



Market regimes, sectorial investments, and time-varying risk premiums

Market regimes

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Abstract

Purpose – This paper aims to extend 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.

Design/methodology/approach – First, the original FF model is augmented to include three additional macro factors – market volatility, yield spread, and credit spread. Then, the FF model is extended to a model with a Markov regime switching mechanism for bull, bear, and transition market regimes.

Findings – It is found that 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.

Research limitations/implications – 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.

Originality/value – This is the first research on Sector Select ETFs with Markov regime switching.

Keywords Markov processes, Time-varying control systems, Risk management, Compensation

Paper type Research paper

1. Introduction

Although empirical asset pricing models have been quite successful in characterizing returns, complex dynamics in asset returns are often ignored or assumed to be absent. Clearly, the financial market moves in 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 the standard linear models insufficient for characterizing equilibrium asset returns. The fact that asset returns are

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time-varying and experience rapid shifts makes it necessary to consider a model that accommodates complex dynamics beyond the standard asset pricing models.

A great deal of research effort has been devoted to relating 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 stated that “both theoretical and empirical developments in asset pricing have taken place within a well-established paradigm”. In this paradigm, asset prices are determined 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).

Active research focuses on the relationship between asset returns and common risk factors. The literature has considered some 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 counter-cyclical variation in stock returns (Fama and French, 1989; Lettau and Ludvigson, 1999).

The presence of stages or regimes in the financial market suggests a regime switching structure. The Markov regime-switching model has been applied to economic and financial modeling for decades. Hamilton (1989) applied a Markov switching model for the US 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 market volatility which switches 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:

- (1) What are plausible market regimes and what are their possible implications?
- (2) How frequently do these regimes switch?
- (3) When do these regimes change and what drives them to change over time?
- (4) Is regime switching predictable?
- (5) How do asset-pricing models for different assets change jointly across different regimes over time?

These questions motivate us to a rethinking of asset pricing models.

This research intends to address four issues that have not been considered in the context of linear factor models for the sector ETFs. First, empirical studies on factor models rely primarily on the standard linear regression analysis, even though market regimes exist and may reflect different market situations in which risk premiums may vary (e.g. Hamilton, 1989; Schaller and van Norden, 1997; Schwert, 1989; Turner *et al.*,

1989; Ang and Bekaert, 2002; Coggi and Manescu, 2004). Second, although 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. Third, not many researchers have investigated the performance of the sector ETFs, even though stock returns do vary across various sectors (e.g. Li *et al.*, 2006) and sector rotation in portfolio management is a common practice. Last, 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; Schwert, 1989) and market volatility has been used to explain bond yield and credit spreads (e.g. Collin-Dufresne *et al.*, 2001; 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. ETFs are attractive for a number of reasons. 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 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. 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 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. We find similar evidence as in Fama and French (1993) about the relation between asset returns and credit and yield spreads. That is, the 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 the returns of most sector 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. Section 2 discusses the regime-switching framework for the sector ETFs returns, the determination of the market regimes, and the estimation method. Section 3 discusses how to implement the regime-switching model and present new empirical findings for the sector 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 I is a typical report in Barron's showing the readings on a number of market sentiment indices such as the Consensus, AAI, 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]. As another example, during the internet bubble period (1998-2002), the stock market was extremely volatile, but the market volatility in the period of 2003–2006 was relatively low. The changes of market volatility sometimes cannot be justified by economic fundamentals alone. It is highly probable that market sentiment, market volatility, and the 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 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.

	Last week (%)	2 weeks ago (%)	3 weeks ago (%)
<i>Consensus Index</i>			
Consensus Bullish Sentiment	66	64	56
<i>AAI Index</i>			
Bullish	41.0	49.2	37.7
Bearish	26.0	23.0	37.7
Neutral	33.0	27.9	24.6
<i>Market Vane</i>			
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

Table I.
Stock market sentiment

Suppose the financial market regimes follow a Markov chain $\{M_t\}$ with a finite number of regimes 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:

$$R_t = \alpha_{M_t} + F_t \beta_{M_t} + \sigma_{M_t} \varepsilon_t \quad (1)$$

where R_t is the vector of returns on sector ETFs at time t , F_t is a vector of common risk factors at time t , and $\varepsilon_t \sim N(0, I)$. The model has a set of parameters $\{\alpha_{M_t}, \beta_{M_t}, \sigma_{M_t}\}$, which depends on the states of a Markov chain, M_t , with an initial state distribution q_0 and a transition probability matrix $P = [p_{ij}]$, where $p_{ij} = Pr[M_{t+1} = j | M_t = i]$ for all $i, j \in K$. 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 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 always provide a good fit for actual financial data, which are characterized by fat tails and multiple modes in empirical distributions. Hence, for the sector 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 exactly distinguish the return generating processes in different market regimes. As shown later in the paper, the sector ETFs returns display substantial skewness and excess kurtosis, which indicate sector ETFs returns indeed behave differently in different market regimes. Some sector 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 market regimes within which the 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 the 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 minimize the BIC index with the selection of the number of regimes K . The optimal number of regimes is the one that leads to the minimum value of $BIC(K)$, which is defined as:

$$BIC(K) = -2\ln(L|K, \Theta(K)) + f(K, \Theta(K))\ln(T). \quad (2)$$

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 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 the estimation of the model parameters. The estimation method is an adaptation of the EM algorithm, 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,

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

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:

$$\Theta^1 = \underset{\Theta}{\operatorname{argmax}} \{E^Q[\ln P(X, Y; \Theta)]\}. \quad (5)$$

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:

$$\Theta^1 = \underset{\Theta}{\operatorname{argmax}} \{E^Q[\ln P(X, Y; \Theta)]\}. \quad (6)$$

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:

$$\Theta^1 = \underset{\Theta}{\operatorname{argmax}} \left\{ \sum_{k=1}^K \sum_{t=1}^T P(M_t = k|X; \Theta^0) \ln P(R_t|M_t = k; \Theta) \right\}.$$

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 heuristic 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 an empirical analysis of 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 obtain the optimal number of market regimes that are inherent in the observed data. These market regimes are associated with market conditions and, eventually, will be used to explain ETFs returns in response to the 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 some research, ETFs can be traded 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 US 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 miss-pricing.

Among different management companies that offer sector ETFs, both Sector Select SPDRs 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 entire US stock market and they have a slightly longer trading history (started December 23, 1998) than other sector ETFs. Out of the ten sectors, the telecommunication sector ETF is not created because this sector consists of only nine companies in the Standard & Poor's 500 stocks. The remaining nine sectors are represented by the following sector ETFs:

- (1) Consumer Discretionary (XLY);
- (2) Consumer Staples (XLP);
- (3) Energy (XLE);
- (4) Financials (XLF);
- (5) Health (XLV);
- (6) Industrials (XLI);
- (7) Materials (XLB);
- (8) Technology (XLK); and
- (9) Utilities (XLU).

The daily returns on the sector 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 percent. 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 II. From the top panel of Table II, we see that Utilities, Consumer Staples, and Health Care ETFs have higher daily returns while Financials, Consumer

	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
<i>Correlation</i>									
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

Table II.
Summary statistics for
sector ETFs returns

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 Staples and Health Care ETFs have lower standard deviations. All sectors exhibit substantial skewness and excess kurtosis. This is a clear indication that the sector ETFs 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 II shows that the sector ETFs returns are all positively correlated. Energy and Health Care sector ETFs and Consumer Stable and Energy sector ETFs 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). While 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.

3.2 Style and macro factors

Following 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 the three macro factors (this is also called the six-factor model). We estimate both the six-factor model with a single regime as well as the regime-switching model with the factors.

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

- (1) the size factor (SMB); and
- (2) book-to-market factor (HML).

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

In addition to the MKT, SMB, and HML factors, other macro factors also influence stock returns. The yield spread (YS) factor is defined as the difference between the yield of the 20-year Treasury bond and the yield of the three-month Treasury bill offered by the US 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. The US 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]. The 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 *et al.* (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 keep the MKT, SMB and HML factors. We suspect that the information in the YS and CS factors may be better utilized in a regime-switching framework. In addition, the VIX factor has been used for bond credit spreads (Collin-Dufresne *et al.*, 2001; 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 Index captures changes in financial market sentiment.

The summary statistics for the chosen style and macro factors for the sample period are reported in Table III. As shown in the top panel of Table III, 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 lower 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 III. It is interesting to identify how these common risk factors are related. Table III 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.

	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
<i>Correlation</i>						
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 percentages

Table III.
Summary statistics for style and macro factors

3.3 Empirical findings

3.3.1 Optimal number of regimes. To identify the optimal number of regimes, we have estimated regime-switching models with different numbers of regimes (e.g. 1, 2, . . . , 5). Then we compare these models by evaluating the BIC. As shown in Table IV, the three-regime model appears to be the optimal choice, balancing the goodness of fit and parsimony, because this model has the lowest value (−6.9137) for BIC. The identification of three regimes appears to be consistent with the classification of bear, transition, and bull market regimes.

3.3.2 Transition probabilities and characterization of regimes. Once the optimal number of the regimes is determined, we can estimate transition probabilities and discuss the regimes of the financial market. The regime transition probabilities estimated for the chosen model are given in the following matrix, where each cell has a probability estimate and its *p*-value in 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 in 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. 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 the basis for interpreting the market regimes. Table V 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 the highest. This situation is 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 corresponds to

No. of regimes	1	2	3	4	5
MLL	3.2584	3.4791	3.5225	3.5383	3.5582
BIC	−6.4731	−6.8706	−6.9137	−6.9013	−6.8974

Table IV.
Optimal number of market returns

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

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

Table V.
Mean style and macro factors across regimes

Note: The numbers are shown as mean daily changes in percentages

a fall in both risk premiums on size and on market volatility. In regime 3, the relationship between the style and macro factors is reversed from that in regime 1, except for 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.

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 the 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 VI and VII.

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 to obtain parameter estimates. 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 to obtain a large sample of parameter estimates that are used to calculate standard errors. With these standard errors, we can perform hypothesis testing for the parameters in the regime-switching model. In Tables VI and VII, the p -values calculated from t -statistics for parameter estimates of the regime-switching model are calculated based on the bootstrap standard errors while those of the FF and the augmented FF models are based on the estimated standard errors.

3.3.4 Determinants of the sector ETFs returns. We now examine Tables VI and VII and discuss why the regime-switching model provides a better fit for the sector ETFs returns. In Table VI, the estimated intercept terms (α 's) in the FF and the augmented FF models 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 captures more market specific information than the FF and augmented FF models do.

Table VI.
Comparison of alpha estimates

	Regime 1		RS model Regime 2		Regime 3		3 Factor model		6 Factor model	
	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value
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

	MKT		SMB		HML		VIX		YS		CS	
	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value
<i>Con. discretionary</i>												
RS model												
Regime 1	0.0097	0.000	0.0038	0.000	0.0021	0.000	0.0510	0.0000	-0.0045	0.0000	0.0019	0.1085
Regime 2	0.0101	0.000	0.0019	0.000	0.0040	0.000	-0.0143	0.2326	0.0003	0.0248	-0.0001	0.5227
Regime 3	0.0096	0.000	0.0002	0.000	-0.0031	0.000	-0.0105	0.0000	0.0001	0.1743	0.0029	0.0000
Three-factor model	0.0096	0.000	0.0032	0.000	0.0013	0.000	-	-	-	-	-	-
Six-factor model	0.0096	0.000	0.0032	0.000	0.0014	0.000	0.0000	0.6450	-0.0003	0.2200	0.0002	0.7690
<i>Con. staples</i>												
RS model												
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
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
Three-factor model	0.0051	0.0000	-0.0003	0.298	-0.0011	0.0000	-	-	-	-	-	-
Six-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
<i>Energy</i>												
RS model												
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
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
Three-factor model	0.0125	0.0000	-0.0021	0.0050	0.0117	0.0000	-	-	-	-	-	-
Six-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
<i>Financials</i>												
RS model												
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
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
Three-factor model	0.0133	0.0000	-0.0039	0.0000	0.0019	0.0000	-	-	-	-	-	-
Six-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
<i>Health care</i>												
RS model												
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
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

(continued)

Table VII.
Comparison of beta estimates

Table VII.

	MKT		SMB		HML		VIX		YS		CS	
	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value
Three-factor model	0.0064	0.0000	-0.0006	0.0650	-0.0032	0.0000	-	-0.0001	-	0.0002	-	0.3120
Six-factor model	0.0064	0.0000	-0.0007	0.0480	-0.0033	0.0000	-	-0.0001	-	0.0002	0.0002	0.3210
<i>Industrials</i>												
RS model												
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
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
Three-factor model	0.0094	0.0000	0.0010	0.0010	-0.0002	0.4150	-	-	-	-	-	-
Six-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
<i>Materials</i>												
RS model												
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
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
Three-factor model	0.0114	0.0000	0.0009	0.0360	-0.0034	0.0000	-	-	-	-	-	-
Six-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
<i>Technology</i>												
RS model												
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
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
Three-factor model	0.0099	0.0000	-0.0007	0.0140	-0.0036	0.0000	-	-	-	-	-	-
Six-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
<i>Utilities</i>												
RS model												
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
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
Three-factor model	0.0073	0.0000	-0.0034	0.0000	-0.0025	0.0000	-	-	-	-	-	-
Six-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

Table VII 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 across the regimes for all sectors. This is consistent with the prediction of the CAPM and the FF model. However, 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. Also, different sector ETFs returns may have different sensitivities to the market portfolio return (MKT) in different market regimes. For example, the Financials sector ETF has the highest sensitivity to the market portfolio return in the bull regime while Energy and Materials sector ETFs have the highest sensitivity to the market portfolio return in the transition regime. Thus, the regime-switching model captures much more specific 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. However, 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, returns 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 were not previously available in the literature.

Now we discuss the two macro factors, CS and YS. The original FF model does not include 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 VIII 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.

To further 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.

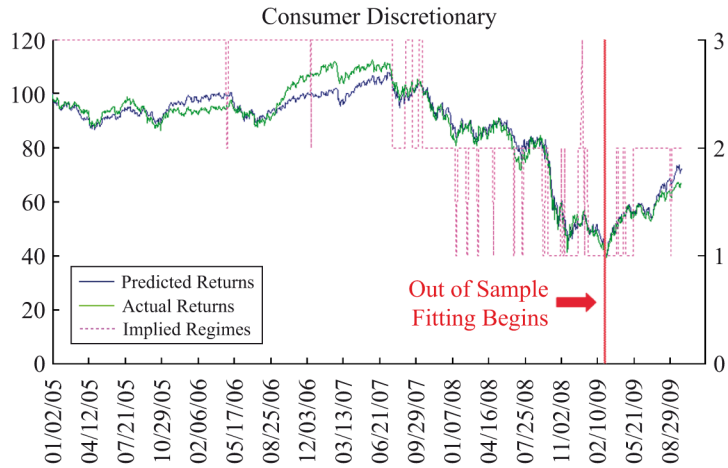
4. Concluding remarks

In this paper, we have extended the analysis of Fama and French (1992, 1993) to study the US Sector Select ETFs returns using a regime-switching model with macro and style factors. Using the novel approach, we find that these sector ETFs returns vary across the bear, transition and bull regimes over time. The volatility in the bear regime tends to be greater than that in the bull regime. The sector ETFs returns in each regime have a higher probability of remaining 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 probability 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.

Con. discretionary		Con. staples		Energy		Financials		Health care		Industrials		Material		Technology		Utility		
<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	<i>n</i>	<i>p</i> -value	
Regime 1																		
Con. Discretionary	0.00223	0.000																
Con. staples	0.00040	0.000	0.00149	0.000														
Energy	0.00023	0.000	-0.00001	0.3596	0.00533	0.000												
Financials	0.00010	0.000	-0.00029	0.000	-0.00206	0.000	0.00042	0.000										
Health care	-0.00012	0.003	0.00040	0.000	0.00012	0.000	-0.00051	0.000	0.00220	0.000								
Industrials	0.00035	0.000	-0.00004	0.2723	0.00041	0.000	0.00029	0.000	0.00029	0.000	0.00151	0.000						
Materials	-0.00010	0.000	-0.00044	0.000	0.00089	0.000	0.00029	0.000	0.00000	0.7952	0.00064	0.000	0.00281	0.000				
Technology	0.00027	0.000	0.00019	0.000	0.00040	0.000	-0.00049	0.000	-0.00027	0.000	-0.00008	0.000	-0.00036	0.000	0.00149	0.000		
Utilities	-0.00042	0.000	0.00051	0.000	-0.00069	0.000	0.00031	0.000	0.00053	0.000	-0.00020	0.000	-0.00055	0.000	0.00002	0.1224	0.00024	0.0000
Regime 2																		
Con. discretionary	0.00068	0.000																
Con. staples	0.00014	0.000	0.00038	0.000														
Energy	-0.00068	0.000	-0.00025	0.000	0.00206	0.000												
Financials	0.00022	0.000	0.00008	0.000	-0.00086	0.000	0.00127	0.000										
Health care	0.00014	0.000	0.00011	0.000	-0.00028	0.000	0.00008	0.001	0.00041	0.000								
Industrials	0.00001	0.000	0.00007	0.000	-0.00016	0.000	-0.00011	0.000	0.00003	0.000	0.00042	0.000						
Materials	-0.00020	0.000	-0.00011	0.000	0.00061	0.000	0.00038	0.000	-0.00009	0.000	0.00005	0.000	0.00069	0.000				
Technology	0.00014	0.000	0.00007	0.000	-0.00037	0.000	0.00004	0.040	-0.00003	0.000	0.00010	0.000	-0.00014	0.000	0.00046	0.000		
Utilities	0.00006	0.0322	0.00010	0.000	0.00019	0.000	-0.00011	0.000	0.00014	0.000	-0.00004	0.000	0.00005	0.0142	-0.00011	0.000	0.00093	0.0000
Regime 3																		
Con. discretionary	0.00014	0.000																
Con. staples	0.00003	0.000	0.00013	0.000														
Energy	-0.00016	0.000	-0.00011	0.000	0.00012	0.000												
Financials	0.00003	0.000	0.00002	0.000	-0.00022	0.000	0.00015	0.000										
Health care	0.00001	0.000	0.00003	0.000	-0.00009	0.000	0.00000	0.2327	0.00016	0.000	0.00014	0.000						
Industrials	0.00004	0.000	0.00001	0.000	-0.00008	0.000	-0.00001	0.2327	-0.00001	0.000	0.00004	0.000	0.00003	0.000				
Materials	-0.00002	0.000	-0.00002	0.000	0.00005	0.000	-0.00003	0.000	-0.00003	0.000	0.00004	0.000	-0.00002	0.000	0.00015	0.000		
Technology	0.00000	0.2800	-0.00001	0.000	-0.00007	0.000	-0.00002	0.000	-0.00003	0.000	0.00000	0.3359	-0.00002	0.000	0.00000	0.1736	0.00032	0.0000
Utilities	-0.00002	0.000	0.00004	0.000	-0.00006	0.000	-0.00001	0.0012	0.00003	0.000	-0.00001	0.000	-0.00006	0.000	0.00000	0.1736	0.00032	0.0000

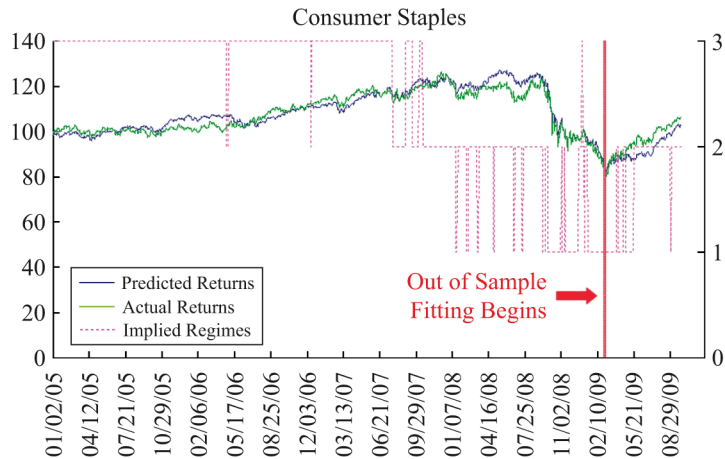
Note: This table reports the variance-covariance estimates for the regime-switching model

Table VIII.
Variance-covariance estimates for regime-switching model



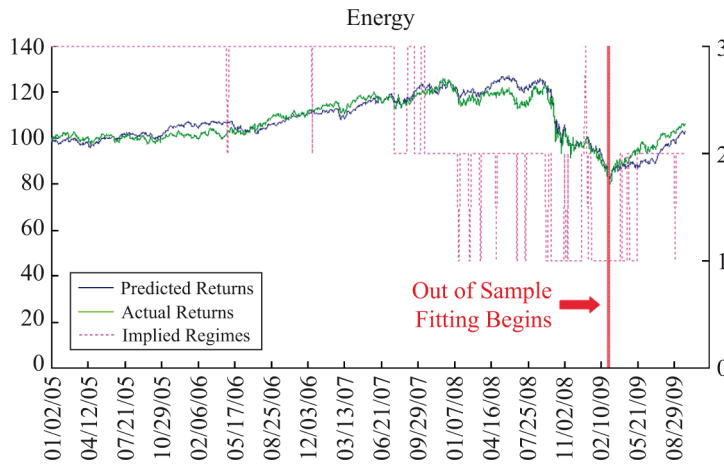
Notes: The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of \$100 USD. The right vertical axis indicates regimes 1, 2, and 3.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

Figure 1.
XLY



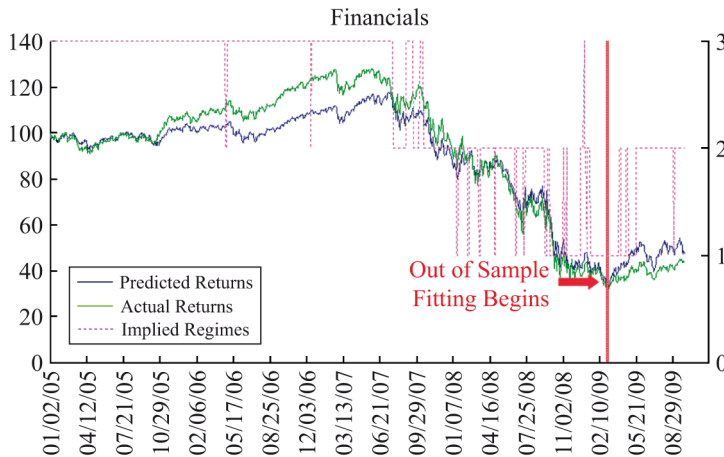
Notes: The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of \$100 USD. The right vertical axis indicates regimes 1, 2, and 3.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

Figure 2.
XLP



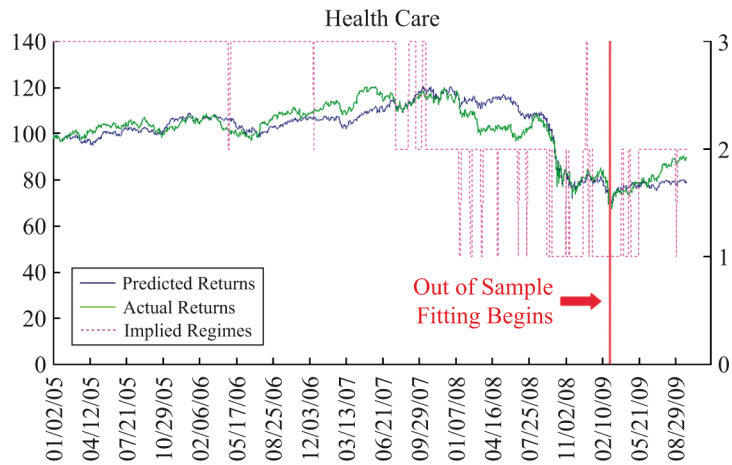
Notes: The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of \$100 USD. The right vertical axis indicates regimes 1, 2, and 3.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

Figure 3.
XLE



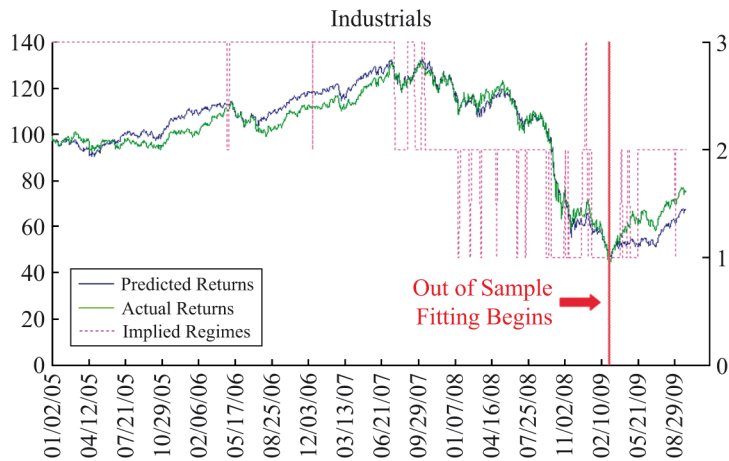
Notes: The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of \$100 USD. The right vertical axis indicates regimes 1, 2, and 3.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

Figure 4.
XLF



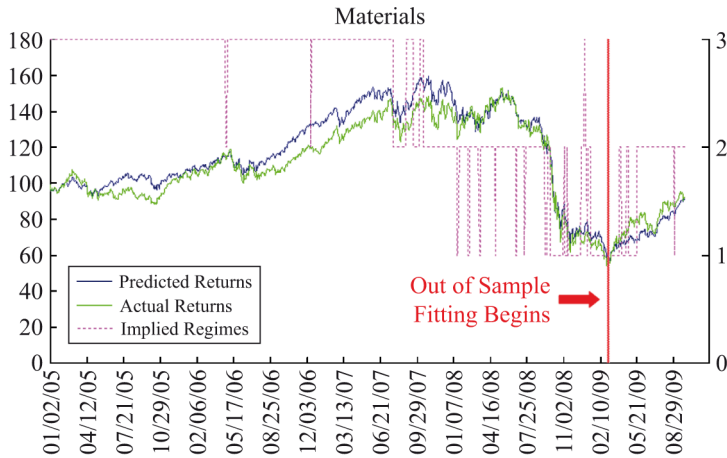
Notes: The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of \$100 USD. The right vertical axis indicates regimes 1, 2, and 3.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

Figure 5.
XLV



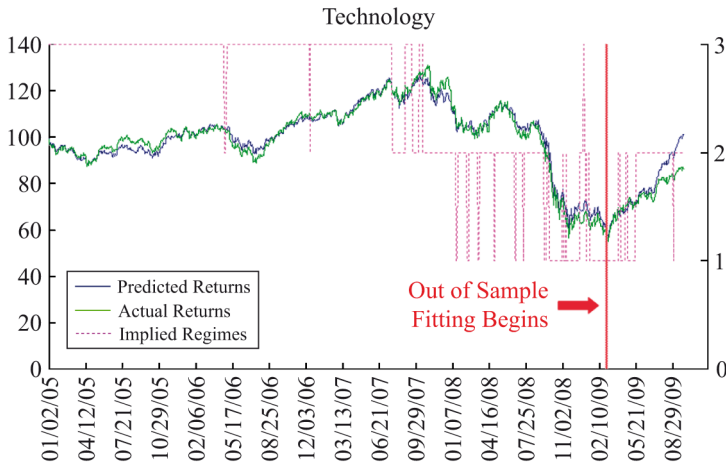
Notes: The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of \$100 USD. The right vertical axis indicates regimes 1, 2, and 3.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

Figure 6.
XLI



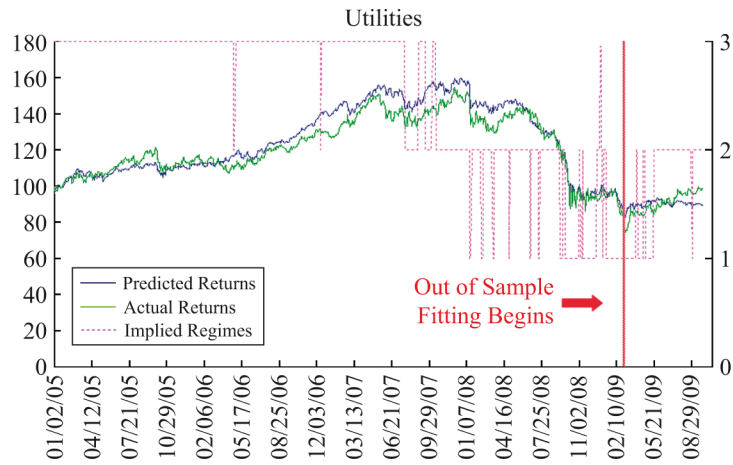
Notes: The actual returns and predicted returns based on the regime-switching model with implied regimes are plotted from January 3, 2009 to September 30, 2009. The left vertical axis indicates the cumulative returns of an investment of \$100 USD. The right vertical axis indicates regimes 1, 2, and 3.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

Figure 7.
XLB



Notes: 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.
XLB



Notes: 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

Consistent with the findings of Fama and French (1992), we find that the market portfolio return has a positive premium, and the size factor has a negative premium on these sector ETFs returns. However, the book-to-market factor is not positively related to the sector ETFs returns. In addition, this research confirms the findings of Fama and French (1993) that the yield and credit spreads do not affect the sector ETFs returns in the augmented FF model. For these sector ETFs returns, alpha estimates in the FF and augmented FF models are not statistically significant.

When regimes are introduced, the empirical results relating returns to factors by regime are somewhat different. In the regime-switching model, the yield and credit spreads contribute different premiums to the sector ETFs returns in different regimes. Finally, market volatility is negatively related to the returns of most 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. Because of its flexibility, the regime-switching model provides additional information about the sector ETF returns beyond the findings based on the FF and the augmented FF models.

Notes

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.
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.
8. In the previous studies, 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.
9. See 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.
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)
12. More specifically,

$$\begin{aligned} \text{SMB} = & \frac{1}{3}(\text{return on small value} + \text{return on small neutral} + \text{return on small growth}) \\ & - \frac{1}{3}(\text{return on big value} + \text{return on big neutral} + \text{return on big growth}). \end{aligned}$$

13. More specifically,

$$\begin{aligned} \text{HML} = & \frac{1}{2}(\text{return on small value} + \text{return on big value}) \\ & - \frac{1}{2}(\text{return on small growth} + \text{return on big growth}). \end{aligned}$$

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

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Further reading

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