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by

Peixin (Payton) Liu
Kuan Xu
Yonggan Zhao

Dalhousie University

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DALHOUSIE UNIVERSITY
HALIFAX, NOVA SCOTIA, CANADA
B3H 3J5

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Peixin (Payton) Liu

Kuan Xu

Yonggan Zhao*

Department of Economics and

School of Business Administration

Dalhousie University

Halifax, Nova Scotia

Canada B3H 3J5

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Keywords: Style Factors, Macro Economic Factors, Sector Exchange Traded Funds, State Dependance, Markov Regime Switching, Time-Varying Risk Premiums

*Contact: Yonggan Zhao, Professor of Finance, Canada Research Chair (Tier II) in Risk Management, School of Business Administration, Dalhousie University, Halifax, Nova Scotia, Canada B3H 3J5. Email: yonggan.zhao@dal.ca, Tel: +1 902 494 6972. Yonggan Zhao acknowledges financial support from the Natural Sciences and Engineering Research Council of Canada, Social Sciences and Humanities Research Council of Canada, and the Canada Research Chairs Program. Kuan Xu acknowledges financial support from Dalhousie University and the visiting research environment provided by Renmin University of China. The authors thank Barry Lesser for his constructive comments.

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Abstract

This paper extends the Fama and French (FF) three factor model in studying time-varying risk premiums of Sector Select Exchange Traded Funds (ETFs) under a Markov regime-switching framework. First, we augment the original FF model to include three additional macro factors—market volatility, yield spread, and credit spread. Then, we extend this augmented FF model to a model with a Markov regime switching mechanism for *bull*, *bear*, and *transition* market regimes. We find all market regimes are persistent with the bull market regime being the most persistent and the bear market regime being the least persistent. Both the risk premiums of the Sector Select ETFs and their sensitivities to the risk factors are highly regime dependent. The regime-switching model has a superior performance in capturing the risk sensitivities of the Sector Select ETFs that would otherwise be missed by both the FF and the augmented FF models.

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1 Introduction

Although empirical asset pricing models have been considerably successful, complex dynamics in asset returns are often ignored or assumed to be absent. Clearly, the financial market evolves in different and alternating states of nature over time, as evidenced in historical extreme episodes, such as the great depression (1929–1933), the stock market crash (October 1987), the Internet bubble (1999–2001), and the recent financial turmoil (2008–2010). This phenomenon renders standard linear regression models insufficient for characterizing equilibrium asset returns. The fact that asset returns are time-varying and influenced by irrational behaviors makes it necessary to consider a model that accommodates complex dynamics of asset returns beyond standard asset pricing models.

A great deal of research effort has been made to relate theories to empirical investigations. As Campbell (2000) noted, the core issue in financial economics is the modeling of uncertainty and the pricing of risky assets. He also noted that "both theoretical and empirical developments in asset pricing have taken place within a well-established paradigm". In this paradigm, asset prices are determined in various states at any point in time so that no arbitrage opportunity exists. Depending on the assumptions about the structure of the economy, asset pricing models may take different forms. In one of the simplest cases, a linear factor model can be used to describe asset returns assuming the stochastic discount factor is linearly related to a set of risk factors [see Campbell (2000), p. 1516].

In empirical finance, active research focuses on the relationship between asset returns and common risk factors that influence asset returns. The existing literature has considered the common factors such as lagged returns [Fama and French (1988a), Poterba and Summers (1988)], the dividend-to-price ratio [Campbell and Shiller (1988a), Fama and French (1988b), Hodrick (1992)], the earnings-to-price ratio [Campbell and Shiller (1988b)], the book-to-market ratio [Lewellen (1999)], the dividend payout ratio [Lamont (1998)], the share of equity in new finance [Nelson (1999), Baker and Wurgler (2000)], yield and credit spreads [Campbell (1987), Fama and French (1989), Keim and Stambaugh (1986)], recent changes in short-term interest rates [Campbell (1987), Hodrick (1992)], and the level of consumption relative to income and wealth [Lettau and Ludvigson (1999)]. Many of these variables are related directly or indirectly to various stages of the business cycle and are used to predict a countercyclical variation in stock returns [Fama and French (1989), Lettau and Ludvigson (1999)].

The Markov regime-switching model has been applied to economic and financial modeling for decades. Hamilton (1989) applied a Markov switching model for the U.S. GDP data and identified the various regimes in the US economy based on the observed data. Schwert (1989) considered that asset returns may be associated with either high or low volatility which switch over time. Ang and Bekaert (2002) studied an international asset allocation model with regime shifts. This modeling approach is very flexible in addressing a variety of interesting questions about capital asset pricing. For example, what are plausible market regimes and what are their possible implications? How frequently do these regimes switch? When do these regimes change and what drive them to change over time? Is regime switching predictable? How do asset pricing models for different assets change jointly across different regimes over time? These questions motivate us to rethink of asset pricing models in the context of sector exchange traded funds.

This research intends to address four issues that have not been considered in the context of linear factor models for Sector Select ETFs. Firstly, empirical studies on factor models rely primarily on standard regression models, though market regimes exist and may reflect different market situations in which risk premiums may be differently characterized [e.g., Hamilton (1989), Schaller and van Norden (1997), Schwert (1989), Turner, Startz and Nelson(1989), and Ang and Bekaert (2002), and Coggi and Manescu (2004)]. Secondly, even if earlier empirical studies have considered the existence of market regimes, not many studies estimate a regime-switching model with a joint distribution for all asset returns across different sectors. Ignoring the correlations of the sectors in practice may result in suboptimal investment strategies. Thirdly, not many researchers have investigated the performance of the sector ETFs, even though stock returns do vary across various sectors [e.g., Li, Vassalou and Xing (2006)] and sector rotation in portfolio management is a common practice. Finally, the standard FF model does not include yield spread, credit spread, and market volatility as relevant factors. In particular, the role of market volatility[1] has been recognized by many researchers [e.g., Black (1976) and Schwert (1989)] and market volatility has been used to explain bond yield and credit spreads [e.g., Collin-Dufresne, Goldstein and Martin (2001) and Schaefer and Strebulaev (2008)].

In this paper, we study the Standard & Poor's Sector Select ETFs returns with a set of macro and style factors within a regime-switching framework. The first advantage of investing in ETFs is their suitability for both individual and institutional investors. The second advantage is that ETFs have lower management expense ratios and transaction costs. The third advantage is that these instruments are regularly tradable on the stock market and hence are very liquid.

We are interested in learning how the determinants of the sector ETFs returns behave in various market conditions within a regime-switching framework. While the ordinary FF model can be useful, the regime-switching model is likely to better accommodate for various market conditions such as bull, transition, and bear regimes. Furthermore, the regime-switching model can be more flexible in relating sector ETFs returns to an enlarged set of common risk factors across regimes. The common risk factors to be considered in this paper include style factors (such as book-to-market[2] and size[3]) and macro factors (such as the market portfolio return, yield spread[4], credit spread[5] and market volatility). Our intention is to explore how the style and macro factors affect the Sector Select ETFs returns in a regime-switching framework over time. This empirical approach echoes the Arrow-Debreau world by analyzing state-dependent asset returns and follows the APT model by relating state-dependent returns to an enlarged set of common risk factors.

We show that the sector ETFs exhibit different return patterns in bear, transition and bull regimes. Firstly, we confirm the findings of Fama and French (1992) that asset returns of sector ETFs are positively related to the market portfolio return and are negatively related

[1] Market volatility is measured by the Chicago Board Options Exchange Volatility Index, as explained later in the paper.

[2] This is measured by the return differential between high and low valuation portfolios.

[3] This is measured by the return differential between high and low capitalization portfolios.

[4] This is measured by the yield differential between long and short bonds.

[5] This is measured by the yield differential between low and high quality bonds that are otherwise identical in every other way.

to the size factor across regimes. However, within the regime-switching framework the sector ETFs returns are not always positively related to the book-to-market factor across regimes. Secondly, we find similar evidence as in Fama and French (1993) about the relation between asset returns and credit and yield spreads. That is, credit spread and yield spread do not have much explanatory power for the risk premiums in the FF model, but they are statistically significant in explaining the sector ETFs returns in the augmented FF model with a regime-switching setting. Finally, market volatility as a macro factor is negatively related to most Sector Select ETFs across market regimes. The Consumer Discretionary, Consumer Staples, Health Care, Industrials, and Materials ETFs are less affected with higher risk premiums when market volatility is higher.

The organization of the rest of the paper is as follows: In section 2, we discuss the regime-switching framework for the Sector Select ETFs returns, the determination of the market regimes, and the estimation method. In section 3, we discuss how to implement the regime-switching model and present new empirical findings for the Sector Select ETFs. Section 4 concludes the paper.

2 A Regime-Switching Framework

From observations on the stock market, investors often characterize the market as bullish, neutral or bearish. Table 1 is a typical report in Barron's showing the readings on a number of market sentiment indices such as the Consensus, AAII, Market Vane, and FC Market Sentiment as of January 10, 2010. The information in the table suggests a slight bullish market sentiment at the beginning of 2010 after the market crash in 2009. It appears that the stock market might be in a bullish regime (state[6]) from that day on for some time, but be subject to changes at a later date.[7] For example, during the Internet bubble period (1998-2002), the stock market was extremely volatile, while the market volatility was relatively low in the period of 2003–2006. The changes of market volatility sometimes cannot be justified by

[6]In this paper, we use "state", which is often used in theory, and "regime", which is often used in econometric modeling, interchangeably.

[7]The views of the interviewees could be very different and these might not be the basis for classifying regimes. This consideration leads to our regime-switching model discussed later.

Table 1: Stock Market Sentiment

	Last Week	2 Weeks Ago	3 Weeks Ago
Consensus Index			
Consensus Bullish Sentiment	66%	64%	56%
AAII Index			
Bullish	41.0%	49.2%	37.7%
Bearish	26.0%	23.0%	37.7%
Neutral	33.0%	27.9%	24.6%
Market Vane			
Bullish Consensus	57%	57%	57%
FC Market Sentiment			
Indicator	57.7%	58.1%	57.7%

Note: High bullish readings in the Consensus Index or in the Market Vane stock index usually are signs of Market peaks and troughs. This table is based on Barron's MARKET WEEK Investor Sentiment Readings, January 11, 2010.

economic fundamentals alone. It is highly probable that market sentiment, market volatility, and asset return processes are state-dependent. By ignoring such a possibility, we may omit some critical state-dependent information by simply averaging information across states or regimes.

2.1 A regime-switching model for the sector ETFs returns

Asset returns are often modeled as functions of economic and financial factors. The celebrated CAPM, APT, and Fama-French (FF) factor models are among the pioneering work falling into this framework. A common feature of these models is that expected asset returns are modeled as linear functions of common risk factors. The assumption underlying this approach is that expected asset returns are linearly related to common risk factors. This relationship is kept constant up to an identical stochastic innovation over time. This paper relaxes the rigid relationship between expected asset returns and common risk factors to accommodate additional economic uncertainty characterized by a hidden Markov regime-switching process endogenously inferred from the observed data.

Suppose the financial market regimes follow a Markov chain with a finite number of regimes, say K. To characterize the sector ETFs returns in different market regimes in relation to a set of common risk factors, we specify the following regime-switching regression model

$$R_t = \alpha_{M_t} + F_t\beta_{M_t} + \sigma_{M_t}\epsilon_t \tag{1}$$

where R_t is the vector of sector ETFs returns at time t, F_t is a vector of common risk factors at time t, and $\epsilon_t \sim N(0, I)$. The model has a set of parameters $\{\alpha_{M_t}, \beta_{M_t}, \sigma_{M_t}\}$, which jointly follow a Markov chain, M_t, with an initial state distribution q_0 and a transition probability matrix P with elements $p_{ij} = \Pr[M_{t+1} = j|M_t = i]$ for all $i, j \in K$ being the transition probability. The set of parameters, $\{\alpha_{M_t},\ \beta_{M_t}, \sigma_{M_t}\}$, is regime dependent and hence the mean return generating processes for the sector ETFs are also regime dependent. This model provides flexibility in quantifying regime dependent relationships jointly between the sector ETFs returns and common risk factors.

The standard asset pricing models, such as the CAPM, the APT, and the FF models, which do not accommodate regime-switching, are special cases of, and therefore nested in, the above general model. That is, when the parameters are not regime dependent, our regime-switching regression models are reduced to mean regression models. It is well-known that mean regression models do not necessarily provide a good fit for actual financial data that are characterized by fat tails and multiple modes in empirical distributions. Hence, for ETFs returns regime-switching regression models are expected to be superior to mean regression models.

2.2 Determination of market regimes

Investors can observe asset returns and other financial market data, but they cannot see the exact return generating processes in different market regimes. As shown later in the paper, sector ETFs returns display substantial skewness and excess kurtosis, which indicate sector ETFs returns indeed behave differently in different market regimes. Some ETFs may generate positive (or negative) returns in the bear regime while others may do so only in the bull market regime. To specify best models, we must use the actual data of ETFs and common risk factors to determine the optimal number of market regimes in which return generating processes can be properly identified.

Identifying the number of regimes is not straightforward, as regimes are not directly observable. However, we may infer the optimal number of regimes based on the Bayesian information criterion (BIC). It is known that the maximum likelihood value increases with a chosen number of regimes but the number of parameters in the likelihood function also increases with the number of regimes. To achieve the balance between the goodness of fit and parsimony in modeling, we wish to minimize the BIC so that the selection by selecting the number of regimes K. The optimal number of regimes K is the one that leads to the minimum value of $BIC(K)$, which is defined as

$$BIC(K) = -2\ln(L|K, \Theta(K)) + f(K, \Theta(K))\ln(T) \tag{2}$$

where L is the likelihood function given the number of regimes K, $\Theta(K) = \{\alpha_{M_t}, \beta_{M_t}, \sigma_{M_t}, p_{ij}\}$ is the set of parameters, $f(K, \Theta(K))$ represents the number of parameters which is, in turn, a function of the number of regimes K, and T is the sample size of the observed data.

2.3 Model estimation method

Given the special structure of the regime-switching model for the sector ETFs returns, it is necessary to develop an algorithm for solving the maximum likelihood estimation problem for the regime-switching model. The estimation method is an adaptation of the EM algorithm [e.g., Dempster et al. (1977)] which consists of two steps, the E-Step (estimation of the missing data for regimes) and the M-Step (maximization of the likelihood based on the estimated missing data on regimes). Given an initial condition, the two steps alternate in updating parameters. The algorithm is modified to accommodate the structure implied by the regime-switching model. After estimating the parameters, a dynamic programming algorithm is applied to characterize the prevailing regime in each period by maximizing the joint probability of regimes given the observed data.

To describe the algorithm used to estimate a regime-switching model, we provide a generic version of the expectation-maximization algorithm. Let Θ be the set of parameters $\{\alpha_{M_t}, \beta_{M_t}, \sigma_{M_t}, p_{ij}\}$ for our model, X the sequence of observations of $\{R_t\}$ with the factors $\{F_t\}$ as known and embedded in the mean of $\{R_t\}$ over time, and Y the sequence of unobservable regimes $\{M_t\}$ over time. Denote $\mathcal{Y}$ the space of all possible regime sequences for the time period. The marginal maximum log-likelihood is expressed as

$$\max_{\Theta}\left\{\ln \sum_{Y\in\mathcal{Y}} P(X,Y;\Theta)\right\}, \tag{3}$$

where $P(X,Y;\Theta)$ is the joint probability distribution function of X and Y. From Jensen's inequality, we have

$$\ln \sum_{Y\in\mathcal{Y}} P(X,Y;\Theta) \geq \sum_{Y\in\mathcal{Y}} Q(Y)\ln \frac{P(X,Y;\Theta)}{Q(Y)}, \tag{4}$$

where Q is an arbitrary distribution on Y. The key idea in the EM algorithm is to start with a set of initial values for the parameters in Θ and then find a tight lower bound to the true maximum likelihood which is the right hand side of (4). The optimal distribution $Q(Y)$ is obtained by maximizing the right hand side of (4) for the current approximation of Θ^0. A standard optimization technique implies the optimal solution to

$$\max_{Q}\left\{\sum_{Y\in\mathcal{Y}} Q(Y)\ln \frac{P(X,Y;\Theta^0)}{Q(Y)}\right\}$$

is such that

$$Q(Y) = P(Y|X;\Theta^0)$$

for the observed data and current estimate Θ^0. Substituting the "optimal" $Q(Y)$ in (4) shows that the lower bound function achieves the log-likelihood $\ln P(X;\Theta^0)$ of the observed data for current parameter estimate Θ^0. This is called the E-Step.

If Θ is the true maximum likelihood estimate,

$$\ln P(X;\Theta) \geq \sum_{Y\in\mathcal{Y}} P(Y|X;\Theta^0)\ln\left(\tfrac{P(X,Y;\Theta)}{P(Y|X;\Theta^0)}\right) \geq \ln P(X;\Theta^0).$$

The M-step is to improve the current estimate Θ^0 by maximizing the middle term in the above inequality, which is equivalent to maximizing the expected log-likelihood of the joint data of X and Y with respect to Θ

$$E^Q[\ln P(X, Y; \Theta)] = \sum_{Y \in \mathcal{Y}} P(Y|X; \Theta^0) \ln P(X, Y; \Theta).$$

Hence, an improved estimate for the parameter set Θ is

$$\Theta^1 = \arg\max_{\Theta} \left\{ E^Q[\ln P(X, Y; \Theta)] \right\}. \tag{5}$$

The algorithm is guaranteed to increase the likelihood at each iteration. When the increase is approaching a very small value that is close to zero, convergence is achieved. An iterative algorithm can be designed as follows:

1. **E-Step**: Set an initial value Θ^0 for the true parameter set Θ, calculate the conditional distribution function, $Q(Y) = P(Y|X; \Theta^0)$, and determine the expected log-likelihood, $E^Q[\ln P(X, Y; \Theta)]$.

2. **M-Step**: Maximize the expected log-likelihood with respect to the conditional distribution of the hidden variable to obtain an improved estimate of Θ. The improved estimate is
$$\Theta^1 = \arg\max_{\Theta} \left\{ E^Q[\ln P(X, Y; \Theta)] \right\}. \tag{6}$$
With Θ^1 as the new initial value for Θ, return to the E-Step.

In the case of the Markov regime-switching model, the above expressions can be simplified as

$$\Theta^1 = \arg\max_{\Theta} \left\{ \sum_{k=1}^{K} \sum_{t=1}^{T} P(M_t = k \mid X; \Theta^0) \ln P(R_t \mid M_t = k; \Theta) \right\}.$$

In the E-step, given the observed data and current estimate of the parameter set, the hidden data are estimated using the conditional expectation. In the M-step, the likelihood function is maximized to obtain an improved estimate Θ^1. The estimate of the hidden variable from the E-step is used in lieu of the actual missing data.

It is guaranteed that the algorithm converges to a local optimal solution. To ensure robustness in estimation, a heuristical method for finding the optimal solution is to apply the algorithm many times by assigning different initial values to the parameters.

3 Empirical Analysis

Given the model structure and the estimation methodology, we now provide a detailed analysis on the sector ETFs returns. Our intention is three-fold. First, we extend the ordinary FF model by including three additional common risk factors. These parameters are representative risk factors for the overall equity market. Second, we test the existence of market regimes and derive the optimal number of market regimes that are inherent in the observed data. These market regimes will be associated with market conditions and, eventually, be used to explain ETFs returns in response to some common risk factors. Third, we will compare the performance of the regime-switching model with those of the FF and augmented FF models.

3.1 Sector ETFs and their returns

A broad equity market consists of many businesses that can be classified into different sectors. To achieve an investment objective in allocating investments into various sectors, investors may invest in stocks in various sectors or invest in sector ETFs. Unlike pseudo portfolios used in other research, ETFs can be traded as stocks and can be used for various sector-oriented portfolio strategies.[8] We use the following criteria to guide us in selecting relevant ETFs. The selected ETFs must represent the sectors of the U.S. stock market, maintain portfolio consistency and eliminate managerial discrepancies, have a long trading history for the purpose of modeling, and have high liquidity and little mis-pricing.

Among different management companies that offer sector ETFs, both Sector Select SP-

[8] In the previous studies (e.g., Tu, 2007), returns on pseudo portfolios formed on the predefined quantiles of size and book-to-market equity are explained by the Fama-French (FF) factors such as the return on the market portfolio (MKT), size factor (SMB), and valuation (HML), for which more discussion will follow. Both the returns on such pseudo portfolios and the FF factors are related to size and book-to-market.

DRs ETFs and iShare Sector ETFs meet the above criteria. In this paper, the Sector Select ETFs (sometimes call SPDRs)[9] are chosen because they represent major sectors of the Standard & Poor's whole U.S. stock market and they have a slightly longer trading history (started December 23, 1998) than other ETFs. Out of the ten sectors, the telecommunication sector ETF is not offered because this sector contains only nine companies in the Standard & Poor's 500 stocks. The remaining nine sectors are represented by the following sector ETFs: Consumer Discretionary (XLY), Consumer Staples (XLP), Energy (XLE), Financials (XLF), Health (XLV), Industrials (XLI), Materials (XLB), Technology (XLK), and Utilities (XLU).

The daily returns on the Sector Select SPDRs ETFs from January 3, 2005 to September 30, 2009 are retrieved from Bloomberg. During this sample period, many market events took place. The bull stock market started in 2005 and peaked in October 2007. Since the beginning of 2008, the bear regime started and continued until March 2009. Starting from March 2009, a mild recovery occurred. By the end of 2009, the stock market gained more than 50%. The selected sample period is very representative of various market regimes.

The summary statistics for the sector ETFs returns during the sample period are reported in Table 2. From the top panel of Table 2, we see that Utilities, Consumer Staples, and Health Care ETFs have higher daily returns while Financials, Consumer Discretionary, and Industrials ETFs have lower daily returns on average.[10] Among all sector ETFs, Energy and Financials ETFs have higher standard deviations while Consumer Stables and Health Care ETFs have lower standard deviations. All sectors exhibit substantial skewness and excess kurtosis. This is a clear indication that the sector SETFs returns cannot be captured by linear models based on the assumption of normality. A suitable choice may be a regime-switching model, which is more flexible in accommodating the mixing of several empirical distributions and, therefore, of regimes.

The bottom panel of Table 2 shows that the sector ETFs returns are all positively correlated. Energy and Health Care sector ETFs and Consumer Stable and Energy sector ETFs

[9]See http://www.sectorspdr.com/.

[10]For the sample period, the average daily returns of these sector ETFs are negative. But some sector ETFs returns are higher than others.

have relatively lower pairwise correlations among their returns. Among all pairs of ETFs returns, Energy and Health Care sectors have the lowest correlation (0.52). But Consumer Discretionary and Industrials ETFs have the highest correlation (0.85). These high and low correlations further suggest that investment in a well-diversified portfolio of the sector ETFs can substantially lower the portfolio risk.

Table 2: Summary Statistics for Sector ETFs Returns

	Con. Dis.	Con. Staples	Energy	Financials	Health Care	Industrials	Materials	Technology	Utilities
Mean Return	-0.0669	-0.0120	-0.03747	-0.0733	-0.0261	-0.0571	-0.0341	-0.0385	-0.0078
Std. Dev.	0.0164	0.0095	0.0267	0.0242	0.0114	0.0147	0.0186	0.0155	0.0141
Skewness	-0.4614	-0.3358	-0.6304	-0.1984	-0.1917	-0.3304	-0.2298	0.2251	0.5447
Ex Kurtosis	7.9327	7.9272	8.8865	11.4654	20.3051	8.6001	8.4923	10.8449	11.7950
Correlation									
Con. Dis.	1.00								
Con. Staples	0.75	1.00							
Energy	0.62	0.53	1.00						
Financials	0.81	0.69	0.55	1.00					
Health Care	0.71	0.72	0.52	0.68	1.00				
Industrials	0.85	0.73	0.67	0.79	0.75	1.00			
Materials	0.73	0.63	0.72	0.71	0.67	0.83	1.00		
Technology	0.82	0.74	0.65	0.77	0.71	0.83	0.76	1.00	
Utilities	0.62	0.68	0.59	0.67	0.69	0.66	0.65	0.68	1.00

Note: The ETFs data from January 3, 2005 to February 27, 2009 are retrieved from Bloomberg. The standard deviations vary across these ETFs. The excess kurtosis is quite high for all ETFs returns. These ETFs returns are positively correlated.

3.2 Style and macro factors

Due to the contributions by Fama and French, the three style factors[11] have attracted much attention in financial research. However, the empirical literature has indicated that three other macro factors, market volatility (VIX), yield spread (YS), and credit spread (CS) are also important in explaining asset returns [e.g. Connor (1995)]. In this study, we augment the FF three factor model by adding three macro factors (this is also called the six factor model) and we estimate both the six factor model as well as the regime-switching model.

Among the macro and style factors used by Fama and French (1992, 1993, and 1996) the market factor (MKT) is the first factor, defined as the value-weighted returns on all NYSE, AMEX, and NASDAQ stocks minus the 30-day U.S. Treasury bill yield. In addition, Fama and French also consider the two other style factors the size factor (SMB) and book-

[11]These are market portfolio returns (MKT), differential returns on small- and large-cap stock portfolios (SML), and differential returns between high and low book-to-market ratio stock portfolios (HML)

to-market factor (HML). These two factors are constructed using the six value-weighted portfolios formed based on different sizes (small and big portfolios) and higher, transition, and lower book-to-market ratios (value, neutral, and growth portfolios). The SMB factor, defined as the average return on three small portfolios minus the average return on three big portfolios, captures the size effect.[12] The HML factor, defined as the average return on two value portfolios minus two average return on two growth portfolios, captures the value effect.[13]

In addition to the MKT, SMB, and HML factors, other macro factors are also influential on stock returns. The Yield Spread (YS) factor is defined as the difference between the yield of 20-year Treasury bond and the yield of three-month Treasury bill offered by the U.S. Department of Treasury. The Credit Spread (CS) factor is defined as the difference between the yield of the top rated bond and the yield of the lowest investment grade bond of the same maturity as the top rated bond. The U.S. 30-year Treasury bond is used as the top rated bond. Moody's Baa Index is used as the lowest investment grade bond. The volatility index (VIX) factor is the Chicago Board Options Exchange Volatility Index, a popular measure of the implied volatility of Standard & Poor's 500 index options.[14] VIX is defined as a weighted blend of implied volatility estimates for a range of options on the Standard & Poor's 500 index. There is a consensus that different levels of market volatility tend to be associated with different market conditions. For example, a bear regime is often associated with high market volatility, while a bull regime is associated with low market volatility.

The existing literature suggests that the YS, CS, and VIX factors might be good measures of financial market conditions. For example, Chen, Roll and Ross (1986) note that the YS factor is negatively related to stock returns while the CS factor is positively related to stock returns. However, Fama and French (1993) note that the YS and CS factors are not statistically significant in their factor model and, hence they exclude the YS and CS and

[12] More specifically, SMB $= \frac{1}{3}$(return on small value + return on small neutral + return on small growth) $-$ $\frac{1}{3}$(return on big value + return on big neutral + return on big growth).

[13] More specifically, HML $= \frac{1}{2}$(return on small value + return on big value) $-$ $\frac{1}{2}$(return on small growth + return on big growth).

[14] The implied volatility of an option contract (such as a put or call option contract) is the volatility implied by the market price of the option based on an option pricing model (such as the Black-Scholes model).

keep the MKT, SMB and HML factors. We suspect that the information in the YS and CS factors may be better utilized by our regime-switching framework. In addition, the VIX factor has been used for bond credit spreads [Collin-Dufresne, Goldstein and Martin (2001) and Schaefer and Strebulaev (2008)] but the VIX has not yet been used for stock returns in a regime-switching framework. It is likely that the VIX will capture changes in financial market sentiment.

The summary statistics for the chosen style and macro factors for the sample period are reported in Table 3. As shown in the top panel of Table 3, the CS and YS factors have, respectively, the first and second highest means while the MKT and YS factors have respectively the first and second highest standard deviations. The VIX factor has the lowest mean and standard deviation. The style factors (SMB and HML) have both lower means and standard deviations. These factors also exhibit substantial skewness and excess kurtosis of varying degrees. These observations may render the regime-switching framework a more suitable choice. The correlations among these factors are reported in the bottom panel of Table 3. It is interesting to identify how these common risk factors are related. Table 3 shows that the VIX and MKT factors have the highest negative correlation (-0.74) while the CS and YS factors have the highest positive correlation (0.67). The VIX factor is not correlated at all with the YS and its correlations with the CS, SMB, and HML factors are negative or close to zero. The correlations among other pairs of these factors are also very low. This indicates that these macro and style factors represent different forces in the financial market.

3.3 Empirical findings

3.3.1 Optimal number of regimes

To identify the optimal number of regimes, at the pre-estimation stage we have estimated regime-switching models with different numbers of regimes (e.g., $1, 2, \ldots, 5$). Then we compare these models by evaluating the values of BIC. As shown in Table 4, the three regime model appears to be the optimal choice which balances the goodness of fit and parsimony because this model has the lowest value (-6.9137) for BIC (in red). The identification of three regimes appears to be consistent with the classification of bear, transition, and bull

Table 3: Summary Statistics for Style and Macro Factors

	MKT	SMB	HML	VIX	YS	CS
Mean	-0.0381	-0.0030	-0.0021	0.0005	0.9979	1.1853
Stdev	1.4912	0.6067	0.6182	0.0302	1.0208	0.6481
Skewness	-0.1643	-0.0725	0.4071	0.5972	0.5385	2.2850
Ex. Kurtosis	11.3866	7.5641	10.1181	4.4875	-0.7564	4.2696
Correlation						
MKT	1.00					
SMB	-0.05	1.00				
HML	0.37	-0.11	1.00			
VIX	-0.74	-0.02	-0.18	1.00		
YS	-0.06	0.00	-0.02	0.00	1.00	
CS	-0.05	0.01	-0.09	-0.01	0.67	1.00

Note: MKT, SMB, HML are the Fama and French factors retrieved from K. French's data library. The VIX, YS and CS data are retrieved from the Datastream database. The sample data are daily from January 3, 2005 to February 27, 2009. The mean return on MKT and mean differential returns on SMB, HML, YS, and CS are in percentage.

market regimes.

Table 4: Optimal Number of Market Regimes

No. of Regimes	1	2	3	4	5
MLL	32584	34791	35225	35383	3.5582
BIC	-6.4731	-6.8706	-6.9137	-6.9013	-6.8974

Note: MLL stands for the maximized log-likelihood function vale. BIC stands for the Bayesian information criterion.

3.3.2 Transition probabilities and characterization of regimes

Once the optimal number of the regimes is determined, we can select the the three regime model and discuss the regime transition probabilities estimated from the chosen model. These probabilities are given in the following matrix, where each cell has a probability estimate and its p-value in the parentheses:

$$\begin{bmatrix} 0.8933(0.0000) & 0.1067(0.0000) & 0.0000(0.0043) \\ 0.0455(0.0000) & 0.9346(0.0000) & 0.0199(0.0032) \\ 0.0000(0.0378) & 0.0098(0.0502) & 0.9902(0.0000) \end{bmatrix}$$

The transition probability from regime i ($i = 1, 2, 3$) to regime j ($j = 1, 2, 3$) is shown as the entry crossed by the i^{th} row and the j^{th} column. Clearly, all three regimes are highly persistent indicated by the high probabilities of remaining in the current regime at any point in time. From these probabilities, we find that each state has a high probability to remain where it was. Overall, regime 3 has the highest retaining probability (0.9902) while regime 1 has the lowest retaining probability (0.8933).

The average performance of the style and macro factors is of great interest to investors in interpreting the market regimes. Table 5 documents the average values of the style and macro factors by regime. In regime 1, the mean MKT factor is the lowest and the mean YS and CS factors are highest. This situation is quite consistent with a bear regime characterization, so we label regime 1 as a "bear" market regime. In regimes 1 and 3, the MKT and SMB factors move in opposite directions. Similarly, the MKT and VIX factors also move in opposite directions. That is, a rise in equity returns correspond to a fall in both risk premiums on size and on market volatility. In regime 3, the style and macro factors are in reversed relations to those in regime 1, except a slight fall in the VIX factor. Thus, we label regime 3 as a "bull" market regime. Finally, regime 2 represents an intermediate state between "bear" and "bull" market regimes and we label it as a "transition" market regime. With these interpretations of market regimes, we can further comment on the transition probabilities. The retaining probability for the bear regime is only about 0.8933, which is lower than the retaining probability, 0.9902, for the bull regime. This shows that the bull regime is more persistent than the bear regime.

Table 5: Mean Style and Macro Factors Across Regimes

Regime	MKT	SMB	HML	VIX	YS	CS
1	-0.3262	0.0304	-0.1440	0.15	2.7225	2.6438
2	-0.1131	-0.0117	-0.0022	0.11	1.6049	1.3438
3	0.0404	-0.0048	0.0211	0.01	0.4618	0.8805

Note: The numbers are shown as mean daily changes in percentage.

3.3.3 Model comparisons: The FF model, the augmented FF model, and the regime-switching models

In order to show that the regime-switching model with the MKT, SMB, HML, VIX, YS and CS factors is appropriate for the sector ETFs returns, we first estimate the FF model with the MKT, SMB, and HML factors. Then, we augment the FF model by adding the VIX, YS, and CS factors. The augmented FF model with the six factor is preferred based on the likelihood ratio test[15]. As elaborated in Fama and French (1993), the YS and CS factors are not statistically significant in their three factor model. For sector ETFs returns, we suspect that, if we incorporate regime-switching into the augmented FF model, we may get a better fit for the data. As discussed previously, the BIC favors the augmented FF model with three regimes.

For the purpose of comparison, we tabulate the α and β coefficient estimates for the FF model, the augmented FF model (or the six factor model) and the augmented FF regime-switching model (or the six factor regime-switching model) in Tables 6 and 7.

For the augmented FF regime-switching model, we apply the parametric bootstrapping method to evaluate the standard errors of parameter estimates. The parametric bootstrapping method is implemented in three steps. First, the regime-switching model is estimated and parameter estimates are obtained. Second, these parameter estimates and the factors data are used to generate pseudo-return data. Third, the pseudo-return data are used to replace the actual return data in estimating the regime-switching model. The second and third steps are repeated many times so that a large sample of parameter estimates are ob-

[15] The likelihood ratio test statistic has a p-value of 0.000006.

Table 6: Comparison of Alpha Estimates

	RS Model				
	Regime 1	Regime 2	Regime 3	3 Factor Model	6 Factor Model
Con. Discretionary	0.0072 (0.0615)	-0.0008 (0.0074)	-0.0027 (0.0000)	-0.0003 (0.2240)	-0.0005 (0.2370)
Con. Staples	-0.0071 (0.0000)	0.0005 (0.0793)	-0.0006 (0.0000)	0.0001 (0.5580)	0.0006 (0.0800)
Energy	0.0015 (0.7297)	0.0057 (0.0000)	0.0054 (0.0000)	0.0001 (0.9070)	0.0012 (0.1930)
Financials	0.0078 (0.0010)	-0.0055 (0.0000)	-0.0006 (0.0000)	-0.0004 (0.1600)	-0.0006 (0.4030)
Health Care	-0.0043 (0.0716)	0.0003 (0.0614)	-0.0010 (0.0000)	0.0000 (0.9860)	0.0006 (0.1860)
Industrials	0.0004 (0.2041)	0.0005 (0.8489)	-0.0033 (0.0000)	-0.0001 (0.4370)	0.0005 (0.1710)
Materials	-0.0010 (0.1510)	0.0021 (0.0000)	0.0033 (0.0000)	0.0001 (0.6490)	0.0009 (0.1150)
Technology	-0.0017 (0.4790)	-0.0005 (0.2488)	-0.0007 (0.0000)	0.0000 (0.8600)	0.0002 (0.6260)
Utilities	-0.0180 (0.0000)	0.0014 (0.0019)	0.0038 (0.0000)	0.0001 (0.6590)	0.0008 (0.1300)

Note: This table reports the estimated α for each of the three- and six-factor models and the regime-switching (RS) model. p-values are shown in the parentheses.

tained to calculate standard errors for the parameter estimates obtained in the first step. With these standard errors, we can perform hypothesis testing for the parameters in the regime-switching model. In Tables 6 and 7, the p-values for parameter estimates of the regime-switching model are calculated based on the bootstrap standard errors while those of the three and six-factor models are based on the estimated standard errors.

3.3.4 Determinants of the sector ETFs returns

We now examine Tables 6 and 7 and discuss why the regime-switching model provides a good fit for the sector ETFs returns. In Table 6, the estimated intercept terms (α's) in the FF three-factor model and the six-factor linear model are statistically insignificant and close to zero across all sector ETFs. However, in the FF six-factor regime-switching model, many intercepts are statistically significant. Apparently, the regime-switching model is able to identify non-zero α's for some sectors in some regimes. For example, Energy, Materials, and Utilities ETFs returns have positive α's in the transition and bull regimes but have zero or negative α's in the bear regime. Hence, the regime-switching model can capture more information than the FF and augmented FF models do.

Table 7 presents the estimated β's for the FF, augmented FF, and regime-switching models. It is shown that the sector ETFs returns are sensitive to the risk factors with different implications for different regimes. In the FF and augmented FF models, the estimated β's are all statistically significant and positive for all sectors. In the regime-switching models, the estimated β's for the market portfolio (MKT) are all statistically significant and positive

Table 7: Comparison of Beta Estimates

		MKT	SMB	HML	VIX	YS	CS
Con. Discretionary							
	Regime 1	0.0097 (0.0000)	0.0038 (0.0000)	0.0021 (0.0000)	0.0510 (0.0000)	-0.0045 (0.0000)	0.0019 (0.1085)
RS Model	Regime 2	0.0101 (0.0000)	0.0019 (0.0000)	0.0040 (0.0000)	-0.0143 (0.2326)	0.0003 (0.0248)	-0.0001 (0.5227)
	Regime 3	0.0096 (0.0000)	0.0002 (0.0000)	-0.0031 (0.0000)	-0.0105 (0.0000)	0.0001 (0.1743)	0.0029 (0.0000)
3 Factor Model		0.0096 (0.0000)	0.0032 (0.0000)	0.0013 (0.0000)	-	-	-
6 Factor Model		0.0096 (0.0000)	0.0032 (0.0000)	0.0014 (0.0000)	0.0000 (0.6450)	-0.0003 (0.2200)	0.0002 (0.7690)
Con. Staples							
	Regime 1	0.0049 (0.0000)	-0.0002 (0.0526)	-0.0010 (0.4131)	0.0066 (0.5195)	0.0010 (0.1311)	0.0009 (0.6708)
RS Model	Regime 2	0.0036 (0.0000)	-0.0003 (0.0000)	0.0007 (0.0004)	-0.0651 (0.0000)	0.0001 (0.0027)	0.0000 (0.2439)
	Regime 3	0.0061 (0.0000)	-0.0024 (0.0000)	-0.0027 (0.0000)	-0.0201 (0.0000)	0.0001 (0.0000)	0.0007 (0.0000)
3 Factor Model		0.0051 (0.0000)	-0.0003 (0.2980)	-0.0011 (0.0000)	-	-	-
6 Factor Model		0.0051 (0.0000)	-0.0003 (0.2890)	-0.0011 (0.0000)	0.0000 (0.5880)	0.0002 (0.4130)	-0.0003 (0.6120)
Energy							
	Regime 1	0.0106 (0.0000)	0.0014 (0.3969)	0.0189 (0.0000)	-0.0715 (0.0023)	-0.0016 (0.1489)	0.0006 (0.4482)
RS Model	Regime 2	0.0128 (0.0000)	-0.0076 (0.0000)	-0.0090 (0.0000)	0.0246 (0.0180)	0.0030 (0.0000)	-0.0080 (0.0000)
	Regime 3	0.0161 (0.0000)	0.0011 (0.0001)	0.0252 (0.0000)	0.0488 (0.0000)	-0.0002 (0.5094)	-0.0059 (0.0000)
3 Factor Model		0.0125 (0.0000)	-0.0021 (0.0050)	0.0117 (0.0000)	-	-	-
6 Factor Model		0.0125 (0.0000)	-0.0020 (0.0060)	0.0117 (0.0000)	0.0000 (0.7930)	-0.0001 (0.8100)	-0.0004 (0.7760)
Financials							
	Regime 1	0.0133 (0.0000)	-0.0055 (0.0000)	-0.0021 (0.0705)	-0.0923 (0.0000)	0.0024 (0.0784)	-0.0049 (0.0979)
RS Model	Regime 2	0.0132 (0.0000)	0.0020 (0.0000)	0.0154 (0.0000)	-0.0863 (0.0000)	-0.0036 (0.0000)	0.0080 (0.0000)
	Regime 3	0.0099 (0.0000)	-0.0032 (0.0000)	-0.0014 (0.0384)	-0.0353 (0.0000)	0.0000 (0.1169)	0.0006 (0.0000)
3 Factor Model		0.0133 (0.0000)	-0.0039 (0.0000)	0.0019 (0.0000)	-	-	-
6 Factor Model		0.0133 (0.0000)	-0.0039 (0.0000)	0.0020 (0.0000)	0.0001 (0.3180)	-0.0002 (0.5500)	-0.0007 (0.5070)
Health Care							
	Regime 1	0.0066 (0.0000)	-0.0001 (0.2836)	-0.0035 (0.0000)	-0.0027 (0.7708)	-0.0004 (0.8850)	0.0013 (0.7699)
RS Model	Regime 2	0.0041 (0.0000)	0.0001 (0.2425)	0.0001 (0.1302)	-0.0757 (0.0000)	-0.0006 (0.0013)	0.0007 (0.0875)
	Regime 3	0.0075 (0.0000)	-0.0034 (0.0000)	-0.0060 (0.0000)	-0.0055 (0.0002)	0.0004 (0.0000)	0.0011 (0.0000)
3 Factor Model		0.0064 (0.0000)	-0.0006 (0.0650)	-0.0032 (0.0000)	-	-	-
6 Factor Model		0.0064 (0.0000)	-0.0007 (0.0480)	-0.0033 (0.0000)	-0.0001 (0.0350)	0.0002 (0.3210)	0.0007 (0.3120)
Industrials							
	Regime 1	0.0087 (0.0000)	0.0009 (0.0033)	-0.0016 (0.0008)	-0.0033 (0.8229)	-0.0022 (0.0000)	0.0010 (0.7401)
RS Model	Regime 2	0.0096 (0.0000)	-0.0005 (0.0000)	0.0007 (0.0002)	-0.0192 (0.0008)	0.0007 (0.0000)	-0.0013 (0.0458)
	Regime 3	0.0090 (0.0000)	-0.0004 (0.0000)	-0.0029 (0.0000)	-0.0137 (0.0000)	0.0003 (0.0000)	0.0038 (0.0000)
3 Factor Model		0.0094 (0.0000)	0.0010 (0.0010)	-0.0002 (0.4150)	-	-	-
6 Factor Model		0.0094 (0.0000)	0.0010 (0.0010)	-0.0003 (0.3540)	-0.0001 (0.0940)	0.0000 (0.8930)	0.0005 (0.4340)
Materials							
	Regime 1	0.0119 (0.0000)	0.0007 (0.0501)	-0.0047 (0.0000)	0.0812 (0.0000)	-0.0021 (0.0002)	0.0017 (0.0865)
RS Model	Regime 2	0.0123 (0.0000)	-0.0002 (0.3834)	-0.0065 (0.0000)	0.0090 (0.0076)	0.0010 (0.0001)	-0.0023 (0.0000)
	Regime 3	0.0121 (0.0000)	0.0024 (0.0000)	0.0045 (0.0000)	-0.0112 (0.0000)	-0.0007 (0.0000)	-0.0033 (0.0000)
3 Factor Model		0.0114 (0.0000)	0.0009 (0.0360)	-0.0034 (0.0000)	-	-	-
6 Factor Model		0.0113 (0.0000)	0.0009 (0.0460)	-0.0035 (0.0000)	-0.0001 (0.0530)	0.0000 (0.9040)	0.0010 (0.2220)
Technology							
	Regime 1	0.0094 (0.0000)	-0.0016 (0.0001)	-0.0024 (0.0101)	-0.0292 (0.0004)	-0.0013 (0.0000)	0.0016 (0.4893)
RS Model	Regime 2	0.0098 (0.0000)	-0.0011 (0.0000)	-0.0032 (0.0000)	0.0103 (0.0778)	0.0016 (0.0000)	-0.0015 (0.0001)
	Regime 3	0.0089 (0.0000)	-0.0009 (0.0000)	-0.0088 (0.0000)	-0.0259 (0.0000)	-0.0001 (0.0257)	0.0012 (0.0000)
3 Factor Model		0.0099 (0.0000)	-0.0007 (0.0140)	-0.0036 (0.0000)	-	-	-
6 Factor Model		0.0099 (0.0000)	-0.0007 (0.0140)	-0.0036 (0.0000)	0.0000 (0.8120)	0.0000 (0.8500)	0.0000 (0.9680)
Utilities							
	Regime 1	0.0074 (0.0000)	-0.0036 (0.0000)	-0.0049 (0.0000)	-0.0708 (0.0000)	0.0039 (0.0000)	0.0021 (0.6637)
RS Model	Regime 2	0.0047 (0.0000)	-0.0035 (0.0000)	-0.0020 (0.0012)	-0.0615 (0.0000)	-0.0005 (0.1610)	-0.0002 (0.0142)
	Regime 3	0.0101 (0.0000)	-0.0027 (0.0000)	0.0101 (0.0000)	0.0147 (0.0000)	-0.0005 (0.0000)	-0.0040 (0.0000)
3 Factor Model		0.0073 (0.0000)	-0.0034 (0.0000)	-0.0025 (0.0000)	-	-	-
6 Factor Model		0.0073 (0.0000)	-0.0034 (0.0000)	-0.0025 (0.0000)	0.0000 (0.6610)	0.0000 (0.9420)	-0.0002 (0.8380)

Note: This table reports the estimated β for each factor for the three- and six-factor models and the regime-switching (RS) model. p-values are shown in the parentheses.

across the regimes for all sectors. This is consistent with the prediction of the CAPM and the FF model. Secondly, Consumer Staples and Health Care are less sensitive, while Energy, Financials, and Materials sector ETFs are more sensitive to the market portfolio return in all three regimes. Thirdly, different sector ETFs returns may have different sensitivities to the market portfolio return (MKT) in different market regimes. For example, the Financials sector has the highest sensitivity to the market portfolio return in the bull regime while Energy and Materials sectors have the highest sensitivity to the market portfolio in the transition regime. Thus, the regime-switching model captures much more information about the sectors in different regimes.

We now examine the two style factors, SMB and HML factors. According to Fama and French (1992), "size (SMB) on average has a negative premium in the cross-section of stock returns, and book-to-market (HML) has a positive premium". For the FF and augmented FF models for various sector ETFs, the estimated β's for the SMB and HML factors are statistically significant. But the size effect in Consumer Discretionary, Industrials and Materials ETFs is positive in the FF and augmented FF models while the size effect is negative in all other sector ETFs. Other than Consumer Discretionary ETFs, the size factor (SMB) contributes a negative or zero premium to all other sector ETFs in some regimes. But the role of the book-to-market ratio (HML) is more mixed across different sector ETFs. For example, the Consumer Discretionary, Energy, and Financials ETFs returns are positively related to the HML factor in the FF and augmented FF models, while other sector ETFs returns are negatively related to the HML factor. In the regime-switching model, even for those sector ETFs returns that are positively related to the HML factor without regime-switching, they can be positively or negatively related to the HML factor in some regimes. For example, in the bull regime, Consumer Discretionary ETF returns are positively related to the HML factor. In the transition regime, Energy ETF returns are negatively related to the HML factor. In both bear and transition regimes, Financials ETF returns are negatively related to the HML factor. These additional findings are not previously available in the literature.

Now we discuss the two macro factors, CS and YS. The original FF model does not contain the CS and YS factors. In the augmented FF model, both the CS and YS factors are statistically insignificant for all of the sector ETFs. However, in the regime-switching model, the CS and YS factors vary significantly across market regimes. Energy, Materials, and Utilities ETFs returns are negatively related to the CS factor in the transition and bull regimes, but Financials and Health Care ETFs returns are positively related to the CS factor in the transition and bull regimes. This is a reflection of the business cycle in different sectors: a higher CS factor usually reduces the ETFs returns for Energy, Materials, and Utilities sectors but increases ETFs returns for Financials and Health Care sectors. The YS factor has mixed impacts across sectors and regimes. The exceptions are Consumer Staples and Industrials ETFs. In these two sectors, the YS factor contributes a positive premium in the transition and bull regimes. Thus, when the yield curve is upward sloping (i.e., a higher YS factor), the Consumer Staples and Industrials sectors command higher risk premiums.

Now we discuss the other macro factor, the VIX factor. We find that, in the augmented FF model, VIX does not contribute any sizeable premium for most sector ETFs returns, with the exception that it contributes a negative premium to the Health Care, Materials, and Industrials ETFs returns. It is likely that the augmented FF model may not be sufficient for characterizing information hidden in the different market regimes. In contrast, in the regime-switching model the VIX factor contributes a negative premium to the Consumer Staples, Health Care, and Industrials ETFs returns in the transition and bull regimes, and to the Financials ETF returns in all three regimes. That is, the market risk proxied by the VIX factor is negatively related to the expected returns in Consumer Staples, Health Care, and Industrials sectors in the transition and bull regimes and it is negatively related to the expected returns in the Financials sector in all three regimes. But market volatility (VIX) does not contribute any positive premium to Consumer Discretionary, Consumer Staples, Health Care, Industrials, and Materials sectors in the bear regime. This suggests that in the bear regime, these sectors can be quite defensive when market volatility is high.

Table 8 shows the variances and covariances of the sector ETFs returns for the regime-switching model. By comparing the variances of the sector regime-switching model (along the diagonal) across the bear, transition, and bull regimes, we note that in the bear regime the variances tend to be greater than those in the transition regime and the variances are smallest in the bull regime. That is, the regime-switching model has a better fit for the observed data but the bear regime is still associated with a great variance even after taking into account the VIX, YS and CS factors beyond the FF three factors—the MKT, SMB, and HML factors.

Table 8: Variance-covariance Estimates for Regime-switching Model

	Con. Discretionary	Con. Staples	Energy	Financials	Health Care	Industrials	Material	Technology	Utility
Regime 1									
Con. Discretionary	0.000233 (0.0000)								
Con. Staples	0.000040 (0.0000)	0.000149 (0.0000)							
Energy	0.000023 (0.0000)	-0.000001 (0.3596)	0.000533 (0.0000)						
Financials	0.000010 (0.0928)	-0.000029 (0.0000)	-0.000206 (0.0000)	0.000402 (0.0000)					
Health Care	-0.000012 (0.0003)	0.000040 (0.0000)	0.000012 (0.0040)	-0.000051 (0.0000)	0.000220 (0.0000)				
Industrials	0.000035 (0.0000)	-0.000004 (0.2723)	0.000041 (0.0000)	-0.000014 (0.0000)	0.000029 (0.0000)	0.000151 (0.0000)			
Materials	-0.000010 (0.0000)	-0.000044 (0.0000)	0.000089 (0.0000)	0.000029 (0.0000)	0.000000 (0.7962)	0.000064 (0.0000)	0.000281 (0.0000)		
Technology	0.000027 (0.0000)	0.000019 (0.0000)	0.000040 (0.0000)	-0.000049 (0.0000)	-0.000027 (0.0000)	-0.000008 (0.0000)	-0.000036 (0.0000)	0.000149 (0.0000)	
Utilities	-0.000042 (0.0000)	0.000051 (0.0000)	-0.000069 (0.0000)	0.000031 (0.0000)	0.000053 (0.0000)	-0.000020 (0.0000)	-0.000056 (0.0000)	0.000002 (0.1224)	0.000204 (0.0000)
Regime 2									
Con. Discretionary	0.000068 (0.0000)								
Con. Staples	0.000014 (0.0000)	0.000038 (0.0000)							
Energy	-0.000068 (0.0000)	-0.000025 (0.0000)	0.000206 (0.0000)						
Financials	0.000022 (0.0000)	0.000008 (0.0000)	-0.000086 (0.0000)	0.000127 (0.0000)					
Health Care	0.000014 (0.0000)	0.000011 (0.0000)	-0.000028 (0.0000)	0.000008 (0.0001)	0.000041 (0.0000)				
Industrials	0.000011 (0.0000)	0.000007 (0.0000)	-0.000016 (0.0000)	-0.000011 (0.0000)	0.000003 (0.0000)	0.000042 (0.0000)			
Materials	-0.000020 (0.0000)	-0.000011 (0.0000)	0.000061 (0.0000)	-0.000038 (0.0000)	-0.000009 (0.0000)	0.000005 (0.0000)	0.000099 (0.0000)		
Technology	0.000014 (0.0000)	0.000007 (0.0000)	-0.000037 (0.0000)	0.000004 (0.0040)	-0.000003 (0.0000)	0.000010 (0.0000)	-0.000014 (0.0000)	0.000046 (0.0000)	
Utilities	0.000006 (0.0322)	0.000010 (0.0000)	0.000019 (0.0000)	-0.000011 (0.0000)	0.000014 (0.0000)	-0.000004 (0.0000)	0.000005 (0.0142)	-0.000011 (0.0000)	0.000093 (0.0000)
Regime 3									
Con. Discretionary	0.000014 (0.0000)								
Con. Staples	0.000003 (0.0000)	0.000013 (0.0000)							
Energy	-0.000016 (0.0000)	-0.000011 (0.0000)	0.000102 (0.0000)						
Financials	0.000003 (0.0000)	0.000002 (0.0000)	-0.000022 (0.0000)	0.000015 (0.0000)					
Health Care	0.000000 (0.4939)	0.000003 (0.0000)	-0.000009 (0.0000)	0.000000 (0.0323)	0.000016 (0.0000)				
Industrials	0.000004 (0.0000)	0.000001 (0.0000)	-0.000008 (0.0000)	0.000001 (0.2027)	-0.000001 (0.0000)	0.000014 (0.0000)			
Materials	-0.000002 (0.0000)	-0.000002 (0.0000)	0.000005 (0.0000)	-0.000003 (0.0000)	-0.000003 (0.0000)	0.000004 (0.0000)	0.000033 (0.0000)		
Technology	0.000000 (0.2800)	-0.000001 (0.0094)	-0.000007 (0.0000)	-0.000002 (0.0000)	-0.000003 (0.0000)	0.000000 (0.6359)	-0.000002 (0.0000)	0.000015 (0.0000)	
Utilities	-0.000002 (0.0000)	0.000004 (0.0000)	-0.000006 (0.0000)	-0.000001 (0.0012)	0.000003 (0.0000)	-0.000001 (0.0000)	-0.000006 (0.0000)	0.000000 (0.1736)	0.000032 (0.0000)

Note: This table reports the variance-covariance estimates for the regime-switching model. p-values are shown in the parentheses.

To evaluate the effectiveness of the regime-switching model, we look into the forecast performance beyond March 2, 2009, as indicated in Figures 1–9. Other than the Health Care and Technology sectors where the forecasted ETFs returns deviate by a relatively large margin from the actual ETFs returns, the regime-switching model predicts the future returns well in all other seven sectors. This confirms the merit of a regime-switching model for characterizing sector ETFs returns.

4 Concluding Remarks

In this paper, we extended the analysis of Fama and French (1992, 1993) to study the U.S. Sector Select ETFs returns using a regime-switching model with macro and style factors. Using the novel approach, we find that sector ETFs returns vary across the bear, transition and bull regimes over time. The volatility in the bear regime tends be great than that in the bull regime. Sector ETFs returns in each regime have a higher probability to remain in their original regime. The sector ETFs returns in the bear regime have a slightly lower probability of remaining in their original regime than they do in the bull regime. The probabilities of jumping over an intermediate regime in the regime-to-regime transition (say from regime 1 to regime 3 or vice versa) is extremely low.

Consistent with the findings in Fama and French (1992), we find that the market portfolio return has a positive premium and the size factor has a negative premium on on sector ETFs returns. However, the book-to-market factor is not positively related to sector ETFs returns. In addition, this research confirms the findings of Fama and French (1993) that yield and credit spreads do not affect the sector ETFs returns in the augmented FF model. For sector ETFs returns, alpha estimates in the FF and augmented FF models are not statistically significant. We show that the regime-switching model is superior to the FF and augmented FF models. For sector ETFs returns, yield and credit spreads in the regime-switching model contribute different premiums in different regimes. Finally, market volatility is negatively related to most of sector ETFs returns. But market volatility does not negatively impact on the ETFs returns for Consumer Discretionary, Consumer Staple, Health Care, Industrials, and Materials sectors. Hence, these sectors are quite defensive when market volatility is high.

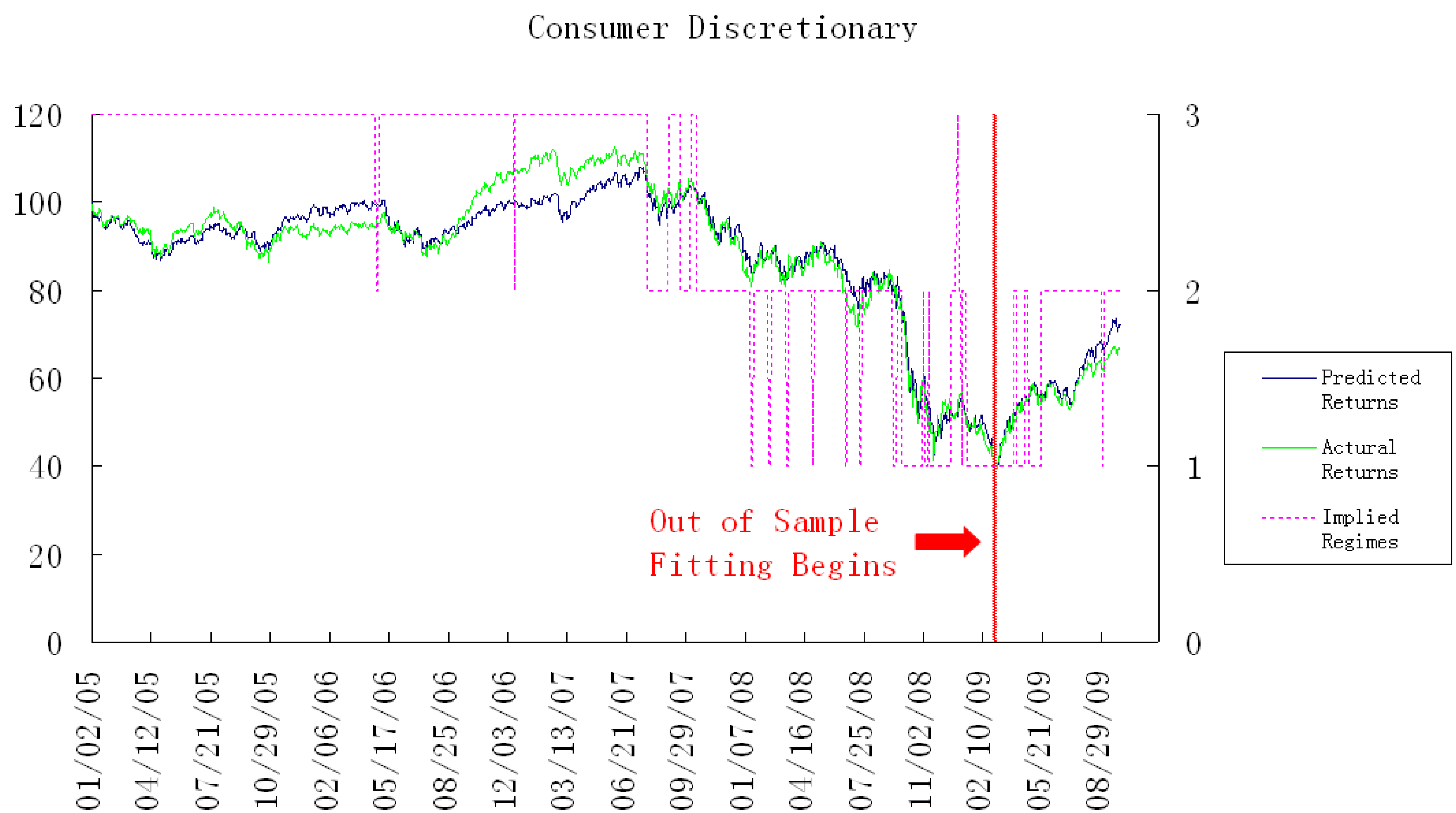

Figure 1: **XLY**. The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of $100 USD. The right vertical axis indicates regimes 1, 2, and 3. Regime 1 represents a bear regime. Regime 2 is considered a regime. Regime 3 is characterized as a bull regime.

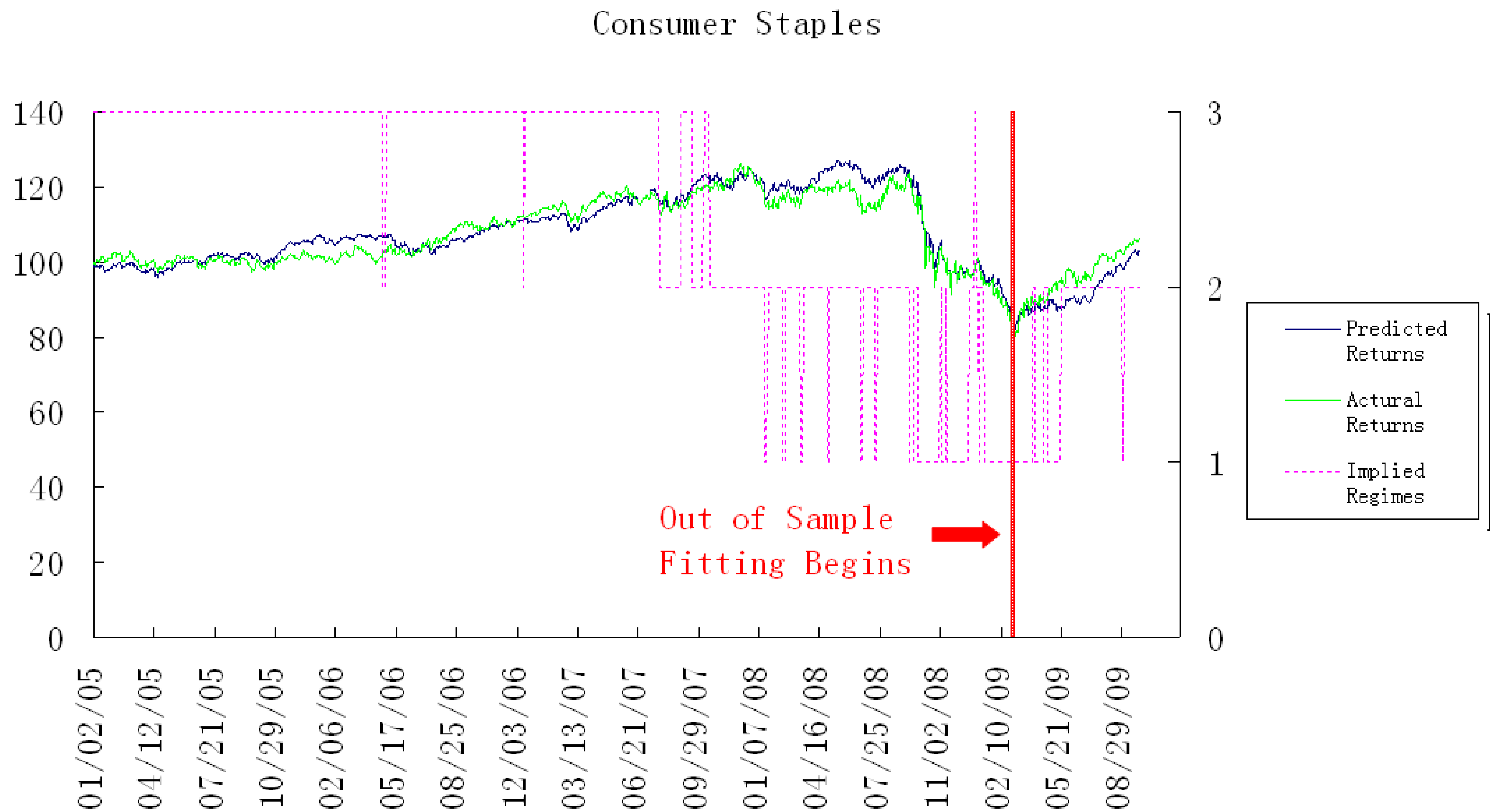

Figure 2: **XLP**. The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of $100 USD. The right vertical axis indicates regimes 1, 2, and 3. Regime 1 represents a bear regime. Regime 2 is considered a transition regime. Regime 3 is characterized as a bull regime.

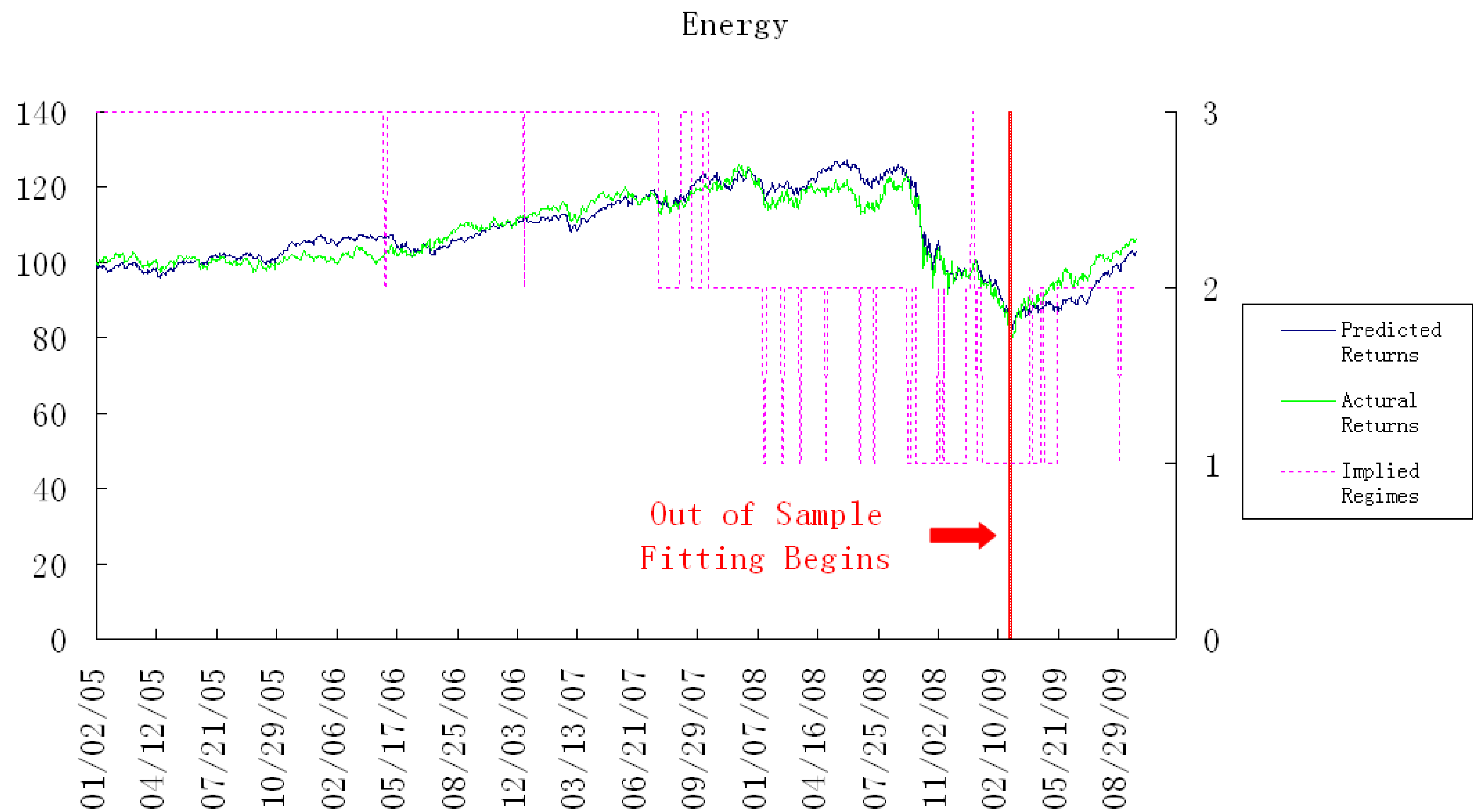

Figure 3: **XLE**. The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of $100 USD. The right vertical axis indicates regimes 1, 2, and 3. Regime 1 represents a bear regime. Regime 2 is considered a transition regime. Regime 3 is characterized as a bull regime.

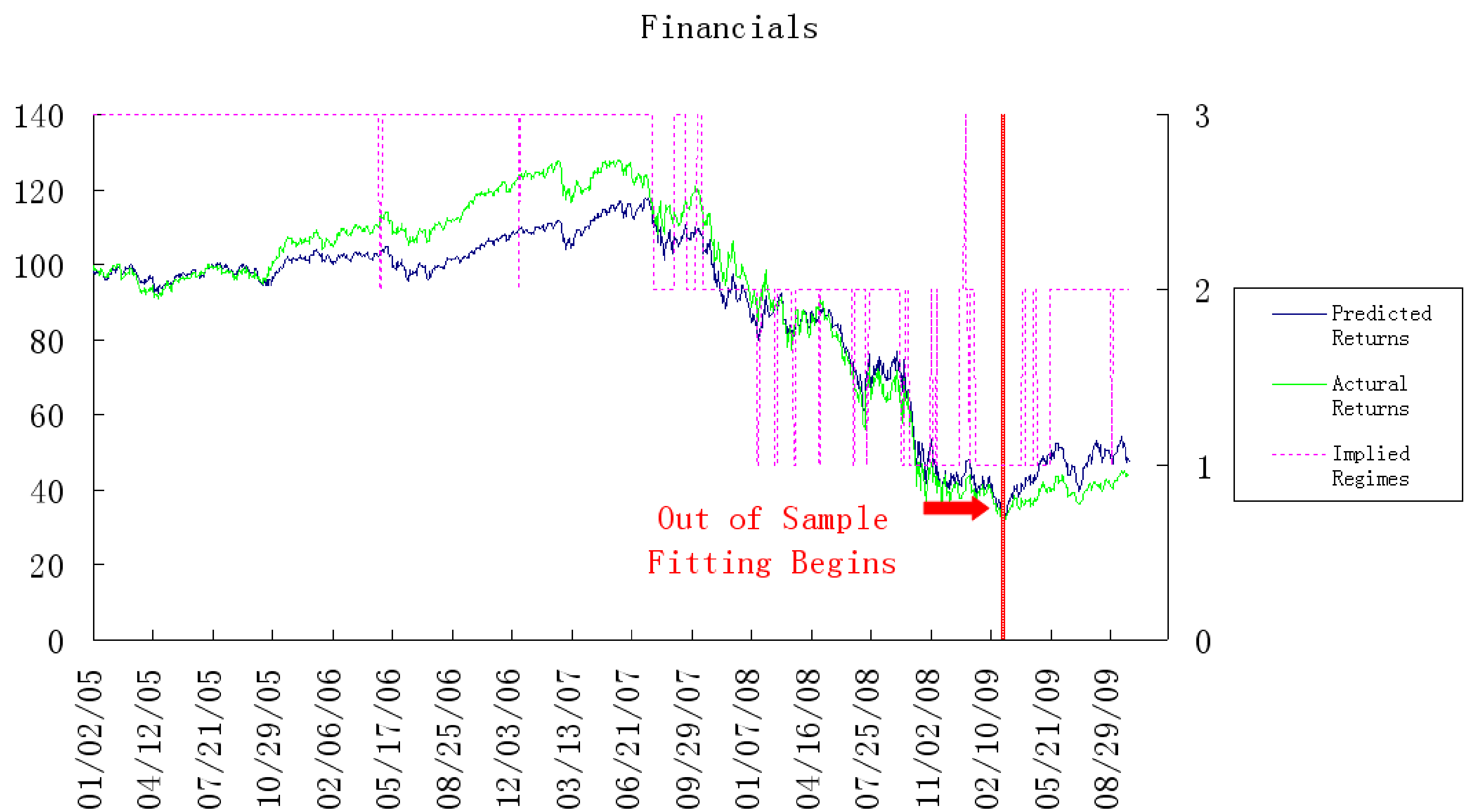

Figure 4: **XLF**. The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of $100 USD. The right vertical axis indicates regimes 1, 2, and 3. Regime 1 represents a bear regime. Regime 2 is considered a transition regime. Regime 3 is characterized as a bull regime.

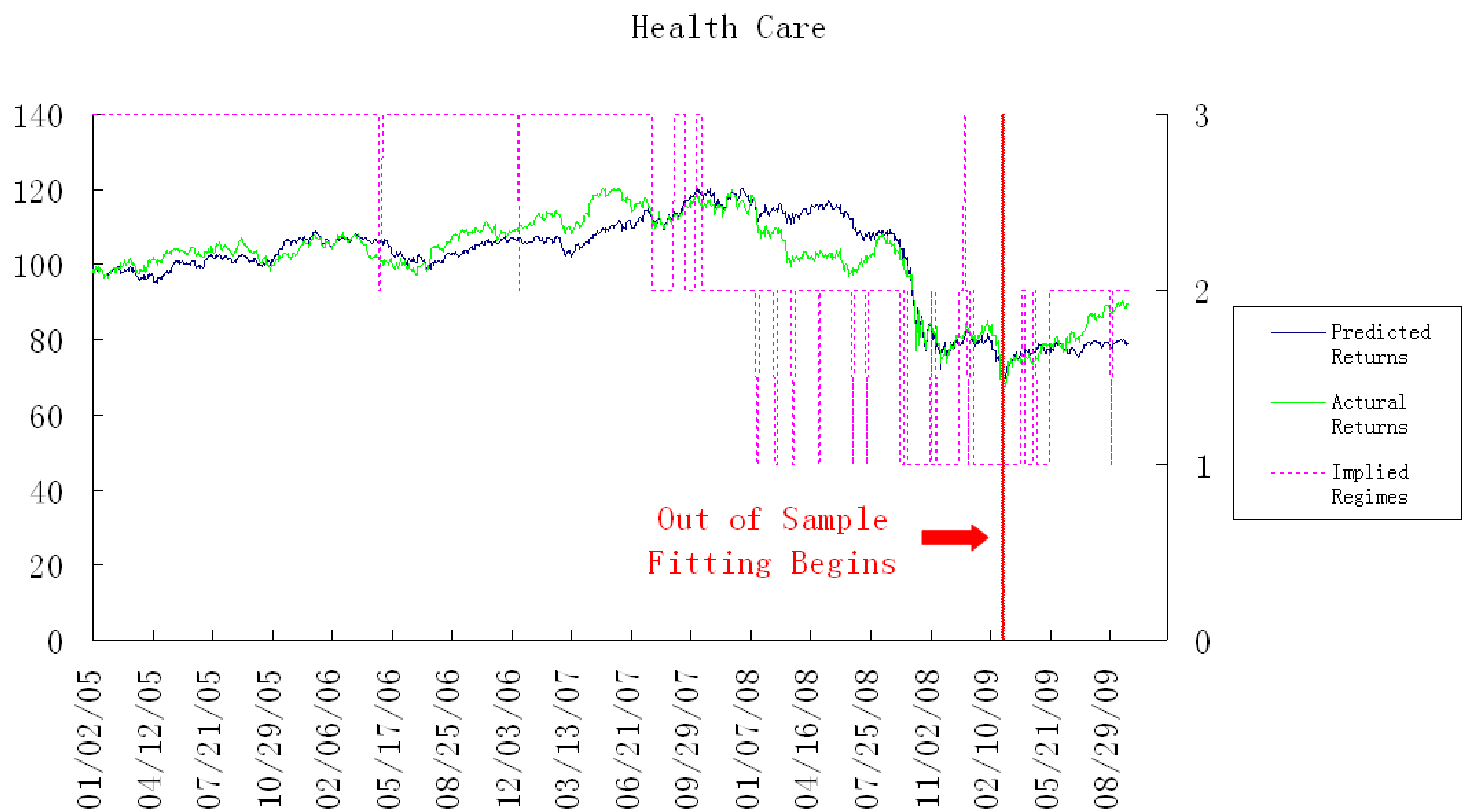

Figure 5: **XLV**. The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of $100 USD. The right vertical axis indicates regimes 1, 2, and 3. Regime 1 represents a bear regime. Regime 2 is considered a transition regime. Regime 3 is characterized as a bull regime.

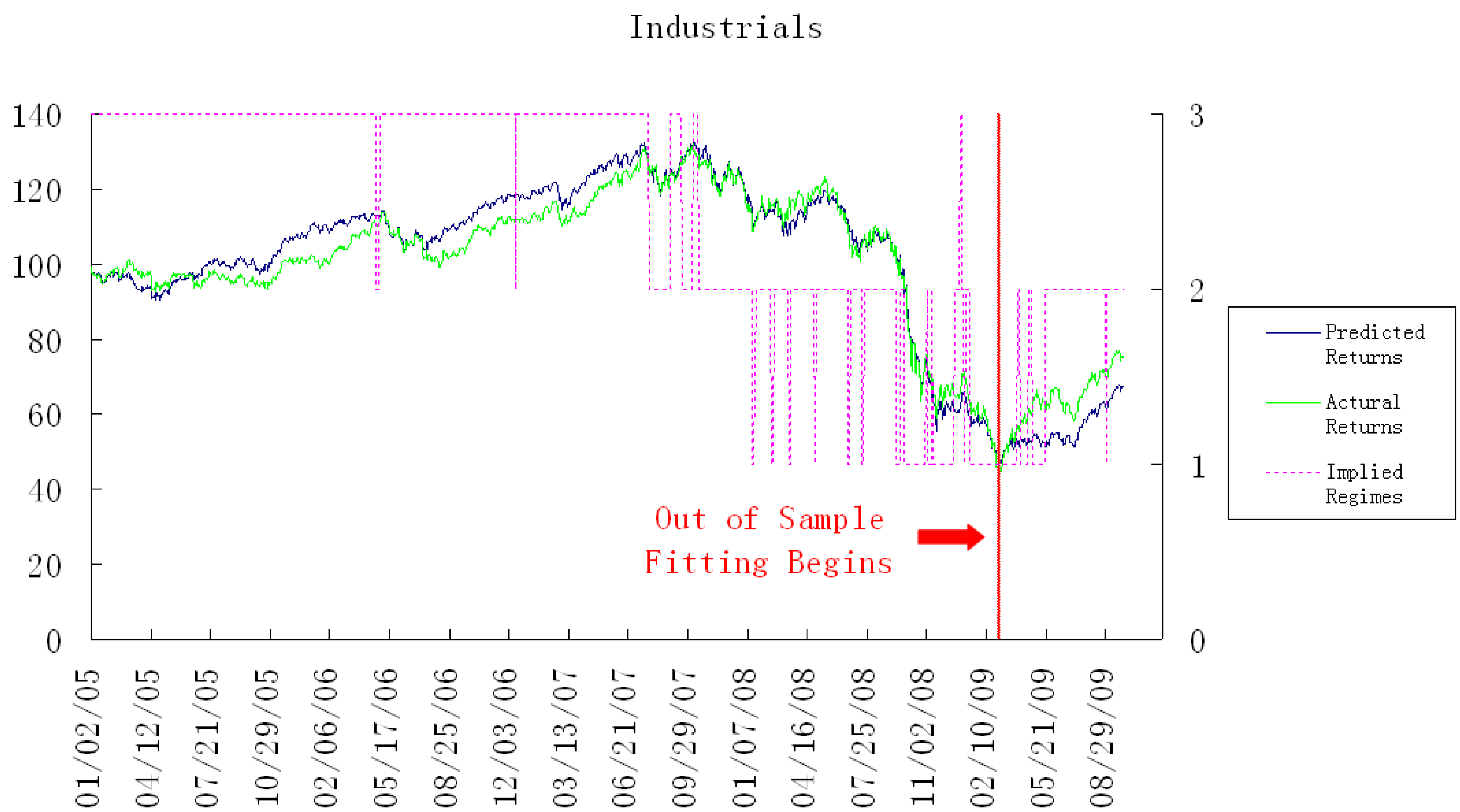

Figure 6: **XLI**. The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of $100 USD. The right vertical axis indicates regimes 1, 2, and 3. Regime 1 represents a bear regime. Regime 2 is considered a transition regime. Regime 3 is characterized as a bull regime.

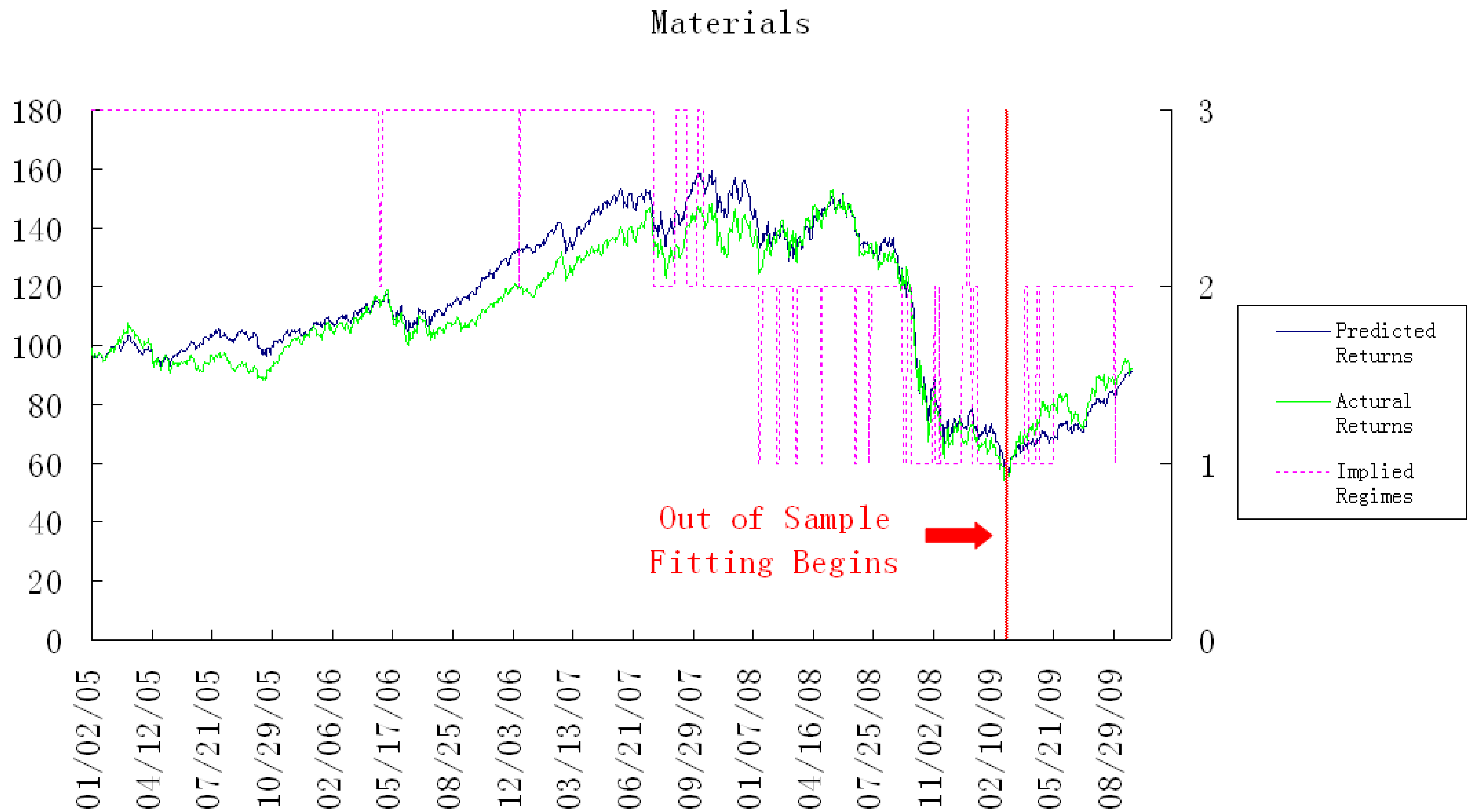

Figure 7: **XLB**. The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of \$100 USD. The right vertical axis indicates regimes 1, 2, and 3. Regime 1 represents a bear regime. Regime 2 is considered a transition regime. Regime 3 is characterized as a bull regime.

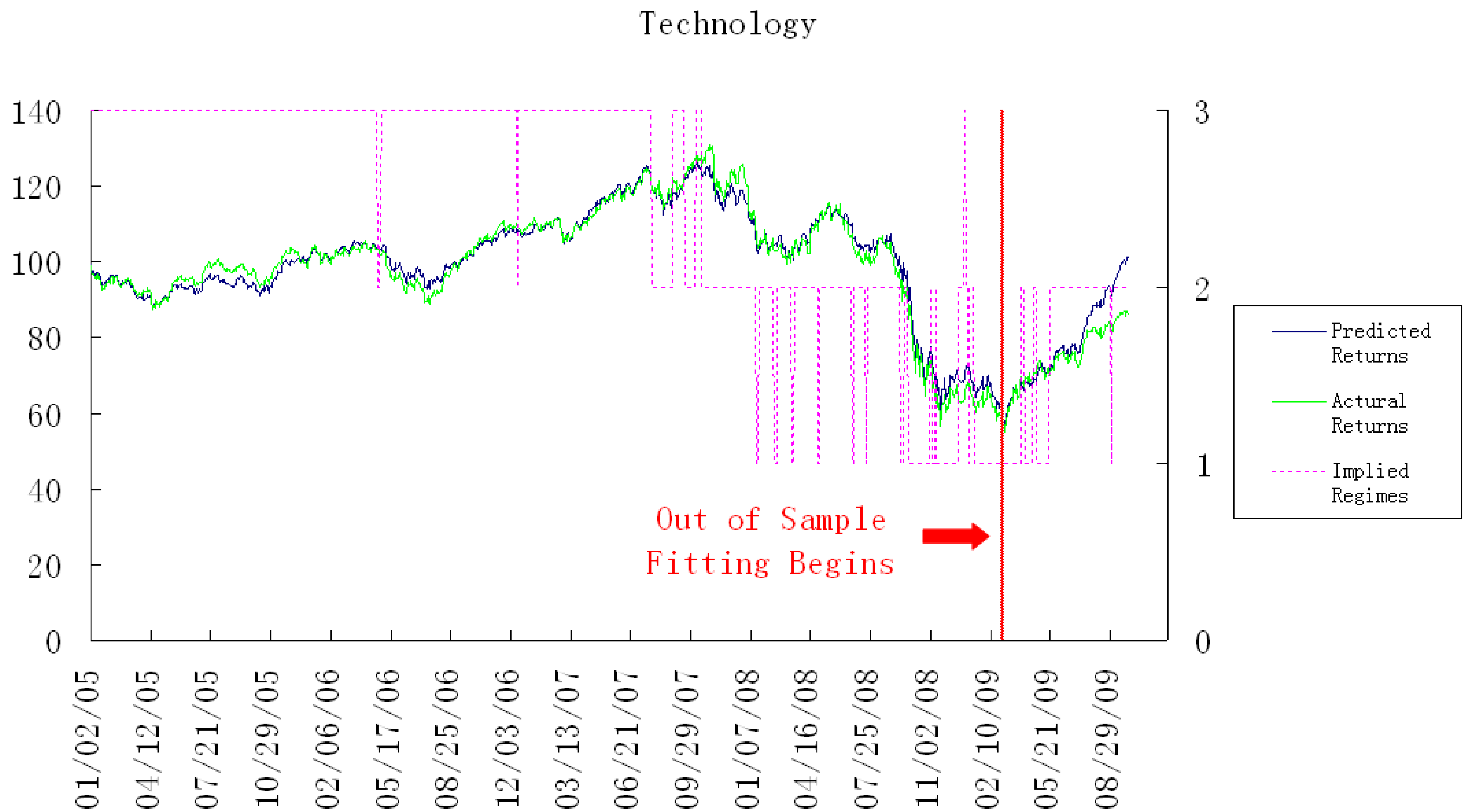

Figure 8: **XLK**. The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of $100 USD. The right vertical axis indicates regimes 1, 2, and 3. Regime 1 represents a bear regime. Regime 2 is considered a transition regime. Regime 3 is characterized as a bull regime.

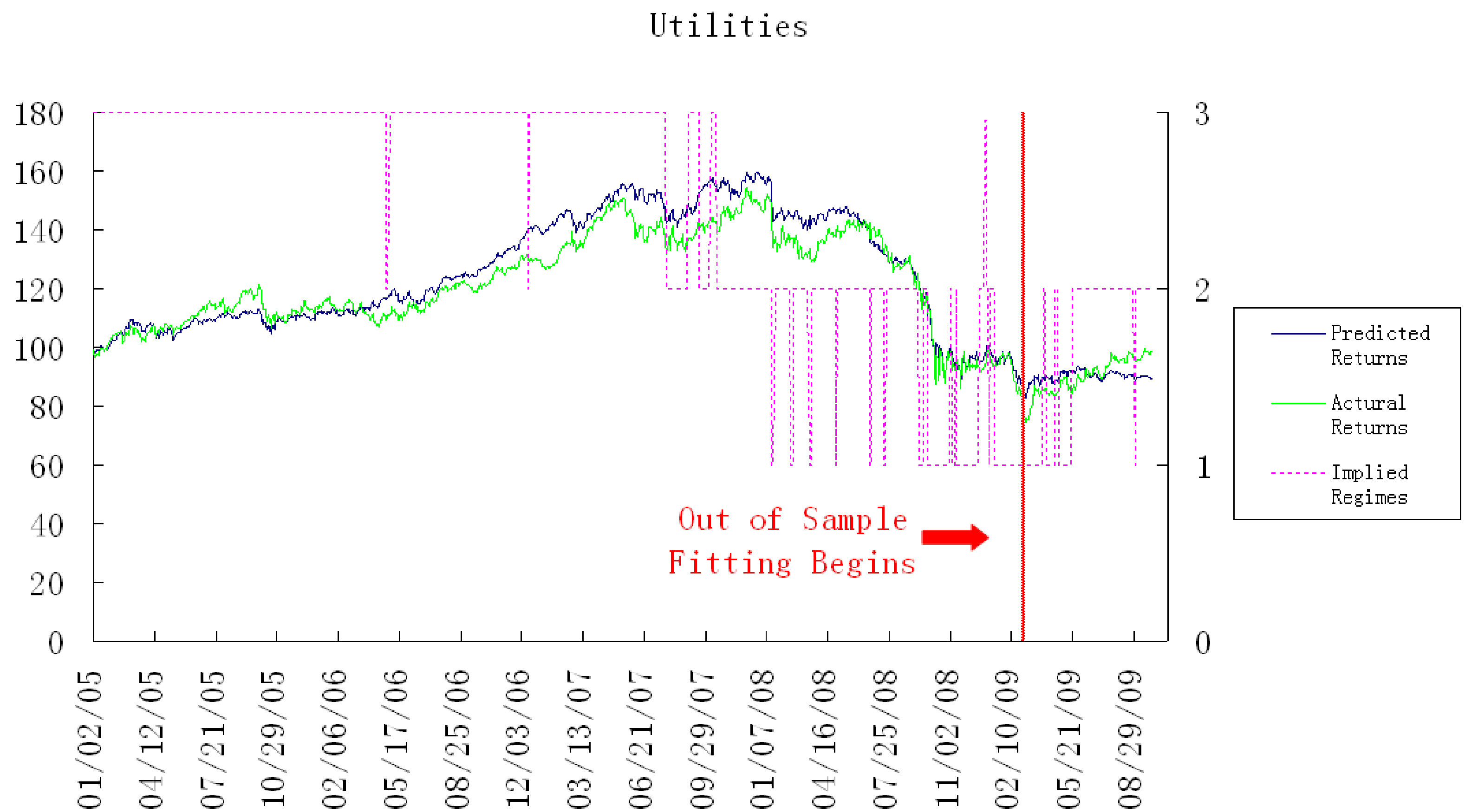

Figure 9: **XLU**. The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of $100 USD. The right vertical axis indicates regimes 1, 2, and 3. Regime 1 represents a bear regime. Regime 2 is considered a transition regime. Regime 3 is characterized as a bull regime.

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