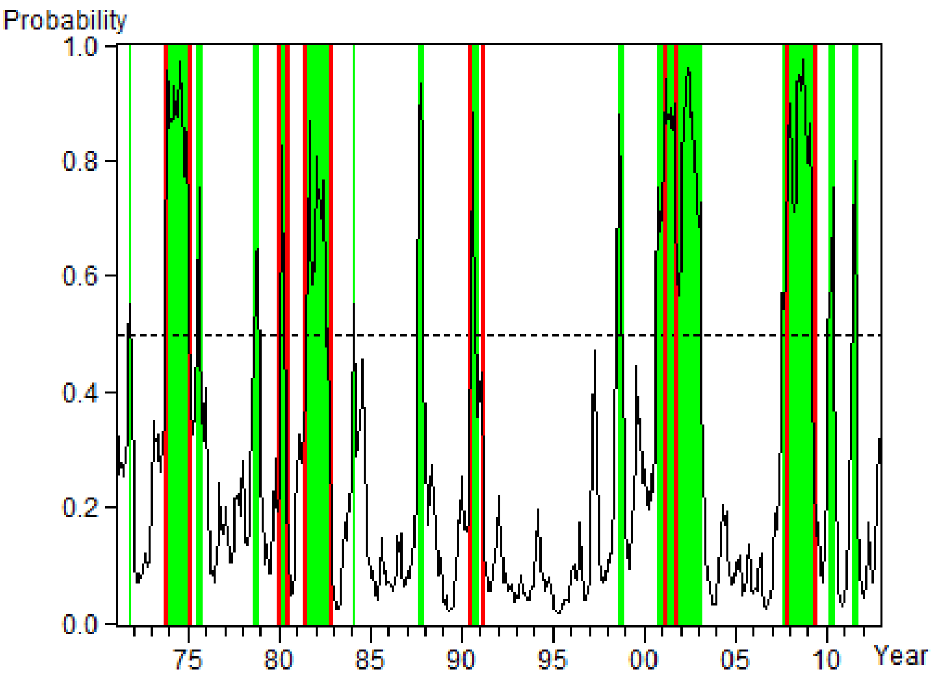
Figure 1 successfully captures all the bear markets in the sample period, namely stock crash in 1973 mainly caused by the economy stagflation and oil price rise, 1980 Silver Thursday sharp stock price drop caused by the silver market crash, 1982 stock price huge decline impacted by Kuwait's stock market losses, 1987 Black Monday stock crash, early 1990s' stock crash caused by the burst of Japanese property price bubble, bear market in 1998 caused by Russian financial crisis, stock crash in late 2001 caused by September 11 terrorist attack, bear market in 2002 generated by the burst of internet technology bubble, stock market crash in 2007 affected by subprime mortgage crisis, and stock market downturn in 2010 and 2011 caused by European sovereign debt crisis. This provides the evidence showing that the two-state Markov switching model successfully captures the dynamics of regime changes between bear market and bull market of the U.S. stock market. This paper applies the 0.5 value cut off line to the smoothed probabilities of bear market as the rule to determine the dates of bear market.

The beginning and ending dates of each bear market is shown in Table 2 and the time periods of bear market is demonstrated by the green area in Figure 2. The areas between red lines in Figure 2 denote the periods of economic recession of the U.S., announced by National Bureau of Economic Research. Figure 2 shows that every economic recession is associated with a bear market, but a bear market is not necessarily associated with a domestic economic recession. It confirms that stock market is related to the domestic economy but more volatile, because the underlying domestic economic condition is just one of the driving factors of stock market fluctuation. Stock market is affected by many other factors besides the domestic economic condition. For instance, the fluctuations of global market influence the U.S. stock market to a large extent. What's more, the U.S. stock market is also substantially affected by political issue, unexpected events, natural disaster, investors' fears, and etc. Most of them do not give rise to turns in business cycle of economy. Another important phenomenon demonstrated by the plot is that the stock market occasionally falls into a bear market in advance of the economic recession, confirming that stock market is a leading indicator of the economy. For example, the stock market switches into a bear market four months before the arrival of 2007 economic recession. This coincides with existing studies showing that the stock index is a leading indicator of business cycle (see, for example, Chauvet 1998/1999, and Chauvet and Potter 2000, 2001). However, Chauvet and Potter (2001) used a dynamic factor model with Markov switching to date turning points of bear and bull markets as well. The data series used by them and their results of turning points dates are very different from those of this paper.

Table 2: The Dates of Turning Points of Bear Market

Begin (Peak)	End (Trough)	Begin (Peak)	End (Trough)
November 1971	November 1971	September 1987	November 1987
October 1973	February 1975	July 1990	October 1990
July 1975	September 1975	August 1998	October 1998
August 1978	November 1978	September 2000	February 2003
March 1980	April 1980	August 2007	March 2009
July 1981	September 1982	March 2010	May 2010
February 1984	February 1984	June 2011	August 2011

Figure 2: The Periods of Bear Market and Economic Recession



Having demonstrated the time periods of U.S. bear/bull market above, we now turn to the question of monetary policy's effects on theses stock market movements across the bull and bear market, as well as different regimes of monetary policy.

Table 3: The Estimation Results of Time-Varying Parameter Model 1

Parameters	Time-Varying Model
σ_u	0.875 (0.032)
σ_0	-0.038 (0.02)
σ_1	0.126 (0.038)
σ_2	0.007 (0.003)
Log likelihood value	697.39

Table 4: The Estimation Results of Time-Varying Parameter Model 2

Parameters	Time-Varying Model
σ_u	0.937 (0.032)
σ_0	0.000 (0.010)
σ_1	0.096 (0.040)
σ_2	0.0013 (0.0007)
Log likelihood value	709.88

Table 5: The Estimation Results of Time-Varying Parameter Model 3

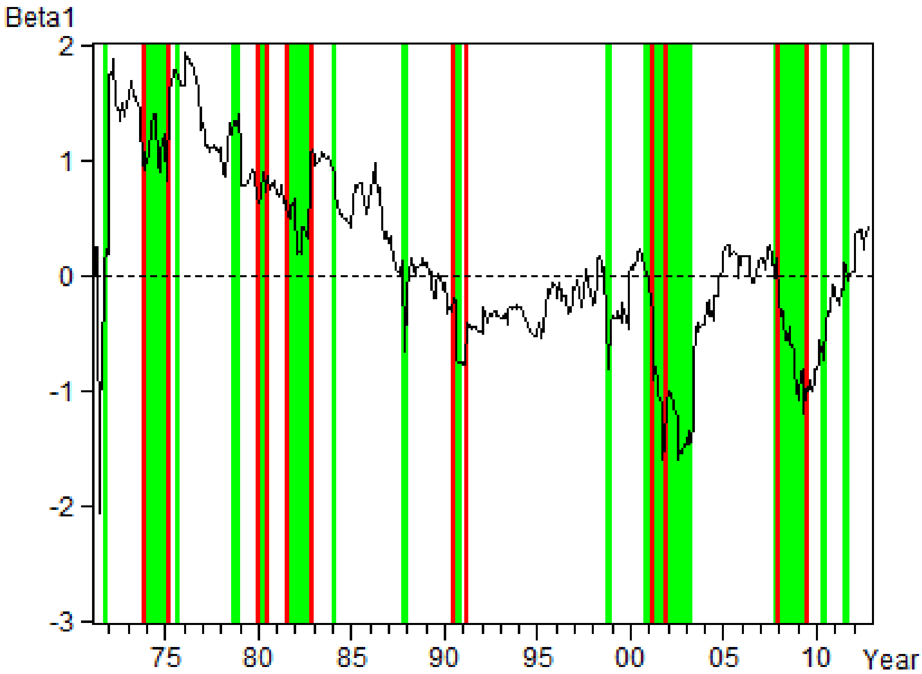
Parameters	Time-Varying Model
σ_u	0.878 (0.034)
σ_0	0.041 (0.019)
σ_1	0.084 (0.048)
σ_2	0.012 (0.004)
Log likelihood value	701.67

Table 6: The Estimation Results of Time-Varying Parameter Model 4

Parameters	Time-Varying Model
σ_u	0.978 (0.031)
σ_0	0.000 (0.016)
σ_1	0.011 (0.019)
σ_2	0.0015 (0.0008)
Log likelihood value	717.48

Time-varying parameter model are chose to examine the potential asymmetry over time. The Maximum likelihood estimation results for time-varying parameter models are shown through Table 3 to Table 6. Figure 3 plots the time-varying coefficient β_{1t} which measures the contemporary relationship between broad monetary aggregate Divisia M4 and stock movements. The time periods of bear market is still depicted by the green area in Figure 3. The areas between red lines indicate the periods of economic recession of the U.S., announced by National Bureau of Economic Research. It is shown that there is a sharp drop in the time-varying parameter in every bear market, indicating the expansionary monetary policy of increasing monetary aggregate is less influential during a bear market. The sign of time-varying parameter has switched from positive to negative since 1987. 1987 is the year when Alan Greenspan became the Federal Reserve chairman and abandoned the monetary aggregate as the monetary target. This leads the conclusion that the signaling effect of monetary policy action of changing monetary aggregate only functions during the periods when it is used as the monetary policy target. A further interpretation of this result is that the Federal Reserve's action of changing monetary aggregate has positive effects on stock return only if it is considered by the market participants as a meaningful indicator of monetary policy. If the monetary aggregate is not used as monetary target, the stock market may not respond to the changes in monetary aggregate in a regular manner, and the negative impacts of monetary aggregate increase on stock performance that explained in the theoretical background would dominate the positive effects. During a bear market, a drop in the correlation makes the negative relationship more negative, which arrives at the conclusion that an expansionary monetary policy action of increasing monetary aggregate can even deteriorate the stock performance during a bear market within the periods when monetary aggregate is not the policy target.

Figure 3: Monetary Aggregate Parameter β_{1t} in Time-Varying Model 1



As is evident from Figure 4, the concurrent relationship between changes in federal funds rate and stock price movements is inconsistent, switching between positive and negative as expected. The positive coefficient means the positive effects shown in the previous theoretical framework section dominate the negative effects, and vice versa. During the periods that the federal funds rate was used as a monetary policy target (1974-1980, and 1990-2008), the sign of the relationship between federal funds rate and stock market is negative, indicating that the expansionary monetary policy of reducing federal funds rate is positively influential on stock performance. This parameter becomes positive during other periods (1980s and after 2008), which illustrates that monetary action of reducing federal funds rate is useless in improving stock performance. This dynamics reinforces the conclusion that the signaling effects of monetary policy influence investors' sentiment successfully only when the market participants believe the Federal Reserve's action is meaningful. Besides, the coefficient also has a sharp decrease during every bear market. These drops make a positive coefficient negative, and a negative coefficient even more negative. If the Federal Reserve wants to apply an expansionary policy to stimulate the stock market by reducing the federal funds rate in a bear market, it will have a substantial effect, given that it is during the periods when federal funds rate is used as an effective monetary target. This result is consistent with the findings of Jansen and Tsai (2010) and Kurov (2010).

Figure 4: Interest Rate Parameter β_{2t} in Time-Varying Model 1

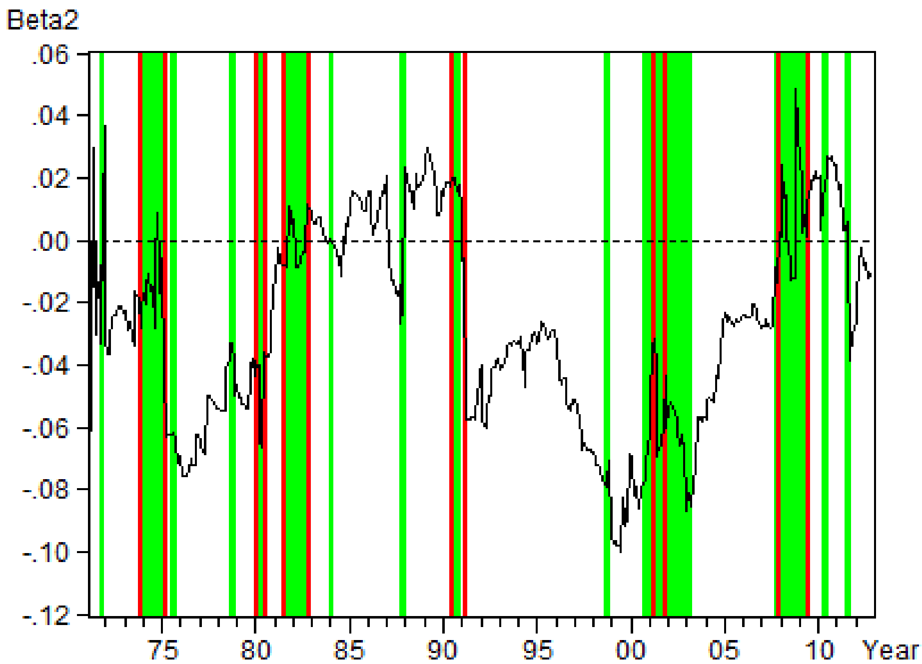


Figure 5 plots the time-varying coefficient β_{1t} which measures the predictive relationship between monetary aggregate Divisia M4 and stock price one month later. One result refers to the fact that there exists a sharp drop in the coefficient in every bear market, indicating that the leading effect of changing monetary aggregate is much weaker in a bear market. In most bear markets, the coefficient reduces even below zero, presenting a negative relationship between money supply and stock market. If the Federal Reserve uses expansionary monetary policy to improve stock market performance during a bear market by increasing money supply, it is futile and may even deteriorate the stock market. Money supply is positively associated with future stock performance during most bull markets, with the exception of time periods in early 1990s and 2000s. The most recent two economic recessions in 2000s were all followed by a slow and sluggish economy recovery. The economic recession in early 1990s was followed by a four-year slow recovery, and the economy started to take off in the middle of 1990s. A positive predictive relationship between money supply and stock market occurs during the periods of robust economic growth, not during the periods of economic recession or slow recovery. The lead-lag relationship between monetary policy and stock market is more related to the business cycle than monetary policy regimes.

Figure 5: Monetary Aggregate Parameter β_{1t} in Time-Varying Model 2

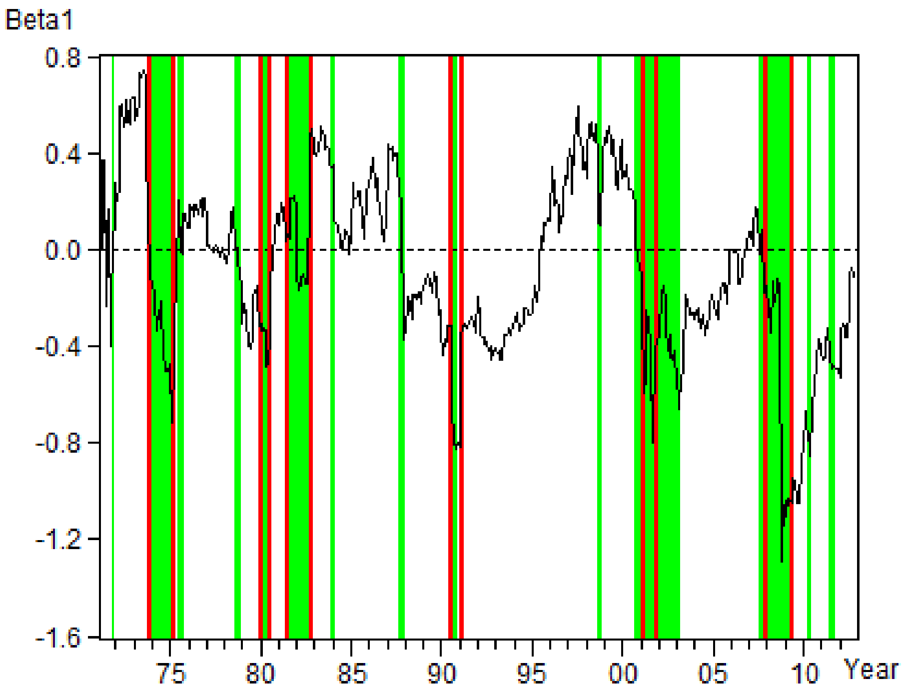
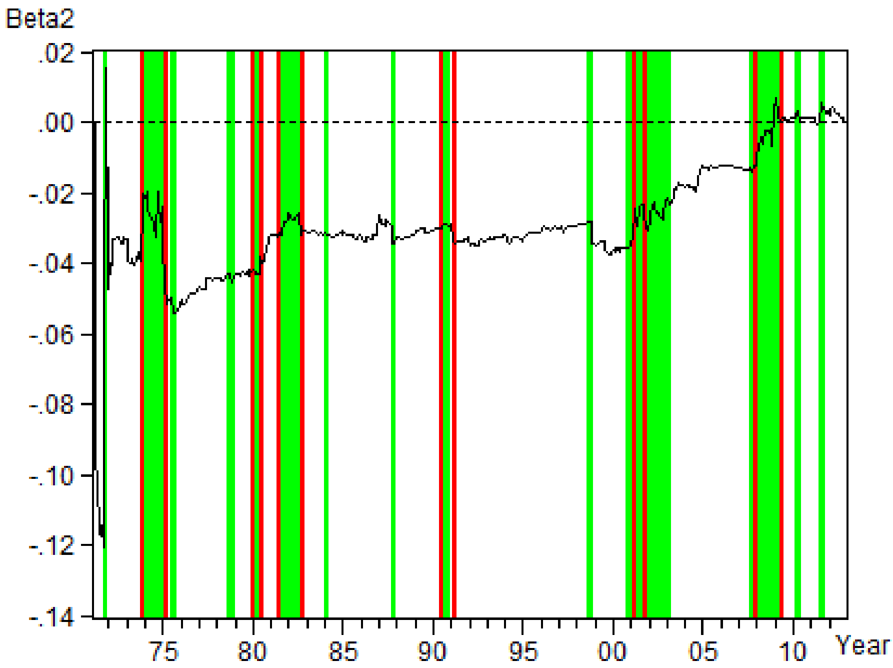


Figure 6 depicts the dynamic association between the changes in stock prices and changes in federal funds rate. It shows the predictive relationship between changes in federal funds rate and stock price movements is negative during all periods. This finding provides the evidence that the expansionary monetary policy of reducing federal funds rate is very influential in all monetary policy regimes and all stock market regimes. This negative relationship becomes weaker since late 2008, where the coefficient of lagged federal funds rate is close to zero. This is due to the fact that the federal funds rate was reduced to the zero lower bound in late 2008, and can't be used as an expansionary monetary tool for further reduction.

Figure 6: Interest Rate Parameter β_{2t} in Time-Varying Model 2



If we replace M4 with M2 in time-varying parameter model 3 and 4, the results are similar. The dynamic pattern of federal funds rate is the same as in model 1 and 2 (see Figure 8 and 10). Figure 7 shows that the concurrent relationship between M2 and stock market is similar to that between M4 and stock. However, the lead-lag relationship between M2 and stock market (see Figure 9) is strikingly different from that between M4 and stock. The curve is very flat and the insignificant parameter of variance indicates that there is no too much volatility in the relationship. The relationship remains positive until 1987, where the parameter reduces fundamentally to zero. This is consistent with the previous finding that the monetary aggregate change's signaling effect only works during periods when monetary aggregate is used as the monetary policy target. The relationship turns into negative during the 2007 financial crisis. The lead-lag relationship between M2 and stock performance does not demonstrate a distinguished feature in different regimes of stock market and different phases of business cycle, confirming the fact that M4 is a broader measure of monetary aggregate.

Figure 7: Monetary Aggregate Parameter β_{1t} in Time-Varying Model 3

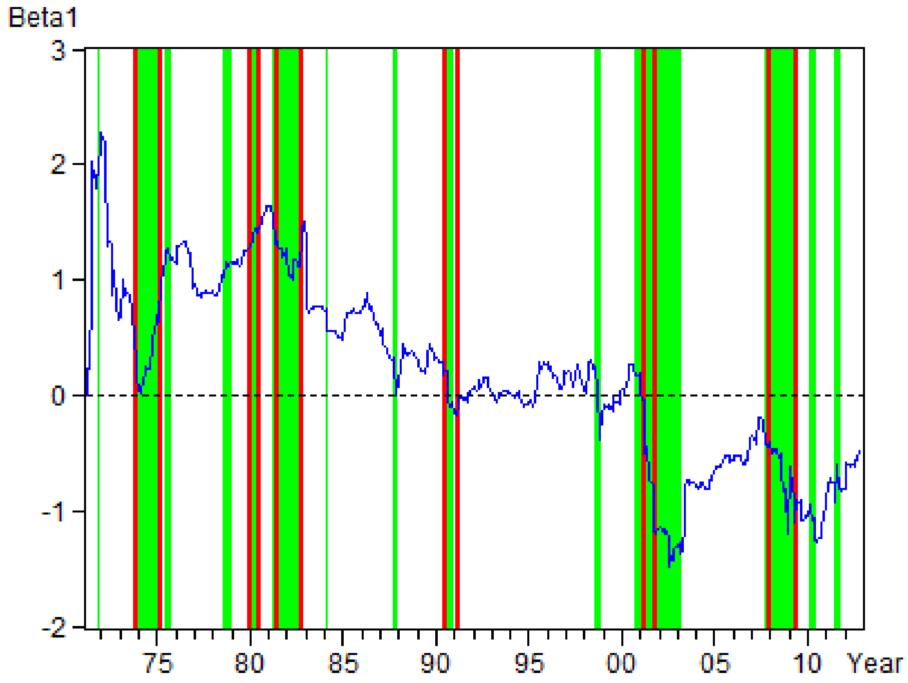


Figure 8: Interest Rate Parameter β_{2t} in Time-Varying Model 3

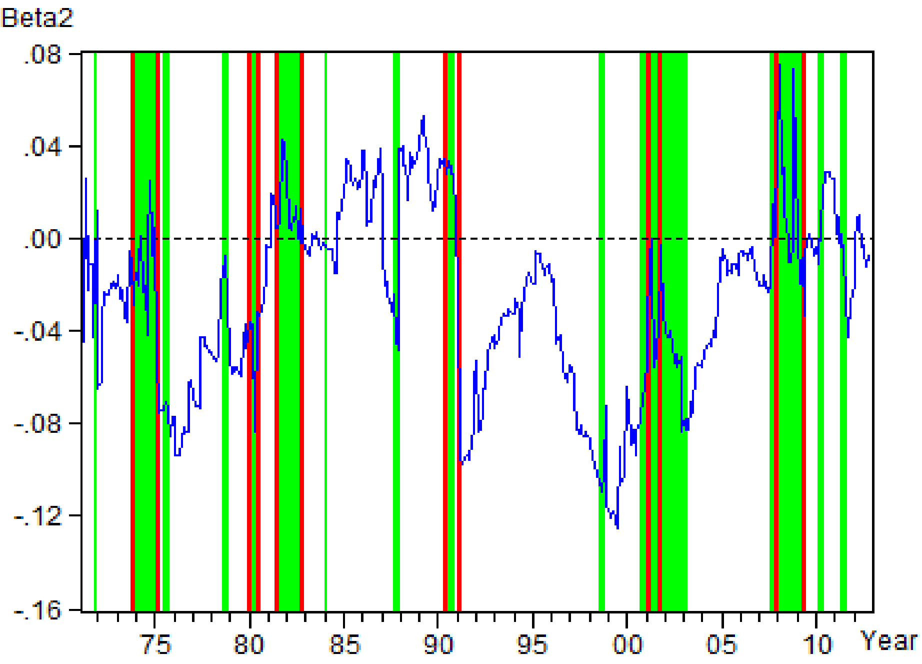


Figure 9: Monetary Aggregate Parameter β_{1t} in Time-Varying Model 4

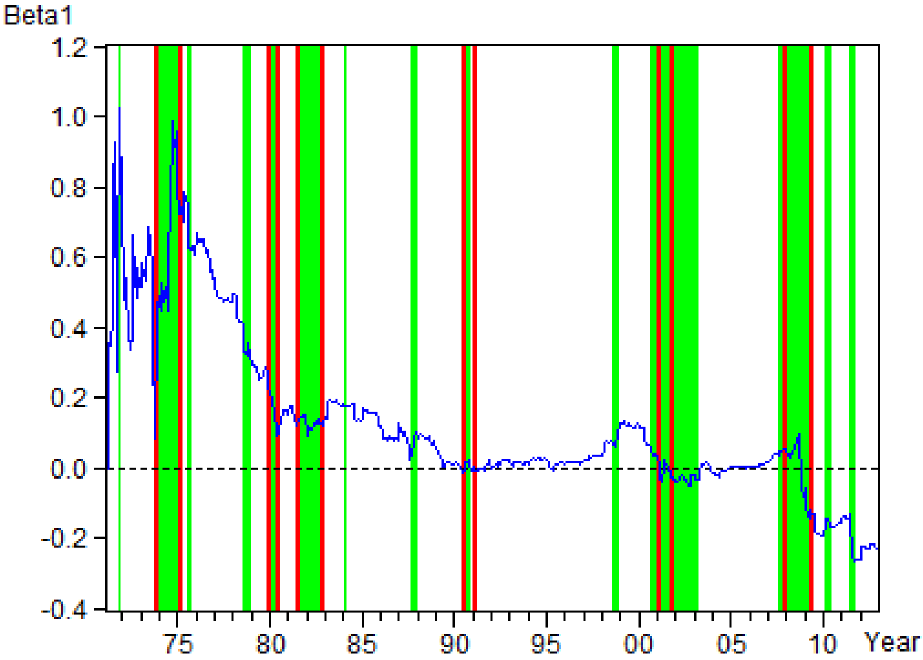
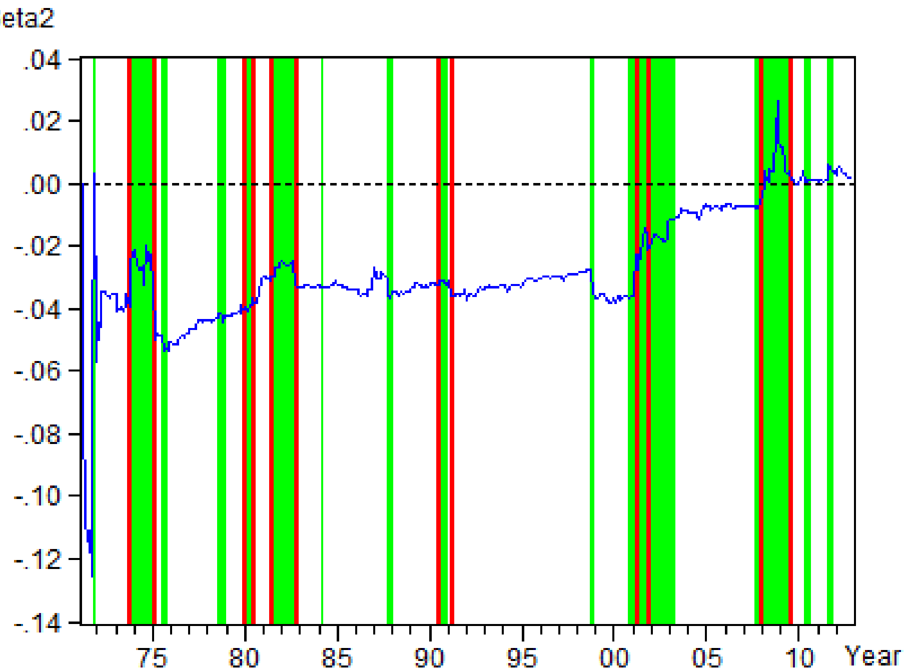


Figure 10: Interest Rate Parameter β_{2t} in Time-Varying Model 4



7 Conclusion

As mentioned in the introduction, previous literatures found that the Federal Reserve's monetary policy has played an important role in affecting stock returns, but the empirical literature on the asymmetric effects of monetary policy on stock returns over time is limited and, unfortunately, mixed. The purpose of this paper is to improve on the earlier literature by conducting another empirical analysis of the time-varying effects of monetary policy on stock performance in different monetary policy regimes and stock market regimes during the last four decades. More specifically, how have the different views on applying monetary policy by Burns in the 1970s, Volcker in the 1980s, Greenspan in the 1990s and early 2000s, and Bernanke from mid 2000s to 2013 affected the stock market? How has the nature of the dynamic relationship between monetary policy and stock return vary during the bull and bear markets? The substantial stock market volatility under current expansionary monetary policy emphasizes the necessity and urgency of the study on this issue.

This paper begins with the exploration of the dates of the turning points of bear and bull markets by applying a Markov-switching dynamic factor model on major stock indices, and produces a new composite measure to represent the overall stock market movement more broadly and comprehensively. The Markov-switching dynamic factor model extracts the comovement among stocks across different sectors and stock exchanges with an unobserved underlying common factor. The Markov-switching feature catches the nonlinear asymmetry in bear and bull market in terms of growth rate and volatility because of its nonlinearity setting, and is capable of statistically identifying the turning points of stock market regimes by using its inherent transition probabilities. It estimates the probabilities of bear market and bull market of every time point in the sample periods. The results successfully capture all the bear markets in the sample history. The findings indicate bear markets are more volatile than bull markets, and the average durations of bear market is shorter than that of bull market. The paper shows that bear markets frequently occur in advance of economic recessions, confirming that stock market is a leading indicator of business cycle of economy. It is also shown that every domestic economic recession is associated with a bear market, but not vice versa. This coincides with the widely accepted notion that underlying domestic economic condition is the most essential driving force for stock market fluctuation, but the stock market fluctuation is also affected by many other factors as well. These findings help to understand in which state of stock market fluctuation cycle is and to which direction the stock market is moving towards.

Having illustrated the characteristics of U.S. stock market movements above, this paper turns to the more difficult question of the dynamic relationship between these stock market movements and monetary policy. The newly extracted unobserved factor is then applied into a time-varying parameter model as a composite measure of stock market movements. The results provide the evidence that the relationship between monetary policy and stock returns varies over time, and the responses of stock returns to monetary policy are asymmetric during bull and bear markets, and across different monetary policy regimes. Specifically, the contemporary signaling effects of increases in monetary aggregates or reductions in federal funds rate are positive on stock returns only during periods when they are used as the monetary policy target by the Federal Reserve. In other words, the desired effects of Federal Reserve's action through changes in monetary aggregates or federal funds rate is strong on stock market only if it is considered by the market participants as a meaningful indicator of monetary policy. The observation of a sharp drop in the value of the correlation between monetary aggregate and stock return in every bear market indicates that the impacts of the monetary policy of increasing monetary aggregates are much weaker in a bear market, and can even deteriorate stock market. However, the expansionary monetary policy of reducing federal funds rate has strong positive effect on stock market performance during a bear market within the periods when federal funds rate is used as monetary policy target by the Federal Reserve.

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Appendix:

Estimation Procedure of Markov-switching Dynamic Factor Model

This paper follows Kim and Nelson (1999) for estimation procedure of Markov-switching dynamic factor model. Let I_t denote the information set which contains the observations available up to time *t*. The forecast of unobserved state vector β_t is not only dependent on information set I_{t-1}, but also based on state variable S_t that takes on the value of *j* and S_{t-1} that takes on the value of *i*. The forecast of state variable β_t and its covariance matrix is as follows:

$$\beta_{t|t-1}^{(i,j)} = E[\beta_t | I_{t-1}\,,\, S_{t-1} = i\,, S_t = j]$$

$$P_{t|t-1}^{(i,j)} = E\left[(\beta_t - \beta_{t|t-1})((\beta_t - \beta_{t|t-1})'|I_{t-1}\,,\, S_{t-1} = i\,, S_t = j\,\right]$$

Based on Markov switching states $S_{t-1} = i$ and $S_t = j$, the Kalman filter is:

$$\beta_{t|t-1}^{(i,j)} = \mu_j + F_j \beta_{t-1|t-1}^{(i)}$$

$$P_{t|t-1}^{(i,j)} = F_j P_{t-1|t-1}^{(i)} F_j' + Q_j$$

$$\theta_{t|t-1}^{(i,j)} = \Delta Y_t - \Delta Y_{t|t-1}^{(i,j)} = \Delta Y_t - H_j \beta_{t|t-1}^{(i,j)}$$

$$\tau_{t|t-1}^{(i,j)} = H_j P_{t|t-1}^{(i,j)} H_j'$$

$$\beta_{t|t}^{(i,j)} = \beta_{t|t-1}^{(i,j)} + P_{t|t-1}^{(i,j)} H_j' [\eta_{t|t-1}^{(i,j)}]^{-1} \theta_{t|t-1}^{(i,j)} = \beta_{t|t-1}^{(i,j)} + K_t \theta_{t|t-1}^{(i,j)}$$

$$P_{t|t}^{(i,j)} = (I - P_{t|t-1}^{(i,j)} H_j' [\tau_{t|t-1}^{(i,j)}]^{-1} H_j) P_{t|t-1}^{(i,j)}$$

where $\beta_{t-1|t-1}^{(i)}$ and $P_{t-1|t-1}^{(i)}$ are inferences on β_{t-1} and P_{t-1} conditional on information up to time *t-1* and $S_{t-1} = i$; $\theta_{t|t-1}^{(i,j)}$ is the prediction error of y_t conditional on information up to time *t-1*, given values of the two states $S_{t-1} = i$ and $S_t = j$; and $\tau_{t|t-1}^{(i,j)}$ is the conditional variance of the prediction error. The details of the derivation of the above Kalman filter can be refereed to Hamilton (1994).

In order to make the loop of above Kalman filter operable, it is necessary to transfer $\beta_{t|t}^{(i,j)}$ and $P_{t|t}^{(i,j)}$ at the end of the each iteration into $\beta_{t|t}^{(j)}$ and $P_{t|t}^{(j)}$, and use $\beta_{t|t}^{(j)}$ and $P_{t|t}^{(j)}$ to represent $\beta_{t-1|t-1}^{(i)}$ and $P_{t-1|t-1}^{(i)}$ for the next period. Kim (1994) showed an algorithm for transferring. The algorithm involves approximation:

$$\beta_{t|t}^{(j)} = \left[\sum pr(S_{t-1} = i, S_t = j|I_t) \beta_{t|t}^{(i,j)}\right] / pr(S_t = j|I_t)$$

$$P_{t|t}^{(j)} = \left[\sum pr(S_{t-1} = i, S_t = j|I_t) P_{t|t}^{(i,j)} + \left(\beta_{t|t}^{(j)} - \beta_{t|t}^{(i,j)}\right)\left(\beta_{t|t}^{(j)} - \beta_{t|t}^{(i,j)}\right)'\right] / pr(S_t = j|I_t)$$

The probability terms $p(S_{t-1} = i, S_t = j|I_t)$ and $pr(S_t = j|I_t)$ in the above equations have to be estimated to complete the Kalman filter involving approximation. By using Hamilton (1989) filter along with Markov switching, the inference on the above probability terms can be calculated and shown as follows:

$$p(S_{t-1}=i,S_t=j|I_{t-1})=pr(S_{t-1}=i|I_{t-1})pr(S_t=j|S_{t-1}=i)$$

$$f(y_t,S_{t-1}=i,S_t=j|I_{t-1})=f(y_t|S_{t-1}=i,S_t=j,I_{t-1})pr(S_{t-1}=i,S_t=j|I_{t-1})$$

$$f(y_t|I_{t-1})=\sum_{S_{t-1}=i}\sum_{S_t=j}f(y_t,S_{t-1}=i,S_t=j|I_{t-1})$$

$$pr(S_{t-1}=i,S_t=j|I_t)=pr(S_{t-1}=i,S_t=j|y_t,I_{t-1})$$

$$=f(y_t,S_{t-1}=i,S_t=j|I_{t-1})/f(y_t|I_{t-1})=f(y_t|S_{t-1}=i,S_t$$

$$=j,I_{t-1})pr(S_{t-1}=i,S_t=j|I_{t-1})/\,f(y_t|I_{t-1})$$

$$pr(S_t=j|I_t)=\sum_i pr(S_{t-1}=i,S_t=j|I_t)$$

The transition probabilities capture the Markov switching between two states and are estimated by Maximum Likelihood estimation as one of the unknown parameters. For the inference of conditional density $f(y_t|S_{t-1}=i,S_t=j,I_{t-1})$, prediction error decomposition involving conditional forecast error and its variance obtained from the previous Kalman filter is used as follows.

$$f(y_t|S_{t-1}=i,S_t=j,I_{t-1})=(2\pi)^{-N/2}\left|[\eta_{t|t-1}^{(i,j)}]^{-1/2}\right|exp\left\{-\frac{1}{2}P_{t|t-1}^{(i,j)}H_j'[\eta_{t|t-1}^{(i,j)}]^{-1}\theta_{t|t-1}^{(i,j)}\right\}$$

$$f(y_t|I_{t-1})=\textstyle\sum_{S_t}\sum_{S_{t-1}}f(y_t|S_{t-1}=i,S_t=j,I_{t-1})\,p(S_{t-1}=i,S_t=j|I_{t-1})$$

$$l(\theta)=\sum_{t=1}^{T}\ln(f(y_t|I_{t-1}))$$

Initial values $\beta_{0|0}^{(j)}$ and $P_{0|0}^{(j)}$ for Kalman filter and $pr(S_0=j|I_0)$ for Hamilton filter are assigned to start the iteration. As soon as the Kalman filter and Hamilton filter are completed, smoothing procedures for β_t, P_t and probability terms begin. The smoothing algorithm iterates backwards and it has the following procedure:

$$\beta_{t|T}^{(j,k)}=\beta_{t|t}^{(j)}+P_{t|t}^{(j)}F_k'\left[P_{t+1|t}^{(j,k)}\right]^{-1}(\beta_{t+1|T}^{(k)}-\beta_{t+1|t}^{(j,k)})$$

$$P_{t|T}^{(j,k)}=P_{t|t}^{(j)}+P_{t|t}^{(j)}F_k'\left[P_{t+1|t}^{(j,k)}\right]^{-1}(P_{t+1|T}^{(k)}-P_{t+1|t}^{(j,k)})P_{t|t}^{(j)}F_k'\left[P_{t+1|t}^{(j,k)}\right]^{-1},$$

$$pr(S_t=j,S_{t+1}=k|\varphi_T)$$

$$\approx pr(S_{t+1}=k|\varphi_T)\,pr(S_t=j|\varphi_t)pr(S_{t+1}=k|S_t=j)/pr(S_{t+1}=k|\varphi_t)$$

$$pr(S_t=j|\varphi_T)=\sum_{k=0}^{1}pr(S_t=j,S_{t+1}=k|\varphi_T)r$$

The initial values for the smoothing $\beta_{T|T}^{(k)}$, $P_{T|T}^{(k)}$ are obtained from the last iteration of

Kalman filter and Hamilton filter. The smoothing algorithm also need to transfer $\beta_{t|T}^{(j,k)}$ and $P_{t|T}^{(j,k)}$ into $\beta_{t|T}^{(j)}$ and $P_{t|T}^{(j)}$. The calculation method is similar to the one of filters.

Estimation Procedure of Time-varying Parameter Model

This study follows Kim and Nelson (1999) for Estimation procedure of time-varying parameter model. In the simple state space model without Markov switching, the goal of Kalman filter is to use a recursive process to produce a forecast of unobserved state vector β_t and its covariance matrix with information available up to time *t-1*. They do not dependent on state information. The forecast of β_t and its covariance matrix of $P_{t|t-1}$ are denoted as

$$\beta_{t|t-1} = E[\beta_t | I_{t-1}]$$

$$P_{t|t-1} = E\big[(\beta_t - \beta_{t|t-1})((\beta_t - \beta_{t|t-1})' | I_{t-1}\big].$$

The Kalman filter iteration process is as follows:

$$\beta_{t|t-1} = \mu + F\beta_{t-1|t-1}$$

$$P_{t|t-1} = FP_{t-1|t-1}F' + Q$$

$$\theta_{t|t-1} = y_t - x_t\beta_{t|t-1}$$

$$\tau_{t|t-1} = x_t P_{t|t-1} x_t' + \sigma_u{}^2$$

$$\beta_{t|t} = \beta_{t|t-1} + P_{t|t-1}x_t'[\tau_{t|t-1}]^{-1}\theta_{t|t-1}$$

$$P_{t|t} = (I - P_{t|t-1}x_t'[\eta_{t|t-1}]^{-1}x_t)P_{t|t-1}$$

where $\theta_{t|t-1}$ is the prediction error of y_t conditional on information up to time *t-1*; and $\tau_{t|t-1}$ is the conditional variance of the prediction error. Initial value of $\beta_{0|0}$ and $P_{0|0}$ are given to start the Kalman filter iteration. Maximum likelihood estimation is conducted for unknown parameters based on the prediction error decomposition. The forecasting error variance equation tells that an investor's uncertainty about the future arises not only from the uncertainty about future random terms, but also from the uncertainty about the accuracy of parameter values of the model.