Would Some Model Please Give Me Some Hints? An Empirical Investigation on Monetary Policy and Asset Return Dynamics

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Abstract

The purpose of this paper is to empirically investigate the forecasting performances for the housing and stock returns of various using SVAR models. Using US data $1975Q2 - 2008Q3$, we study various combinations of models with and without regime-switching. We then examine the in-sample and out-of-sample forecasts of these model, in particular, the out-of-sample forecasting on housing and stock returns for $2006Q1 - 2008Q3$.

Key words: monetary policy, term spread, stock prices, house prices, Markov Regime Switching, forecasting

JEL classification: E5, G0, R0

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"*The subprime crisis is the name for what is a historic turning point in our economy and our culture. It is, at its core, the result of a speculative bubble in the housing market that began to burst in the United States in 2006 and has now caused ruptures across many other countries in the form of financial failures and a global credit crunch... It is impossible to predict the nature and extent of the damage that the current economic and social dysphoria and disorder will create. But a good part of it will likely be measured in slower economic growth for years to come.*"

Robert Shiller, The Subprime Solution.

1 Introduction

The large fluctuations in house price and stock prices in recent years, and the subsequent subprime crisis, have posed challenges for economists and policymakers across countries. Take the recent real estate cycle for an example, the US average house price has grown consecutively around 1.6% for the period $1995Q4 - 2005Q4$, reaching a total of 89% in net gains. Figure 1 shows all the variables we are interested in: federal funds rates (hereafter FFR), term spreads (SPR), and growth rates of GDP (GDP), the return of the stock price index ($SRET$) and that of the house price index ($HRET$), covering the period of $1975Q1 - 2008Q3$. As shown in Figure 1, the return on housing started to decline around $2006Q1$ and then precipitated in the following quarters when the subprime mortgage problem aggravated.[1] Figure 1 also demonstrates the well known fact that the fluctuations of the stock returns are clearly much larger than those of housing returns.

(figure 1 about here)

[1]These are calculated using Office of Federal Housing Enterprise Oversight (OFHEO) house price index. The figures are more dramatic when S&P Case-Shiller U.S. National Home Price Index is used: the average growth rate is *2.1%* for the same period 1995Q4-2005Q4, resulting a total net gain of *135%*. The subsequent decline in house price growth was even more significant. However, the S&P Case-Shiller house price index traces back only from 1987Q1. Therefore, our empirical estimation in this paper uses OFHEO price index which can be traced back to 1975Q1.

Such fluctuations in asset prices and returns can have real effects. First, a continuous decline in asset price could lead to significant wealth effect in consumption (see Case, Quigley and Shiller, 2005, Campbell and Cocco, 2007, among others). Since the aggregate consumption constitutes almost *70%* of the total GDP, and since many countries target their export to the USA, such wealth effect can have important implications to the economies of both the U.S. and many countries. Second, a continuous decline in house prices can cause a quick decay of collateral quality and value, leading to a severe credit crunch and subsequent sharp rise in bankruptcy and foreclosures. Therefore, due to the importance of asset prices in collateralized lending and the role of asset prices in monetary transmission mechanism (Mishkin, 2001, 2007, and others), it is primarily important for researchers and policymakers to look ahead and predict the future movement of these asset prices. As a matter of fact, many financial intermediations have failed and the National Bureau of Economic Research, among others, has also admitted that an economic recession has started in the first quarter of 2008. When it will end, however, is still a topic for debate.

As many are writing on this topic, this paper complements the literature by focusing on a simple objective, which is to take an initial step in comparing the forecasting performances for the housing and stock returns of several models. To be more specific, we use US data $1975Q2-2008Q3$, and study various versions of SVAR (Structural Vector Auto-Regressive) models, with and without regime-switching. We then examine the in-sample forecasts for the period $1975Q1-2005Q4$ and the out-of-sample forecasts for the period $2006Q1-2008Q3$ of these models. Our choices can be easily justified. We choose $2005Q4$ as the cut-off point because the rises of house price growth rate starting 1990s peaked around the end of 2005. As it will become clear, we actually allow the models to "learn," i.e. allow the econometricians to regularly update their models as the subprime crisis unfold.

This paper differs from the literature in several dimensions. First, we use multi-variate regime-switching SVAR models, while many existing studies either use single-variate (i.e., the variable to be forecasted) model or employ linear VAR models and implicitly ruled out the possibility of regime switching. It may be a serious issue in monetary policy research. Sims and Zha (2006) employ sophisticated Bayesian econometrics techniques and find that the changes of monetary policy "were of uncertain timing, not permanent, and not easily understood, even today" and that models which "treat policy changes as permanent, nonstochastic, transparent regime changes are not useful in understanding this history." In addition, scholars have found that the stock market is better characterized as by a regime-switching model than a linear model (among others, see Maheu and McCurdy, 2000). Furthermore, the conduct of monetary policy has changed over time along changes in the chairman of the Fed and several episodes that dramaticall affect inflation and economic activity (such as oil price shocks). Thus, the multi-variate and comparison between single-regime (i.e. linear) and regime-switching models may be appropriate.

Second, we conduct out-of-sample forecasting using two different approaches: conditional expectations and simulation-based methods. While it is easier to conduct forecasting following the former, confidence intervals are not readily available. Following Sargent, Williams and Zha (2006) , we adopt the simulation-based approach to calculate the median path and the confidence interval. More discussion on this will be followed.

Third, we conduct forecasting on two asset prices, namely stock and housing, at the same time. Obviously, these two assets are the major forms of "store of value" in the modern economies. And for many, the retirement funds tie closely to the performance of the stock market. Therefore, the asset prices are not only "financial problems" but also important "macroeconomic problems." Needless to say, the literature of the predicting the two asset prices are long and huge. For the case of stock prices, they include those using financial ratios as predictive variables, such as the dividend-price ratio, the earnings-price ratio, and the book-to-market ratio (Fama and French (1988), Campbell and Shiller (1988), Goetzmann and Jorion (1993), Hodrick (1992), Pontiff and Schall (1998), and others), and dividend growth (Lettau and Ludvigson (2001), Menzly et al. (2004)). But recently others find these indicators less conclusive (Bossaerts and Hillion (1999), Goyal and Welch (2003), Lewellen (2004)). The forecasting of house prices may have achieved more success. Among others, Case and Shiller (1990), Clapp and Giaccotto (1994) and others, used a number of macro and local economic variables to forecast prices and excess returns to housing for periods up to one year ahead. Brown et al. (1997) add to earlier studies of British housing by allowing some coefficients of the forecasting equation to vary over time. Zhou (1997) uses a VAR model with time series data to conduct several tests of forecasting power using regressions on predicted values.

It is also easy to see why we study the house price and stock price in one paper. Usually, the returns of the two asset are imperfectly correlated and it is natural for agents to form some kind of portfolio in a dynamic setting (among others, see Yao and Zhang, 2005; Leung, 2007). Recent works identify channels in which the housing markets and stock returns are closely related (Lustig and Van Nieuwerburgh, 2005; Piazzesi, Schneider and Tuzel, 2007). Sutton (2002) presents evidence that a significant part of house price fluctuations can be explained by stock prices in six countries (USA, UK, Canada, Ireland, the Netherlands and Australia). A study by the Bank for International Settlements (2003) also shows that, for a large group of countries, house prices tend to follow the stock market with a 2–3 year lag. Kakes and End (2004) find that stock prices in Netherlands significantly affect house prices. On the other hand, Lustig and Van Nieuwerburgh (2005) find that U.S. housing collateral ratio predicts aggregate stock returns and investors seem to demand a larger risk compensation in times when the housing collateral ratio is low. Yoshida (2008) finds that the housing component serves as a risk factor in the pricing kernel of equities and this mitigates the equity premium puzzle and the risk-free rate puzzle.

Our inclusion of monetary policy variable in the study of asset price dynamics is motivated by a long history of discussion. For instance, the Federal Reserve was given credit for alleviating the negative macroeconomic impacts of the stock market crash in 1987 (Blinder and Reis, 2005). Some authors find evidence that monetary authorities may have responded to the stock market (Rigobon and Sack, 2003; Bohl et al., 2007). Further impulse for this debate comes from the more widely discussions and importance over the past several years given to the roles of the stock and housing market in the monetary transmission process (Chami et al., 1999; Mishkin, 2001, 2007). In this paper, we choose FFR to represent the movement of the monetary policy as Sims (1980a), among others, found that a considerable amount of the variations in monetary aggregates is predictable once information on past interest rates is taken into account.

We differ from some of the literature by explicitly including the interest rate spread in the empirical model. It is well known that the term structure contains information about future inflation, future real economic activities as well as asset returns.[2] Thus, it

[2]This statement has been confirmed by the data of the U.S. as well as other advanced countries. Among others, see Campbell (1987), Chen (1991), Fama (1990), Ferson (1989), Plosser and Rouwenhorst

may be instructive to include the term structure as a (partly) "forward-looking variable" in the regression without taking any stand on the formation of future inflation or interest rate expectation.[3] Furthermore, theoretically, asset returns and particularly real estate related assets returns, should respond at least as much to the long-term interest rate as to the short-term interest rate. Yet typically central banks can only influence the short rate directly. Thus, the transmission mechanism of how a monetary policy change leads to the asset market reactions in the presence of an endogenously adjusted term structure can be very interesting. Furthermore, there are studies relating the term structure and stock returns (e.g., Campbell, 1987). Hjalmarsson (2008) uses a panel of 40 countries and find that the short interest rate and the term spread are robust predictors of stock returns in developed markets. In contrast, earnings- and dividend-price ratios are found to have no strong or consistent evidence of predictability. In light of all these studies, it seem appropriate to introduce the interest rate spread into the empirical model.

The rest of the paper is organized as follows. Section 2 describes the econometric model and gives a statistical summary of the data. Section 3 presents the empirical estimation results with the baseline model, ...

2 The Econometric Analysis

2.1 Data

In this paper we use U.S. data for our analysis. Since the Office of Federal Housing Enterprise Oversight (OFHEO) house price index is available only in quarterly data, other variables originally available in monthly are transformed into quarterly. The federal funds rate is taken from H.15 statistical release ("Selected Interest Rates") issued by the Federal Reserve Board of Governors. As for the term spread, we follow Estrella

(1994), Estrella and Mishkin (1997), Estrella and Hardouvelis (1991), and the reference therein. For a review of the more recent literature, see Estrella (2005), Estrella and Turbin (2006), among others.

[3] In the literature of term structure, a lot of efforts have been devoted to verify the "expectation hypothesis." However, Collin-Dufresne (2004) shows that there are several versions of the expectation hypothesis and they are not consistent with one another. Thus, the explicit formulation of the expectation may matter to the final empirical result.

and Trubin (2006) by choosing the difference between ten-year Treasury bond yield and three-month T-bill rate, both are released by the Federal Reserve Board of Governors. Since the constant maturity rates are available only after 1982 for 3-month T-bills, we use the secondary market three-month T-bill rate expressed on a bond-equivalent basis.[4] Real GDP is taken from the Department of Commerce, Bureau of Economic Analysis, and finally, the S&P 500 stock price index is obtained from the DataStream. We compute stock and housing returns by taking the growth rates of the stock price index and housing price index respectively, thus the estimation covers the period $1975Q2 - 2008Q3$.

Table 1 gives a statistical summary for the variables in the data. The stock returns have a higher mean than housing returns, and have an even larger volatility than the housing returns. The simple correlation coefficients displayed in Table 2 shows that only the federal funds rate is significantly and negatively correlated with the spread, which is around -0.55. The housing market returns are only slightly positively correlated with stock returns. Other pairwise correlation coefficients are in generally low. A more careful investigation of the data will show that these variables are indeed significantly related, and the tool that we employ will be explained in the next section.[5]

(Table 1, 2 about here)

[4]The 3-month secondary market T-bill rate provided by the Federal Reserve System is on a discount basis. We follow Estrella and Trubin (2006) by converting the three-month discount rate (r^d) to a bond-equivalent rate (r): $r = \frac{365 \times r^d/100}{360 - 91 \times r^d/100} \times 100$. They argue that this spread provides an accurate and robust measure in predicting U.S. real activity over long periods of time.

[5]Notice that throughout this paper, nominal returns are used. Some recent studies of housing market also use nominal prices and returns instead of the real ones, including Himmelberg, Mayer, and Sinai (2005), Hott and Monnin (2008), among others. If we use real asset return, we would need to add the inflation rate as an additional variable. Due to the regime-switching nature of the model, the number of parameters to be estimated will significantly increase and will be a burden given our limited dataset. Also, the inflation rate would be correlated to the short rate and the long rate, which means that adding the inflation rate in the system could create some degree of multicollinearity. More importantly, to calculate the interest spread in real terms, we will need some independent measure for long term inflation expectation, which does not seem to be available. In fact, the literature tend to use the interest rate spread to "extract" long term inflation expectation.

2.2 The Econometric Model

The structural form of time varying vector autoregression model with lag length p for a process y_t:

$$A_0(s_t) y_t = \gamma(s_t) + A_1(s_t) y_{t-1} + A_2(s_t) y_{t-2} + ... + A_p(s_t) y_{t-p} + u_t(s_t), \qquad (1)$$

where we allow for all parameters, including intercept coefficients, autoregressive coefficients, and covariance matrix of stochastic terms to be contingent on the unobservable state variable $s_t \in S$. Structural VAR model is chosen because it imposes (relatively) less presumptions on the data structure, and it also conveniently parameterize the dynamic interactions within a system.[6] The time varying coefficients capture possible nonlinearities or time variation in the lag structure of the model. The stochastic volatility allows for possible heteroskedasticity of the stochastic terms.

The variables of interest $y_t = (y_{1,t}, y_{2,t}, .., y_{m,t})'$ is a $m \times 1$ vector. The stochastic intercept term $\gamma(s_t) = (\gamma_1(s_t), \gamma_2(s_t), .., \gamma_m(s_t))'$ captures the difference in the intercept under different states. $A_0(s_t)$ is a $m \times m$ state-dependent matrix which measures the contemporaneous relationship between variables and the econometric identification of the model is obtained through restrictions on $A_0(s_t)$. $A_k(s_t)$ is a $m \times m$ matrix with each element which is state-dependent $a_k^{(ij)}(s_t)$, $i, j = 1, .., m$, $k = 1, .., p$. The stochastic error term u_t will be explained below.

The corresponding reduced form of the above model can be obtained by pre-multiplying (1) by $A_0^{-1}(s_t)$, which yields:

$$y_t = \delta(s_t) + \Phi_1(s_t) y_{t-1} + \Phi_2(s_t) y_{t-2} + ... + \Phi_p(s_t) y_{t-p} + \epsilon_t(s_t), \qquad (2)$$

where $\delta(s_t) = A_0^{-1}(s_t)\gamma(s_t)$, $\Phi_k(s_t) = A_0^{-1}(s_t) A_k(s_t)$, and $\epsilon_t(s_t) = A_0^{-1}(s_t) u_t(s_t)$, $k = 1, 2, ...p$. $\Phi_k(s_t)$ is a $m \times m$ matrix with each element which is state-dependent $\phi_k^{(ij)}(s_t)$, $i, j = 1, .., m$, $k = 1, .., p$. We further define

$$\delta(s_t) \equiv c + \alpha(s_t),$$

which will be explained below. The vector of stochastic error term ϵ_t can be further expressed as

$$\epsilon_t = A_0^{-1}(s_t) u_t = \Lambda(s_t) H^{1/2} v_t(s_t),$$

[6] Among others, see Sims (1980) for more discussion on these issues and the potential biases that could be eliminated by the VAR method.

where H is a $m \times m$ diagonal matrix with diagonal elements σ_j^2, $j = 1, .., m$, $\Lambda(s_t)$ is a $m \times m$ diagonal matrix with diagonal elements $\lambda_j(s_t)$, $j = 1, .., m$,

$$\Lambda(s_t) = \begin{bmatrix} \lambda_1(s_t) & 0 & \cdots & 0 \\ 0 & \lambda_2(s_t) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_m(s_t) \end{bmatrix},$$

which captures the difference in the intensity of volatility, and $v_t(s_t)$ is a vector of standard normal distribution, $v_t(s_t) \sim N(0, \Sigma(s_t))$, where the covariance matrix is given by

$$\Sigma(s_t) = \begin{bmatrix} 1 & r_{21}(s_t) & \cdots & r_{m1}(s_t) \\ r_{12}(s_t) & 1 & \cdots & r_{m2}(s_t) \\ \vdots & \vdots & \ddots & \vdots \\ r_{1m}(s_t) & r_{2m}(s_t) & \cdots & 1 \end{bmatrix}. \tag{3}$$

2.3 Two-state Markov Process

Following the literature of Markov Switching, and being limited by the sample size, we assume that there are only two states, i.e., $s_t \in S = \{1, 2\}$. The procedure of the identification of the regime of the economy for a given period will be discussed below. The Markov switching process relates the probability that regime j prevails in t to the prevailing regime i in $t-1$, $Pr(s_t = j \mid s_{t-1} = i) = p_{ij}$. The transition probabilities are assumed to be fixed and the transition matrix is given by:

$$P = \begin{pmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{pmatrix}.$$

Given that the economy can be either in state 1 or state 2, the term $\alpha_j(s_t)$, $j = 1, .., m$, defined above, captures the difference in the intercept under different states. For convenience, we set $\alpha_j(1) = 0$ for $s_t = 1$, thus $\alpha_j(2)$ measures the difference in the intercept between state 2 and state 1. Furthermore, we set the diagonal element of $\Lambda(s_t)$ at state 1 to be unity, i.e., $\lambda_j(1) = 1$, so that if $\lambda_j(2) > 1$, then the intensity of volatility in state 2 is larger than that in state 1, and vice versa.

Since $v_t(s_t)$ is a vector of standard normal distribution and $\lambda_j(1)$ is set to be one, the variance of $y_{j,t}$, $j = 1, .., m$, at state 1 is σ_j^2, and the variance is $\lambda_j^2(2)\sigma_j^2$.

2.4 Identification of Regimes

We then discuss the identification of regimes in this model. Since the state of the economy is unobservable, we identify the regime for given a time period by Hamilton's (1989, 1994) smoothed probability approach, in which the probability of being state s_t at time t is given by $\pi(s_t \mid \Omega_T)$, where $\Omega_T = \{y_1, y_2, ..., y_t, ..., y_T\}$. The idea is that we identify the state of the economy from an ex post point of view, and thus the full set of information is utilized. Notice that we only allow for two regimes in this paper, i.e., $s_t \in S = \{1, 2\}$. Thus, if $\pi(s_t = j \mid \Omega_T) > 0.5$, then we identify the economy most likely to be in state j, $j = 1, 2$.

2.5 Forecasting

After we have estimated all the above models, we use the calculated the smoothed probabilities for evaluating the forecasting performances of house and stock prices across various models. Following the convention of the literature, we examine both in-sample and out-of-sample forecasting performances.

We conduct out-of-sample forecasting starting $2006Q1$, and thus we divide the sample into in-sample period $1975Q2 - 2005Q4$ and out-of-sample period $2006Q1 - 2008Q3$. We then proceed out-of-sample forecasting in two different approaches.

First, given the estimation window $1975Q2 - 2005Q4$ and a forecasting horizon $h = 1, ..., 4$, the estimated parameters are used to forecast house and stock prices h-steps ahead outside the estimation window, using the smoothed transition probabilities. The h-steps ahead forecasted value of z_{t+h} based on information at time t, Ω_t, is given by

$$E(z_{t+h} \mid \Omega_t) = \sum_{i=1}^{2} E[z_{t+h} \mid s_{t+h} = i, \Omega_t] \times p(s_{t+h} = i \mid \Omega_t),$$

where $z_t \in y_t$. The estimation window is then *updated* consecutively with one observation and the parameters are re-estimated. Again the h-steps ahead forecasts of house and stock prices are computed outside the new estimation window. The procedure is iterated till the final observation $2008Q3$. The forecasts based on this method is basically to compute the h-steps ahead conditional expectations of the variable being predicted. Most existing (non-Bayesian) works follow this method.

Second, instead of computing the conditional expectations of the variable being predicted, we simulate the path of the forecasted values by repeated drawings. The procedure is as follows.

- (Step 1) We estimate the model using the estimation window $1975Q2-2005Q4$ and obtain the parameters, transition probabilities, and variance-covariance matrix. Given the estimation results we compute the smoothed probabilities to identify the regime at the period $2005Q4$.

- (Step 2) Given the regime at the period $2005Q4$, we simulate the path of h-step ahead regimes by random drawing, $h = 1, ..., 4$.[7] Given this particular path of h-step ahead regimes, we can obtain the path of predicted values of $z_t \in y_t$ from (2).

- (Step 3) We iterate step 1 and 2 for $50,001$ times to obtain the median of the h-step ahead forecasted values during $2006Q1-2006Q4$ and their corresponding confidence intervals.

We then update the data with four observations and repeat Step 1-3 to simulate the path of predicted values for the next four quarters. This procedure is repeated till the end of our sample.

An advantage over computing the mean of possible future values in the first approach is that this method takes full account of the regime switching model by determining the path of future regimes using random drawing, rather than simply taking expectations over transition probabilities. Another advantage is that we can generate a confidence interval by which to evaluate its forecasting performances.

To evaluate the performances of in-sample and out-of-sample forecasts, we compute two widely-used measures for forecasting a variable $z_t \in y_t$, Root Mean Square Errors ($RMSE$) and Mean Absolute Errors (MAE), which are defined respectively as

$$RMSE(h) = \left[\frac{1}{T-h} \sum_{t=1}^{T-h} \left(z_{t+h} - \widehat{z}_{t+h|t} \right)^2 \right]^{1/2},$$

[7] For example, suppose the regime identified at the time $2005Q5$ is state 1, we use the transition probabilities p_{11} and p_{12} to generate the state at the period $2006Q1$. Specifically, we draw a value v from a uniform distribution $U[0,1]$. The state at $2006Q1$ is state 1 if $v \in (0, p_{11})$, and is state 2 if otherwise. Suppose we have identified the state at $2006Q1$ to be state 2, then we use the transition probabilities p_{21} and p_{22} to generate the state at the period $2006Q2$. Therefore, we will be able to simulate the path of h-step ahead regimes.

$$MAE(h) = \frac{1}{T-h}\sum_{t=1}^{T-h}\left|z_{t+h} - \widehat{z}_{t+h|t}\right|,$$

where $\widehat{z}_{t+h|t} \equiv E\left(z_{t+h} \mid \Omega_t\right)$.

3 Estimation Results

We will estimate a series of models and compare their forecasting performances. Due to limited availability of data, we keep the model as parsimonious as possible to constrict the number of parameters to be estimated. We estimate the following five models: Model A (Single-regime model (FFR, SPR, GDP, $SRET$, $HRET$)); Model B (Single-regime model (FFR, GDP, $SRET$, $HRET$)); Model C (Two-regime model (FFR, GDP, $SRET$, $HRET$)); Model D (Single-regime model (FFR, SPR, $SRET$, $HRET$)); Model E (Two-regime model (FFR, SPR, $SRET$, $HRET$)).[8] When considering regime switching models, we allow all parameters to be state contingent. As discussed above, the purpose for considering GDP and term spread respectively is that both variables may contain information for future movements of asset returns. Furthermore, the interactions of stock returns and housing returns may also affect the movement of either one of these returns.

The estimation results of the five models using the estimation window $1975Q2-2005Q4$ are displayed in Table 3-5. In general, a model allowing for regime switching attains a low value of Akaike's information criterion (AIC) and a higher log-likelihood value. Furthermore, among these five models, the two-regime model (FFR, SPR, $SRET$, $HRET$) has the best goodness of fit, i.e., a significantly lower value of AIC than other models.

(Table 3, 4, 5 about here)

For the Markov switching model, recall that we set the volatility at regime 1 $\lambda_j(1) = 1$, thus the element $\lambda_j(2)$ measures the relative volatility of regime 2 over regime 1. From Table 4 (model C) and Table 5 (model E), we can see that the estimated values of relative

[8]For the purpose of parsimony and model comparison, we set the lag period of all models to be one ($p = 1$). It turns out that most models with one lag period have the lowest value of AIC, compared with models having more than one lag periods. Details are available upon request.

volatility $\lambda_j(2)$ are all significantly less than one for $j = 1$ and 2, which means that for both federal funds rate and the spread the volatility in regime 2 is lower than in regime 1. On the other hand, most of the $\lambda_3(2)$ and $\lambda_4(2)$ are insignificant, suggesting that for the quarterly stock and housing returns there is *no significant difference in volatility across regimes*. Thus, the regime-switching Model C and Model E here identifies two regimes for this monetary policy tool: a high volatility regime (regime 1) and a low volatility regime (regime 2). The transition probability matrix for (FFR, GDP, $SRET$, $HRET$) is given by

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} = \begin{pmatrix} 0.939 & 0.061 \\ 0.010 & 0.990 \end{pmatrix},$$

and for (FFR, SPR, $SRET$, $HRET$),

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} = \begin{pmatrix} 0.948 & 0.052 \\ 0.010 & 0.990 \end{pmatrix},$$

which shows that both regimes are highly persistent for both models. For example, the expected duration of regime 1 is $1/(1 - p_{11}) = 16$ quarters for the former model and $1/(1 - p_{11}) = 19$ quarters for the latter. In other words, it may not be easy to predict the timing of a change in regime.

Given the estimated parameters, transition probabilities, and variance-covariance matrix, we compute the smoothed probabilities for Model C and Model E, respectively, as shown in Figure 2 and 3. The left panels show the probabilities of the economy being in regime 1 (high volatility regime) at a given period. The right panels mirror the left, showing the probabilities of being in regime 2 (low volatility regime). The periods that are identified as regime 1 are close for these two models: for the model (FFR, GDP, $SRET$, $HRET$), the periods $1978Q2 - 1982Q3$ are in regime 1, taking up 14.63% of the total sample periods, while for the model (FFR, SPR, $SRET$, $HRET$), the periods $1979Q4 - 1985Q1$ are in regime 1, accounting for 17.89% of the sample. The periods in regime 1 correspond to the aftermath of the second oil crises and P. Volcker being appointed as Chairman of the Federal Reserve.[9]

(Figure 2, 3 about here)

[9]Among others, Goodfriend and King (2005), Goodfriend (2007) provides a summary of the history of monetary policy during that period.

4 Forecasting

We now proceed to forecast stock and housing returns from 2006Q1 to 2008Q3. As discussed above we first conduct in-sample forecasting and then examine the out-of-sample forecasts using respectively the expectations-based and simulation-based methods.

4.1 In-Sample Forecasting

Tables 6-8 show $RMSE$ and MAE of in-sample h-steps ahead forecasts, $h = 1, ..., 4$, for each variable across five models. There are several findings. First, for the in-sample forecasts of house price, both $RMSE$ and MAE are increasing monotonically in forecasting horizon. That is, the forecasting performance is getting poorer as the forecasting horizon is longer. This is true for both criteria and for all models, single-regime or regime-switching model.

(Tables 6, 7, 8 about here)

Second, the in-sample forecasts of stock price are mixed. For single-regime models (Model A, B, D), the forecasting performances are getting better as the forecasting horizon is longer, though non-monotonically in some cases. For regime-switching models (Model C and E), except the criterion $RMSE$ for the model (FFR, SPR, $SRET$, $HRET$), the performances get worse non-monotonically in the forecasting horizon.

Third, except for the housing returns in the single-regime model, the 4-variate model with term spread (SPR) *in general performs better* than the model with GDP. This suggests that over the entire period for which data are available the average relationship between asset returns and the term spread are closer than that between asset returns and GDP.

Finally, When focusing on 4-quarter ahead forecasts, the regime-switching model (FFR, SPR, $SRET$, $HRET$) is a clear winner on all accounts for forecasting both stock and housing returns.

4.2 Out-of-Sample Forecasting

As mentioned above, we focus on out-of-sample forecasts of housing and stock returns beginning $2006Q1$, at the time when the growth of housing returns began to decline and the sub-prime crisis started to unfold.

We first conduct out-of-sample forecasting by using the conditional-expectations predictions. Tables 6, 9, and 10 display $RMSE$ and MAE of out-of-sample h-steps ahead forecasts, $h = 1, ..., 4$, for each variable across five models.

A number of interesting observations can be made. First, as the in-sample forecasts of house price, the forecasting performances are decreasing monotonically in forecasting horizon, for both criteria and for all models. Second, unlike the in-sample forecasts of stock price, the performances for out-of-sample forecasts of stock returns are decreasing monotonically in forecasting horizon, for both criteria and for all models. Third, in contrast to the in-sample forecasts, the 4-variate model with term spread (SPR) does not necessarily perform better than the model with GDP for out-of-sample forecasts. *Finally, for out-of-sample forecasts of housing returns, the regime-switching model (FFR, SPR, $SRET$, $HRET$) performs best. But for out-of-sample forecasts of stock returns, the single-regime model (FFR, SPR, GDP, $SRET$, $HRET$) performs best.*

(Tables 9, 10 about here)

We next turn to simulation-based forecasting. We consider a forecasting window of 4 quarters starting 2006Q1, with h-quarter ahead forecasts, $h = 1, ..., 4$. After simulating the out-of-sample path 2006$Q1 -$ 2006Q4 based on observations up to 2005Q4, the data is updated with four observations and the parameters are re-estimated. The procedure is iterated till the final observation 2008Q3. The purpose of this exercise is to see how the performances of the models change when information is updated. The simulated paths together with their 90-percent confidence intervals are shown in Figures 4-6 for stock returns and Figures 7-9 for housing returns.

(Figures 4-6 about here)

For the predictions of stock returns, the predicted paths of the first two forecasting windows (Figure 4 and 5) and actual data are well within the boundaries of the 90-percent confidence intervals for all five models. In a sense, although the models did not predict what have actually happened in 2006 and 2007, the models' predictions are not that "far off the mark." But the last window (2008$Q1 -$ 2008Q3 in Figure 6) performs less well: the data of the first and third quarters of 2008 lie outside the confidence interval of the simulated path across five models. In other words, the stock returns in 2008 are the real "surprises." And there are no clear winners in the prediction of stock returns.

For the predictions of housing returns, the forecasting performances of all five models in a sense "deteriorate" much faster than the predictions for stock returns. Figure 7 shows that the models basically capture the downward trend of the housing return in 2006 and although the path of housing return declines much faster than all models' prediction, it is still contained in the 90% confidence intervals. Unfortunately, figure 8 seems to suggest that the models to be misled by the "bound back" of housing return in *2006Q4*, which results in basically "flat predictions" of the 2007 returns. The reality is much worse and hence the year 2007 are basically outside the confidence intervals of all models. Interestingly, figure 9 shows that there is another "bound back" of housing return in the *2007Q4*. This time all the models even predict that the housing returns will increase continuous and the confidence intervals are increasing in values over time. The reality again disappoints. As a result, for the forecasting window $2008Q1-2008Q3$, the data lie completely outside the confidence interval. Furthermore, the direction of the predicted paths is also wrong. And again, there is no clear winner in the house return out-of-sample forecasting.

(Figures 7-9 about here)

To further illustrate the results of simulation-based forecasts, we display forecasts of housing and stock returns based on these two approaches side by side together with data in Figures 10-15. Also for expositional clarity, we show those three models that perform better based on criteria $RMSE$ and MAE demonstrated above, Model A: Single-regime model (FFR, SPR, GDP, $SRET$, $HRET$); Model C: Two-regime model (FFR, GDP, $SRET$, $HRET$); and Model E: Two-regime model (FFR, SPR, $SRET$, $HRET$). In each figure, the left-hand-side panel shows the conditional-expectations predicting paths, and the right-hand-side panel shows the the simulation-based predicting paths. In figures 10-12, they look very similar to each other. In figure 13, it shows a slight difference. On the left hand side, the conditional means of the two regime-switching models (C and E) basically follow the same trend as the data, yet there is a gap in terms of the values. On the right hand side, the median path from simulation continue to decrease after the data path "rebounds" and hence fails to capture the "trend." Yet the difference between the model predictions and the data are actually decreasing. Thus, the conditional mean method seems to be (marginally) better in capturing the trend, while the simulation-based method is better in closing the gap between the data and the model predictions. Figure 14 shows the same pattern. On the left hand side, as the data rebounds in the 2007Q4, so are the (conditional mean) predictions of the two regime-switching models (C and E). On the right hand side, the median path from simulation-based method are almost flat and hence the gap between the data and the model prediction are actually smaller after the 4th quarter rebounds. Thus, there may be a trade-off in choosing models for forecasting.

(Figures 10-15 about here)

5 Concluding Remarks

Dramatic movements in asset prices often occupy media headlines and carry implications in real economic activities, even political personnel changes. Thus, market practitioners, academic researchers and policymakers alike share strong interest in the understanding as well as the prediction of the asset price dynamics. Yet forecasting asset prices and returns are always difficult, especially at a time of financial crisis. Sanders (2008, p.261) expresses a similar view, "The sudden paradigm shift in 2005 and 2006 demonstrates that markets can change dramatically and the most sophisticated models can be taken by surprise." This paper presents the in-sample fitting as well as the out-of-sample forecasting of the asset return dynamics, with the effect of GDP growth and monetary policy taken into consideration. While the in-sample fitting is reasonably well, the out-of-sampling forecasting performances are somewhat disappointing. Given the data from 1975 to 2005, the path of 2006 housing and stock returns are actually within the 90% confidence intervals of our models. When the model is updated with the 2006 data, the 2007 stock returns are still within the 90% confidence intervals of the models. The 2007 housing returns, however, are well outside those intervals. In the year 2008, there is no model which can provide a 90% confidence interval for either the stock or housing returns.

In terms of the out-of-sample forecasting, we actually compare the performance of two methods: those based on conditional mean computation, and the median path that based on simulation. We find that in the case of stock returns, the two methods do not display any difference. In the case of housing return, however, the conditional mean seems to capture the "trend" of the data movement. In terms of the absolute difference between the data and the prediction, the median path method seems to perform better. This may mean that there are indeed trade-offs for different forecasting methods and perhaps it is advisable to use multiple methods in practice.

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Table 1 Statistical Summary of Federal Funds Rate, Term Spread, Gross Domestic Production Grwoth Rate, Stock Index Return and Housing Market Return (1975Q2-2008Q3)

	FFR	SPR	GDP	SRET	HRET
Mean	6.397	1.502	0.759	1.968	1.344
Median	5.563	1.604	0.731	2.263	1.313
Maximum	17.780	3.611	3.865	18.952	4.511
Minimum	0.997	−2.182	−2.038	−26.431	−2.713
Std. Dev.	3.508	1.335	0.750	7.659	1.040
Skewness	1.037	−0.627	−0.127	−0.664	−0.040
Kurtosis	4.283	2.941	6.150	4.070	4.691
Observations	134.000	134.000	134.000	134.000	134.000

Note: FFR denotes the federal funds rate, SPR denotes term spread, GDP means the gross domestic production grwoth rate, SRET means stock index return, and HEIT means housing market return.

Table 2 Correlation Coefficients (1975Q2-2008Q3)

	FFR	SPR	GDP	SRET	HRET
FFR	1.000	−0.557	−0.104	0.009	0.015
SPR		1.000	0.145	0.021	−0.115
GDP			1.000	0.030	0.111
SRET				1.000	0.055
HRET					1.000

Table 3 The Estimation Results for (FFR, SPR, GDP, SRET, HRET) (1975Q2-2005Q4)

Parameter	Estimate	S.E.
c_1	−0.579	1.132
$\phi_1^{(11)}$	0.977***	0.086
$\phi_1^{(12)}$	0.001	0.306
$\phi_1^{(13)}$	0.227	0.193
$\phi_1^{(14)}$	0.018	0.015
$\phi_1^{(15)}$	0.341*	0.189
σ_1^2	0.894***	0.302
c_2	0.561	0.659
$\phi_1^{(21)}$	0.001	0.052
$\phi_1^{(22)}$	0.853***	0.169
$\phi_1^{(23)}$	−0.061	0.101
$\phi_1^{(24)}$	−0.016	0.010
$\phi_1^{(25)}$	−0.180*	0.109
σ_2^2	0.419***	0.096
c_3	0.248	0.274
$\phi_1^{(31)}$	−0.010	0.028
$\phi_1^{(32)}$	0.133*	0.070
$\phi_1^{(33)}$	0.236**	0.106
$\phi_1^{(34)}$	0.015*	0.008
$\phi_1^{(35)}$	0.116	0.085
σ_3^2	0.477***	0.095

(continued next page)

Table 3 The Estimation Results for (FFR, SPR, GDP, SRET, HRET) (Continued)

Parameter	Estimate	S.E.
c_4	1.735	5.324
$\phi_1^{(41)}$	0.099	0.404
$\phi_1^{(42)}$	0.199	1.263
$\phi_1^{(43)}$	0.793	1.010
$\phi_1^{(44)}$	−0.034	0.136
$\phi_1^{(45)}$	−0.728	0.754
σ_4^2	59.094***	9.588
c_5	0.743**	0.291
$\phi_1^{(51)}$	−0.024	0.025
$\phi_1^{(52)}$	−0.029	0.067
$\phi_1^{(53)}$	0.045	0.158
$\phi_1^{(54)}$	0.000	0.010
$\phi_1^{(55)}$	0.611***	0.087
σ_5^2	0.535***	0.083
r_{12}	−0.783***	0.065
r_{13}	0.286***	0.088
r_{14}	−0.163	0.134
r_{15}	−0.225	0.172
r_{23}	−0.124	0.120
r_{24}	0.009	0.079
r_{25}	0.056	0.133
r_{34}	−0.004	0.150
r_{35}	−0.050	0.088
r_{45}	0.005	0.024
$\ln L$	-903.297	
AIC	15.419	

Notes: *, **, and *** represent the significance at 10%, 5%, and 1%, respectively.

Table 4 The Estimation Results for (FFR, GDP, SRET, HRET) (1975Q2-2005Q4)

	Non-Switching Model		Markov Switching Model			
	Single Regime		Regime 1		Regime 2	
Parameter	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
c_1	−0.576**	0.281	−1.152	3.526	−1.152	3.526
$\alpha_1(2)$					0.781	3.506
$\phi_1^{(11)}$	0.977***	0.039	0.985***	0.209	0.953***	0.025
$\phi_1^{(12)}$	0.227	0.150	0.002	0.131	0.441***	0.080
$\phi_1^{(13)}$	0.018	0.013	0.124	0.099	0.005	0.006
$\phi_1^{(14)}$	0.341***	0.132	0.708	0.620	0.138***	0.053
σ_1^2	0.864***	0.286	3.397***	0.999	3.397***	0.999
$\lambda_1(2)$					0.253***	0.042
c_2	0.706***	0.192	2.728	2.132	2.728	2.132
$\alpha_2(2)$					−2.339	2.115
$\phi_1^{(21)}$	−0.041	0.026	−0.196	0.141	0.010	0.021
$\phi_1^{(22)}$	0.252**	0.102	0.008	0.287	0.376***	0.100
$\phi_1^{(23)}$	0.015*	0.008	−0.002	0.053	0.012*	0.007
$\phi_1^{(24)}$	0.078	0.083	0.051	0.345	0.041	0.069
σ_2^2	0.493***	0.099	1.349***	0.460	1.349***	0.460
$\lambda_2(2)$					0.446***	0.080
c_3	2.420	2.478	17.932	26.717	17.932	26.717
$\alpha_3(2)$					−16.115	25.836
$\phi_1^{(31)}$	0.052	0.281	−1.067	1.371	0.292	0.338
$\phi_1^{(32)}$	0.817	1.087	0.577	1.174	0.604	1.494
$\phi_1^{(33)}$	−0.033	0.121	−0.170	0.231	−0.049	0.095
$\phi_1^{(34)}$	−0.785	0.590	−1.439	4.337	−1.183	0.725
σ_3^2	59.131***	9.567	41.596***	10.825	41.596***	10.825
$\lambda_3(2)$					1.202	0.190

(continued next page)

Table 4 The Estimation Results for (FFR, GDP, SRET, HRET) (Continued)

	Non-Switching Model		Markov Switching Model			
	Single Regime		Regime 1		Regime 2	
Parameter	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
c_4	0.642***	0.195	3.664	3.198	3.664	3.198
$\alpha_4(2)$					−3.025	3.190
$\phi_1^{(41)}$	−0.018	0.021	−0.185	0.175	−0.028	0.030
$\phi_1^{(42)}$	0.041	0.136	0.035	0.582	0.093	0.123
$\phi_1^{(43)}$	−0.000	0.009	−0.007	0.085	−0.002	0.008
$\phi_1^{(44)}$	0.619***	0.084	0.222	0.490	0.615***	0.089
σ_4^2	0.532***	0.080	0.943***	0.347	0.943***	0.347
$\lambda_4(2)$					0.673**	0.130
r_{12}	0.277***	0.103	0.358***	0.117	0.128	0.094
r_{13}	−0.163*	0.095	−0.473**	0.239	−0.160*	0.092
r_{14}	−0.145	0.160	−0.272	0.372	−0.170*	0.090
r_{23}	0.001	0.082	−0.203	0.242	−0.010	0.102
r_{24}	−0.042	0.160	−0.068	0.262	−0.078	0.115
r_{34}	0.026	0.085	−0.208	0.367	0.057	0.141
P_{11}			0.939*** (0.044)			
P_{22}			0.990*** (0.010)			
$\ln L$	-849.817		-766.550			
AIC	14.306		13.472			

Notes: *, **, and *** represent the significance at 10%, 5%, and 1%, respectively. Values next to the estimates of transition probability P_{ii} are standard deviations.

Table 5 The Estimation Results for (FFR, SPR, SRET, HRET) (1975Q2-2005Q4)

	Non-Switching Model		Markov Switching Model			
	Single Regime		Regime 1		Regime 2	
Parameter	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
c_1	−0.431	0.593	1.089	3.406	1.089	3.406
$\alpha_1(2)$					−1.627	3.410
$\phi_1^{(11)}$	0.974***	0.054	0.772***	0.218	1.014***	0.028
$\phi_1^{(12)}$	0.016	0.112	−0.200	0.333	0.082	0.055
$\phi_1^{(13)}$	0.018	0.012	0.056	0.068	0.008	0.006
$\phi_1^{(14)}$	0.358**	0.142	1.363**	0.656	0.202***	0.048
σ_1^2	0.893***	0.262	2.582***	0.625	2.582***	0.625
$\lambda_1(2)$					0.298***	0.045
c_2	0.521	0.338	2.190	1.766	2.190	1.766
$\alpha_2(2)$					−1.559	1.771
$\phi_1^{(21)}$	0.002	0.033	−0.056	0.114	−0.048*	0.025
$\phi_1^{(22)}$	0.849***	0.067	0.728***	0.199	0.861***	0.054
$\phi_1^{(23)}$	−0.016*	0.009	−0.095***	0.036	−0.002	0.007
$\phi_1^{(24)}$	−0.185**	0.080	−0.729**	0.357	−0.119***	0.042
σ_2^2	0.418***	0.091	0.907***	0.134	0.907***	0.134
$\lambda_2(2)$					0.466***	0.048
c_3	2.252	4.278	−4.936	13.810	−4.936	13.810
$\alpha_3(2)$					7.382	13.756
$\phi_1^{(31)}$	0.089	0.358	0.362	0.932	0.321	0.433
$\phi_1^{(32)}$	0.253	0.977	1.577	1.381	−0.274	0.927
$\phi_1^{(33)}$	−0.034	0.084	0.206	0.187	−0.092	0.094
$\phi_1^{(34)}$	−0.670	0.652	0.877	2.060	−0.880	0.627
σ_3^2	59.445***	9.768	43.284***	11.866	43.284***	11.866
$\lambda_3(2)$					1.180	0.199

(continued next page)

Table 5 The Estimation Results for (FFR, SPR, SRET, HRET) (Continued)

	Non-Switching Model		Markov Switching Model			
	Single Regime		Regime 1		Regime 2	
Parameter	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
c_4	0.772***	0.296	3.024*	1.630	3.024*	1.630
$\alpha_4(2)$					−2.469	1.601
$\phi_1^{(41)}$	−0.025	0.023	−0.129	0.104	−0.011	0.047
$\phi_1^{(42)}$	−0.026	0.064	−0.281*	0.144	−0.005	0.076
$\phi_1^{(43)}$	−0.000	0.009	0.034	0.029	−0.008	0.009
$\phi_1^{(44)}$	0.614***	0.089	−0.111	0.270	0.699***	0.081
σ_4^2	0.533***	0.079	0.427***	0.145	0.427***	0.145
$\lambda_4(2)$					1.053	0.192
r_{12}	−0.773***	0.062	−0.923***	0.028	−0.635***	0.076
r_{13}	−0.146	0.098	−0.551***	0.149	−0.084	0.107
r_{14}	−0.135	0.145	−0.199	0.247	−0.002	0.086
r_{23}	0.001	0.091	0.390**	0.183	−0.026	0.151
r_{24}	−0.033	0.129	0.113	0.258	−0.117	0.094
r_{34}	0.031	0.092	−0.168	0.194	0.066	0.089
P_{11}			0.948*** (0.043)			
P_{22}			0.990*** (0.010)			
$\ln L$	-786.534		-703.646			
AIC	13.277		12.450			

Notes: *, **, and *** represent the significance at 10%, 5%, and 1%, respectively. Values next to the estimates of transition probability P_{ii} are standard deviations.

Table 6 Forecasting Performance for (FFR, SPR, GDP, SRET, HRET)

	In-Sample		Out-of-Sample	
Horizon (h)	RMSE	MAE	RMSE	MAE
Panel A: The First Series (FFR)				
1	0.9276	0.5666	0.4345	0.3284
2	1.3839	0.9080	0.6930	0.5283
3	1.6156	1.1686	1.0277	0.8079
4	1.8450	1.3800	1.2579	1.0118
Panel B: The Second Series (SPR)				
1	0.6422	0.4560	0.3655	0.2816
2	0.9047	0.6889	0.5967	0.4718
3	1.0207	0.8217	0.8330	0.7599
4	1.1257	0.9128	0.9716	0.9202
Panel C: The Thrid Series (GDP)				
1	0.6925	0.5132	0.4920	0.4176
2	0.7046	0.5148	0.5059	0.4401
3	0.7348	0.5339	0.5228	0.4812
4	0.7275	0.5232	0.5106	0.4689
Panel D: The Forth Series (SRET)				
1	7.6530	5.7625	6.5581	5.3720
2	7.5877	5.7041	6.5687	5.3013
3	7.5893	5.6993	6.7627	5.4980
4	7.5687	5.6791	6.9781	5.6542
Panel E: The Fifth Series (HRET)				
1	0.7316	0.5734	1.0630	0.8648
2	0.7931	0.6068	1.5982	1.2726
3	0.8104	0.6294	1.8355	1.5131
4	0.8467	0.6534	2.0158	1.7315

Notes: RMSE and MAE refer to the root mean squared error and mean absolute error, respectively.

Table 7 In-Sample Forecasting Performance for (FFR, GDP, SRET, HRET) (1975Q2-2005Q4)

	Non-Switching Model		Markov Switching Model	
Horizon (h)	RMSE	MAE	RMSE	MAE
Panel A: The First Series (FFR)				
1	0.9276	0.5665	0.8443	0.5406
2	1.3847	0.9077	1.2090	0.8664
3	1.6173	1.1659	1.4626	1.0978
4	1.8474	1.3856	1.9390	1.4531
Panel B: The Second Series (GDP)				
1	0.7053	0.5187	0.6891	0.4967
2	0.7290	0.5387	0.6888	0.4988
3	0.7553	0.5568	0.7305	0.5265
4	0.7511	0.5482	0.7988	0.5540
Panel C: The Third Series (SRET)				
1	7.6557	5.7569	7.5982	5.6446
2	7.6004	5.6907	7.5453	5.6305
3	7.6185	5.6950	7.5664	5.6229
4	7.5904	5.6715	7.6411	5.6640
Panel D: The Forth Series (HRET)				
1	0.7322	0.5723	0.7310	0.5644
2	0.7926	0.6057	0.7956	0.6111
3	0.8081	0.6250	0.8155	0.6324
4	0.8445	0.6506	0.8286	0.6508

Notes: RMSE and MAE refer to the root mean squared error and mean absolute error, respectively.

Table 8 In-Sample Forecasting Performance for (FFR, SPR, SRET, HRET) (1975Q2-2005Q4)

	Non-Switching Model		Markov Switching Model	
Horizon (h)	RMSE	MAE	RMSE	MAE
Panel A: The First Series (FFR)				
1	0.9433	0.5914	0.8489	0.5657
2	1.4125	0.9502	1.3163	0.9461
3	1.6456	1.2068	1.5454	1.2006
4	1.8681	1.4216	1.8439	1.4851
Panel B: The Second Series (SPR)				
1	0.6438	0.4608	0.5716	0.4537
2	0.9116	0.6943	0.8141	0.6656
3	1.0262	0.8287	0.9918	0.8252
4	1.1305	0.9202	1.1977	0.9904
Panel C: The Third Series (SRET)				
1	7.6764	5.7719	7.6163	5.5440
2	7.5654	5.6629	7.5780	5.6328
3	7.5904	5.6867	7.5563	5.5955
4	7.5690	5.6699	7.5103	5.5922
Panel D: The Forth Series (HRET)				
1	0.7324	0.5760	0.6888	0.5529
2	0.7983	0.6127	0.7664	0.5785
3	0.8157	0.6340	0.7802	0.6040
4	0.8504	0.6565	0.7974	0.6361

Notes: RMSE and MAE refer to the root mean squared error and mean absolute error, respectively.

Table 9 Out-of-Sample Forecasting Performance for (FFR, GDP, SRET, HRET) (2006Q1-2008Q3)

	Non-Switching Model		Markov Switching Model	
Horizon (h)	RMSE	MAE	RMSE	MAE
Panel A: The First Series (FFR)				
1	0.4369	0.3318	0.4546	0.4182
2	0.6844	0.5156	0.8899	0.7574
3	1.0406	0.7944	1.3303	1.0076
4	1.3138	1.0084	1.7209	1.2667
Panel B: The Second Series (GDP)				
1	0.5166	0.4760	0.5315	0.4807
2	0.5894	0.5307	0.5772	0.5145
3	0.6406	0.5861	0.6087	0.5637
4	0.6434	0.5766	0.6577	0.5883
Panel C: The Third Series (SRET)				
1	6.6399	5.3966	6.7651	5.4591
2	6.6623	5.3988	6.7203	5.4397
3	6.8516	5.5645	6.9365	5.6727
4	7.1295	5.8187	7.2027	5.8760
Panel D: The Forth Series (HRET)				
1	1.0684	0.8569	1.0641	0.8500
2	1.6090	1.2776	1.6018	1.2733
3	1.8556	1.5119	1.8595	1.5199
4	2.0365	1.7243	2.1303	1.8739

Notes: RMSE and MAE refer to the root mean squared error and mean absolute error, respectively.

Table 10 Out-of-Sample Forecasting Performance for (FFR, SPR, SRET, HRET) (2006Q1-2008Q3)

	Non-Switching Model		Markov Switching Model	
Horizon (h)	RMSE	MAE	RMSE	MAE
Panel A: The First Series (FFR)				
1	0.4633	0.3501	0.4839	0.3934
2	0.7169	0.5113	0.8719	0.6821
3	1.0388	0.8175	1.2131	0.9830
4	1.2746	1.0003	1.4291	1.2240
Panel B: The Second Series (SPR)				
1	0.3624	0.2779	0.3803	0.3174
2	0.5964	0.4769	0.6273	0.5394
3	0.8304	0.7639	0.8864	0.8286
4	0.9692	0.9170	1.0769	1.0100
Panel C: The Third Series (SRET)				
1	6.5369	5.2428	6.6309	5.2644
2	6.5543	5.4007	6.6810	5.4486
3	6.8157	5.5494	7.0191	5.7462
4	7.0370	5.7133	7.3392	6.0156
Panel D: The Forth Series (HRET)				
1	1.0677	0.8703	0.9993	0.8345
2	1.6162	1.2831	1.5172	1.1759
3	1.8474	1.5253	1.7120	1.3841
4	2.0250	1.7428	1.9161	1.7198

Notes: RMSE and MAE refer to the root mean squared error and mean absolute error, respectively.

A Summary of Goodness of Fit for All Five Models

		AIC
Model A	Single-regime model (FFR, SPR, GDP, SRET, HRET)	15.419
Model B	Single-regime model (FFR, GDP, SRET, HRET)	14.306
Model C	Two-regime model (FFR, GDP, SRET, HRET)	13.472
Model D	Single-regime model (FFR, SPR, SRET, HRET)	13.277
Model E	Two-regime model (FFR, SPR, SRET, HRET)	12.450

A Summary of Forecasting Performances Based on Conditional-Expectations Method

(a) In-sample Forecasts (4-Quarter Ahead Forecasts)

		Stock Returns		Housing Returns	
		RMSE	MAE	RMSE	MAE
Model A	Single-regime model (FFR, SPR, GDP, SRET, HRET)	7.5787	5.6791	0.8467	0.6534
Model B	Single-regime model (FFR, GDP, SRET, HRET)	7.5904	5.6715	0.8445	0.6505
Model C	Two-regime model (FFR, GDP, SRET, HRET)	7.6411	5.6640	0.8286	0.6508
Model D	Single-regime model (FFR, SPR, SRET, HRET)	7.5690	5.6699	0.8504	0.6565
Model E	Two-regime model (FFR, SPR, SRET, HRET)	7.5103	5.5922	0.7974	0.6361

(b) Out-of-Sample Forecasts (4-Quarter Ahead Forecasts)

		Stock Returns		Housing Returns	
		RMSE	MAE	RMSE	MAE
Model A	Single-regime model (FFR, SPR, GDP, SRET, HRET)	6.9781	5.6542	2.0158	1.7315
Model B	Single-regime model (FFR, GDP, SRET, HRET)	7.1295	5.8187	2.0365	1.7243
Model C	Two-regime model (FFR, GDP, SRET, HRET)	7.2027	5.8760	2.1303	1.8739
Model D	Single-regime model (FFR, SPR, SRET, HRET)	7.0370	5.7133	2.0250	1.7428
Model E	Two-regime model (FFR, SPR, SRET, HRET)	7.3392	6.0156	1.9161	1.7198

Figure 1 Federal Funds Rate (FFR), Term Spread (SPR), Percentage Changes in Gross Domestic Production (GDP), Stock Index Return (SRET), Housing Market Return (HRET)

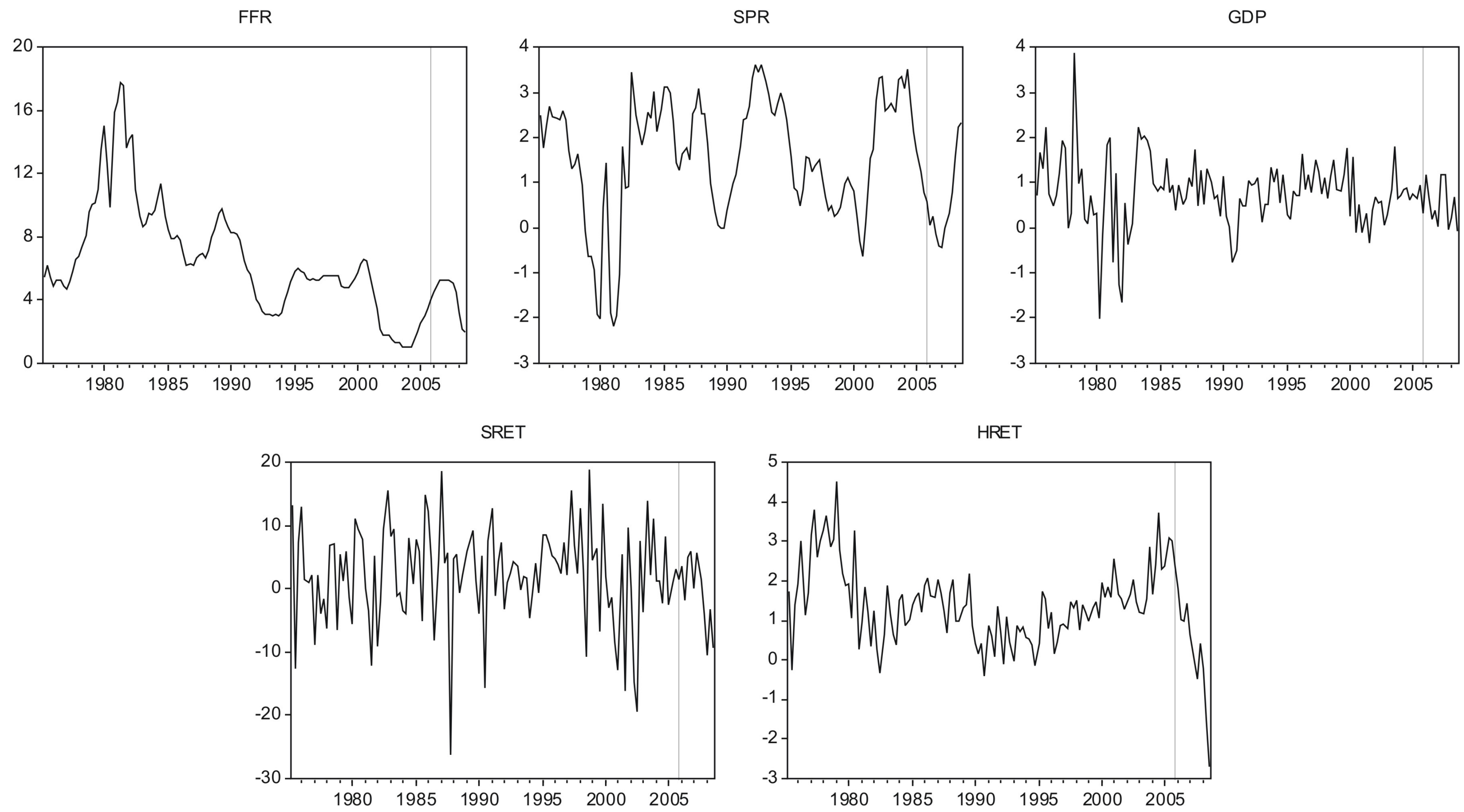


Figure 2 Smoothed Probabilities for VAR(1) Model of (FFR, GDP, SRET, HRET)

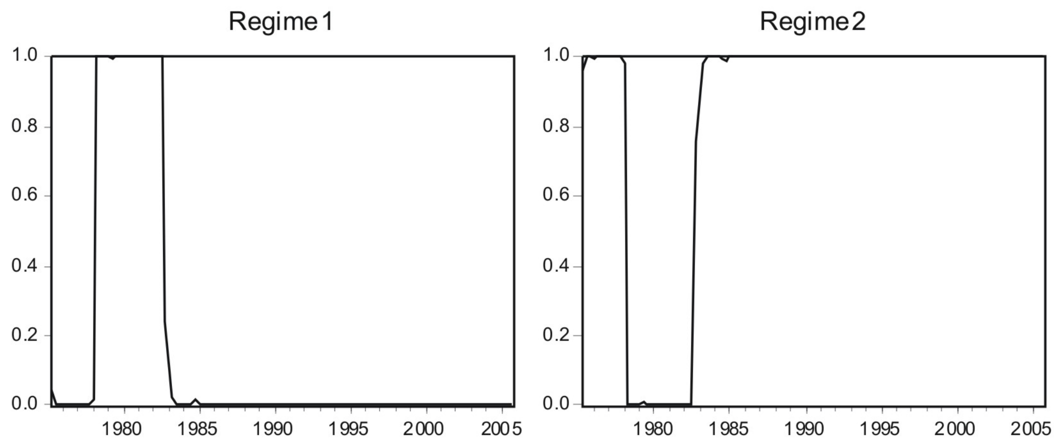


Figure 3 Smoothed Probabilities for VAR(1) Model of (FFR, SPR, SRET, HRET)

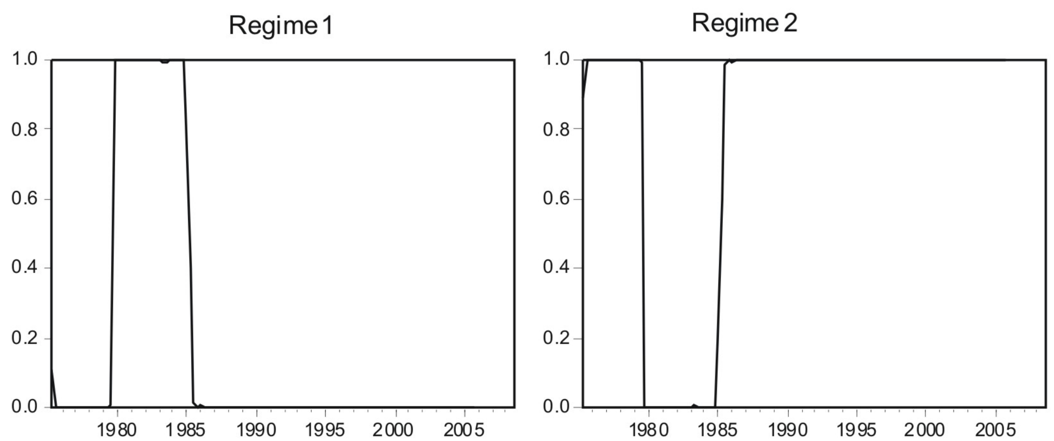


Figure 4 Simulation-Based Out-of-Sample Forecasts of Stock Returns with 90-Percent Confidence Interval (CI) from 2006Q1-2006Q4 Based on Information Available at 2005Q4

Model A: Single-Regime (FFR,SPR,GDP,SRET,HRET); Model B: Single-Regime (FFR,GDP,SRET,HRET); Model C: Two-Regime (FFR,GDP,SRET,HRET); Model D: Single-Regime (FFR,SPR,SRET,HRET); Model E: Two-Regime (FFR,SPR,SRET,HRET)

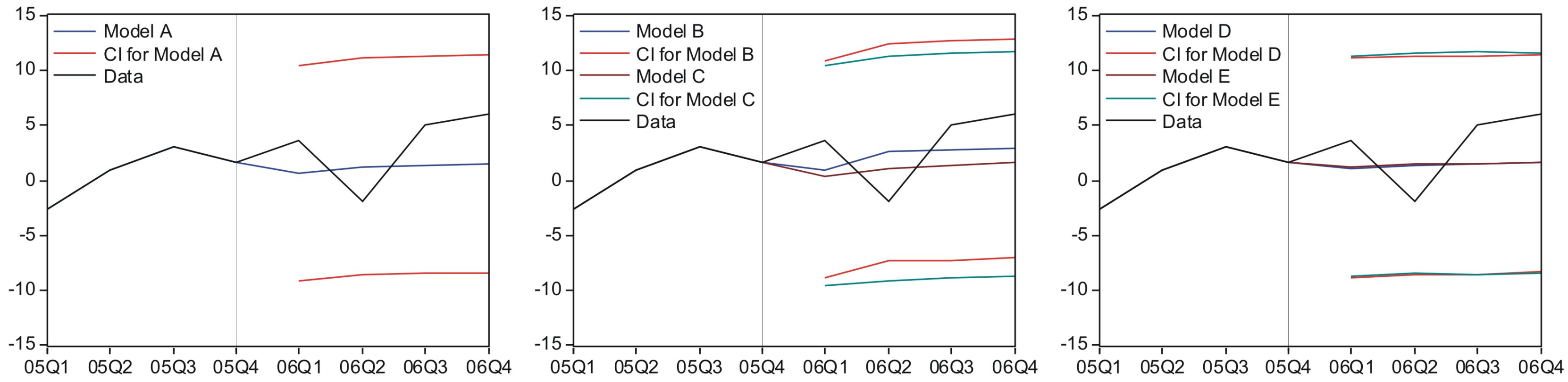


Figure 5 Simulation-Based Out-of-Sample Forecasts of Stock Returns with 90-Percent Confidence Interval (CI) from 2007Q1-2007Q4 Based on Information Available at 2006Q4

Model A: Single-Regime (FFR,SPR,GDP,SRET,HRET); Model B: Single-Regime (FFR,GDP,SRET,HRET); Model C: Two-Regime (FFR,GDP,SRET,HRET); Model D: Single-Regime (FFR,SPR,SRET,HRET); Model E: Two-Regime (FFR,SPR,SRET,HRET)

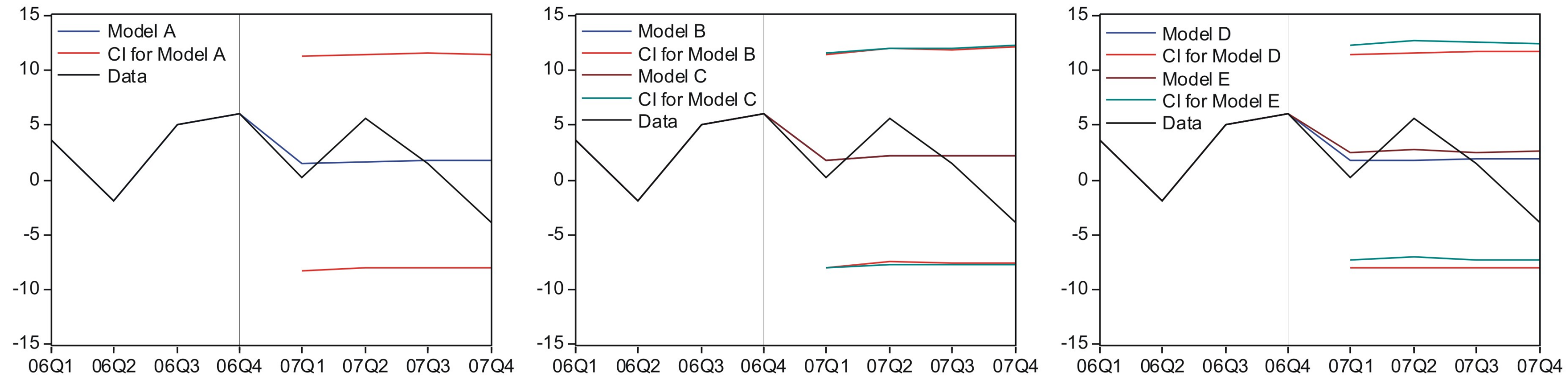
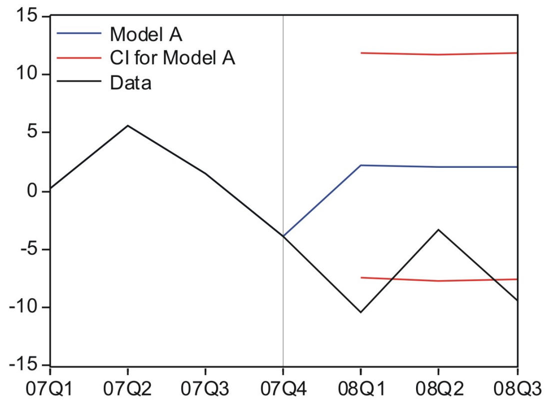
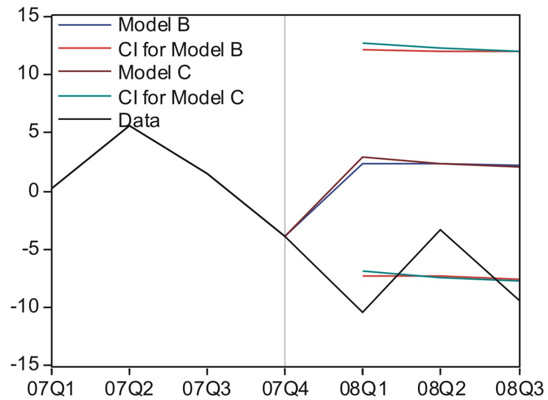


Figure 6 Simulation-Based Out-of-Sample Forecasts of Stock Returns with 90-Percent Confidence Interval (CI) from 2008Q1-2008Q3 Based on Information Available at 2007Q4

Model A: Single-Regime (FFR,SPR,GDP,SRET,HRET); Model B: Single-Regime (FFR,GDP,SRET,HRET); Model C: Two-Regime (FFR,GDP,SRET,HRET); Model D: Single-Regime (FFR,SPR,SRET,HRET); Model E: Two-Regime (FFR,SPR,SRET,HRET)





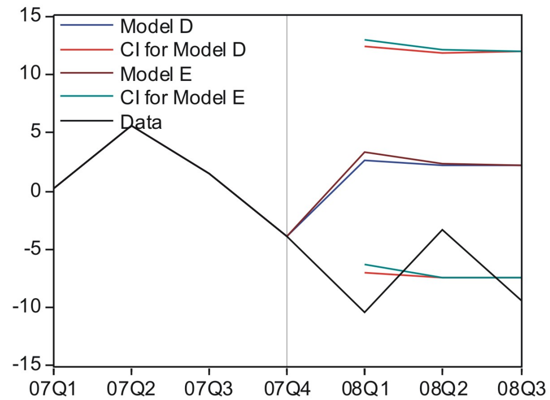
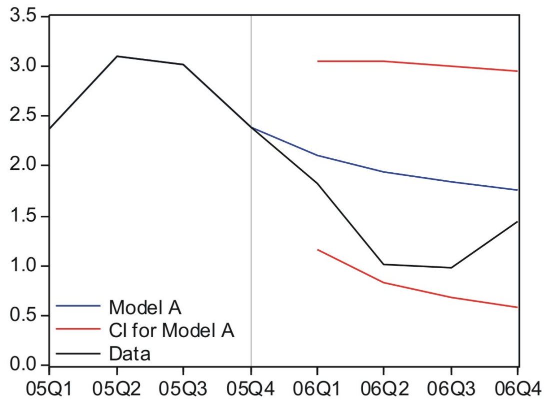
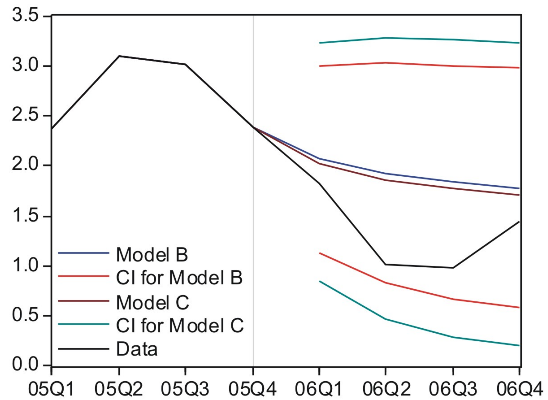


Figure 7 Simulation-Based Out-of-Sample Forecasts of Housing Returns with 90-Percent Confidence Interval (CI) from 2006Q1-2006Q4 Based on Information Available at 2005Q4

Model A: Single-Regime (FFR,SPR,GDP,SRET,HRET); Model B: Single-Regime (FFR,GDP,SRET,HRET); Model C: Two-Regime (FFR,GDP,SRET,HRET); Model D: Single-Regime (FFR,SPR,SRET,HRET); Model E: Two-Regime (FFR,SPR,SRET,HRET)





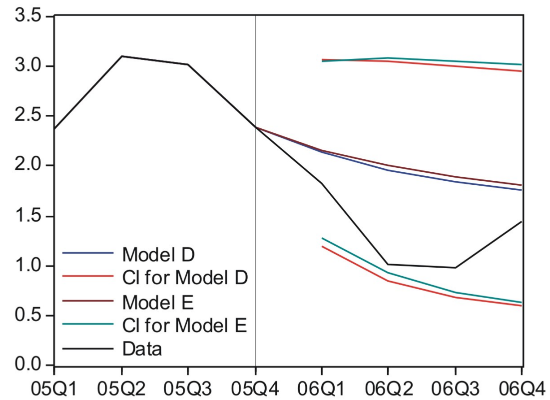


Figure 8 Simulation-Based Out-of-Sample Forecasts of Housing Returns with 90-Percent Confidence Interval (CI) from 2007Q1-2007Q4 Based on Information Available at 2006Q4

Model A: Single-Regime (FFR,SPR,GDP,SRET,HRET); Model B: Single-Regime (FFR,GDP,SRET,HRET); Model C: Two-Regime (FFR,GDP,SRET,HRET); Model D: Single-Regime (FFR,SPR,SRET,HRET); Model E: Two-Regime (FFR,SPR,SRET,HRET)

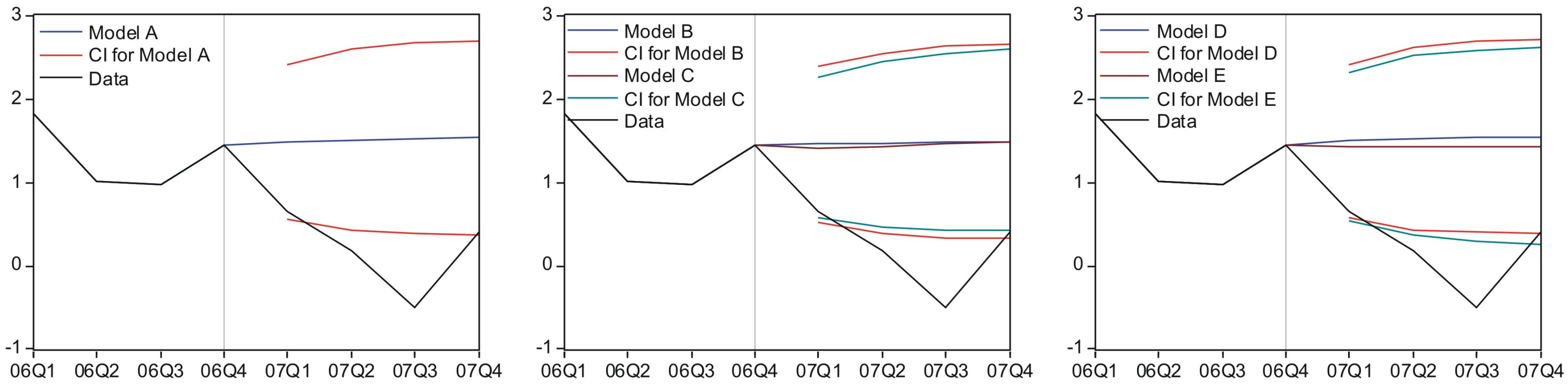


Figure 9 Simulation-Based Out-of-Sample Forecasts of Housing Returns with 90-Percent Confidence Interval (CI) from 2008Q1-2008Q3 Based on Information Available at 2007Q4

Model A: Single-Regime (FFR,SPR,GDP,SRET,HRET); Model B: Single-Regime (FFR,GDP,SRET,HRET); Model C: Two-Regime (FFR,GDP,SRET,HRET); Model D: Single-Regime (FFR,SPR,SRET,HRET); Model E: Two-Regime (FFR,SPR,SRET,HRET)

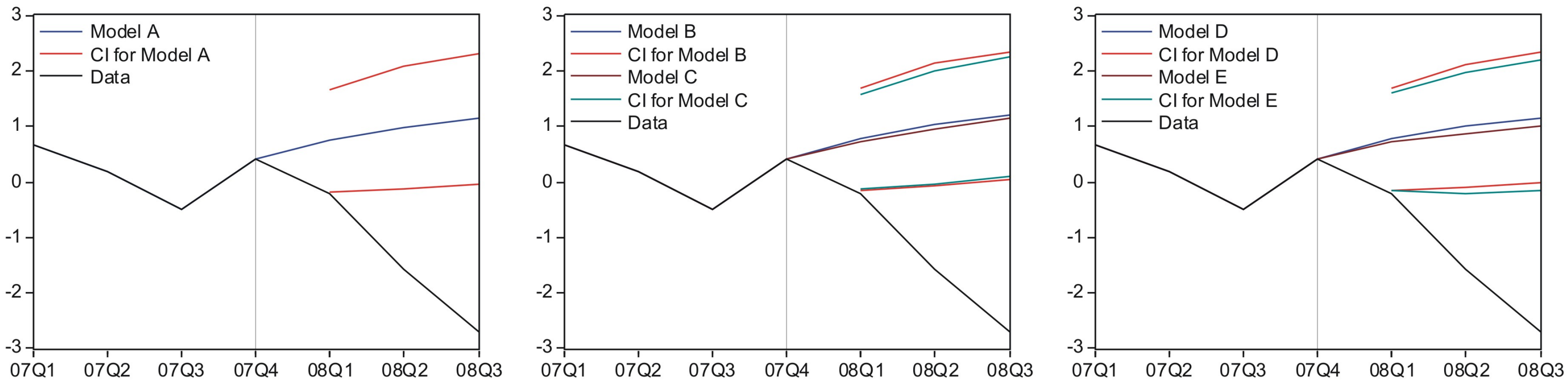
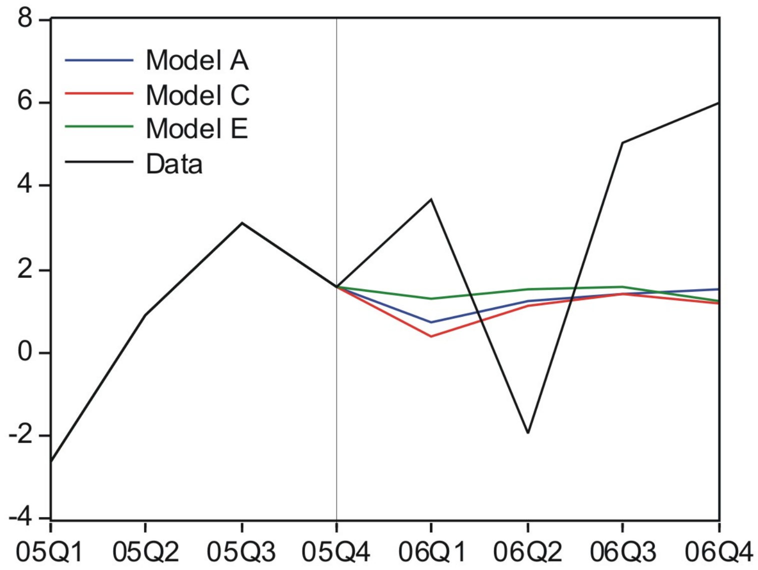


Figure 10 Out-of-Sample Forecasts of Stock Returns from 2006Q1-2006Q4 Based on Information Available at 2005Q4 (Left Panle: Conditional Mean by Conditional-Expectations Method; Right Panel: Median by Simulaton Method)

Model A: Single-Regime (FFR,SPR,GDP,SRET,HRET); Model C: Two-Regime (FFR,GDP,SRET,HRET); Model E: Two-Regime (FFR,SPR,SRET,HRET)



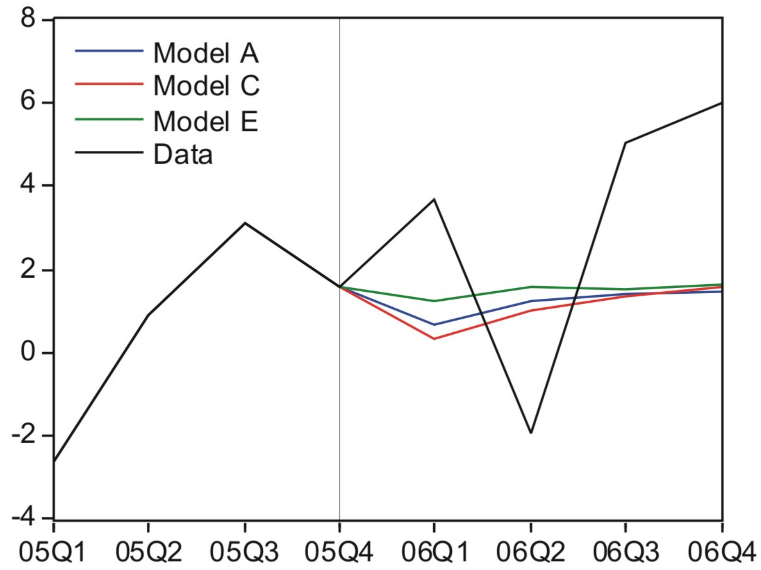


Figure 11 Out-of-Sample Forecasts of Stock Returns from 2007Q1-2007Q4 Based on Information Available at 2006Q4 (Left Panle: Conditional Mean by Conditional-Expectations Method; Right Panel: Median by Simulaton Method)

Model A: Single-Regime (FFR,SPR,GDP,SRET,HRET); Model C: Two-Regime (FFR,GDP,SRET,HRET); Model E: Two-Regime (FFR,SPR,SRET,HRET)

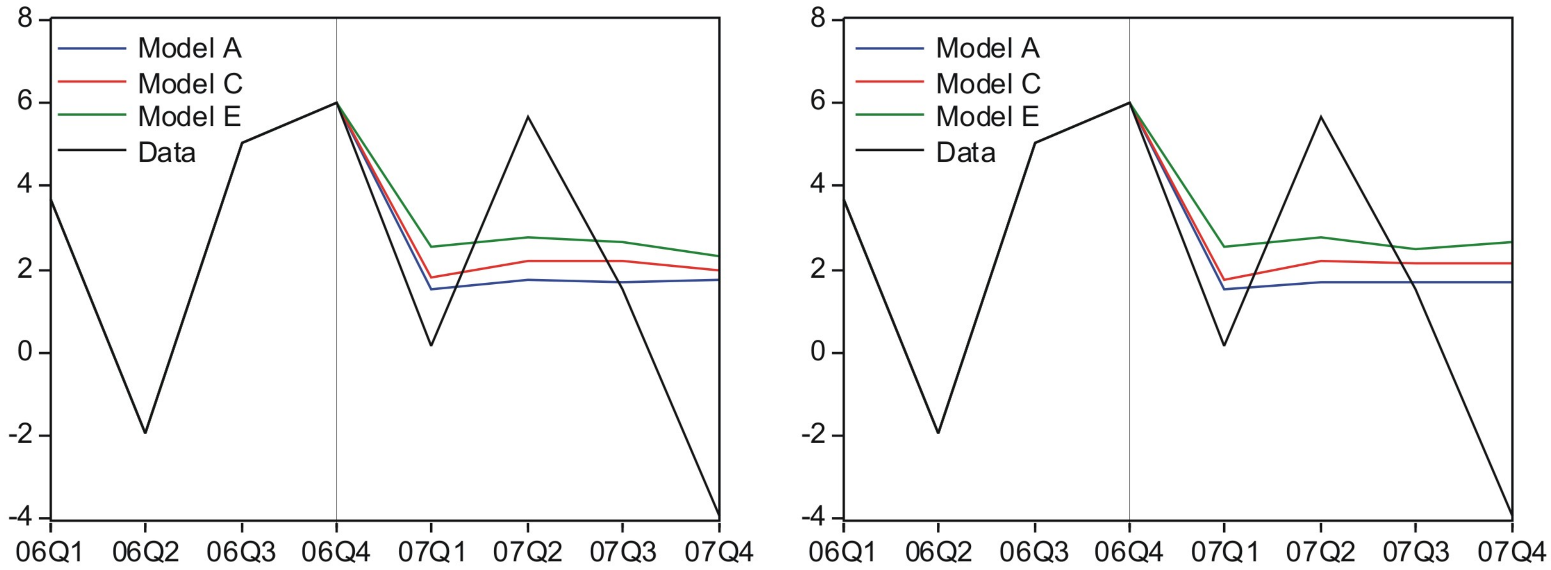
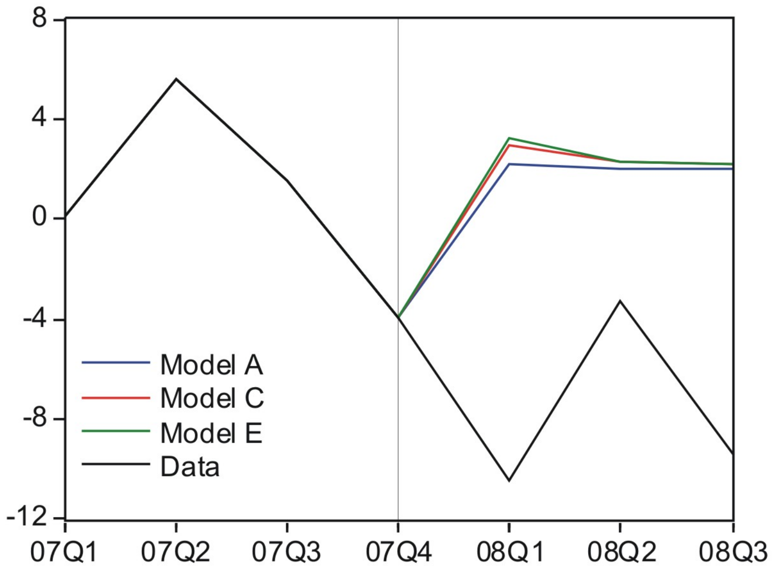


Figure 12 Out-of-Sample Forecasts of Stock Returns from 2008Q1-2008Q3 Based on Information Available at 2007Q4 (Left Panle: Conditional Mean by Conditional-Expectations Method; Right Panel: Median by Simulaton Method)

Model A: Single-Regime (FFR,SPR,GDP,SRET,HRET); Model C: Two-Regime (FFR,GDP,SRET,HRET); Model E: Two-Regime (FFR,SPR,SRET,HRET)



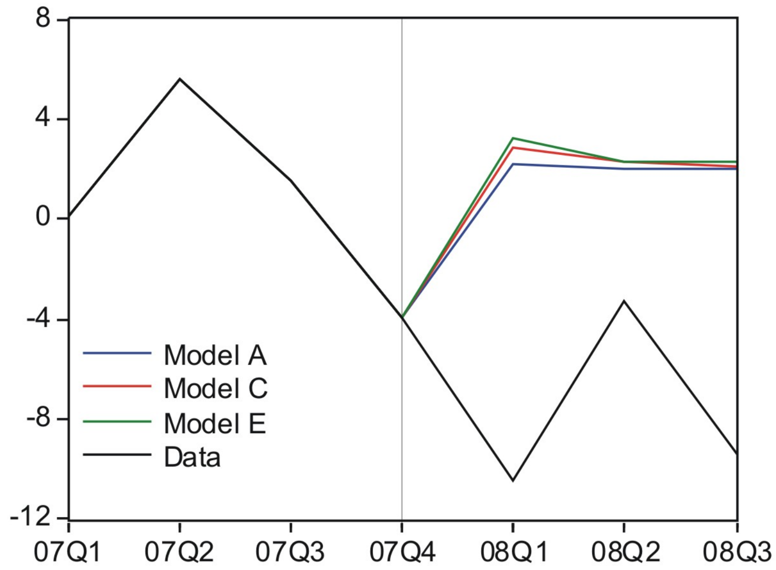
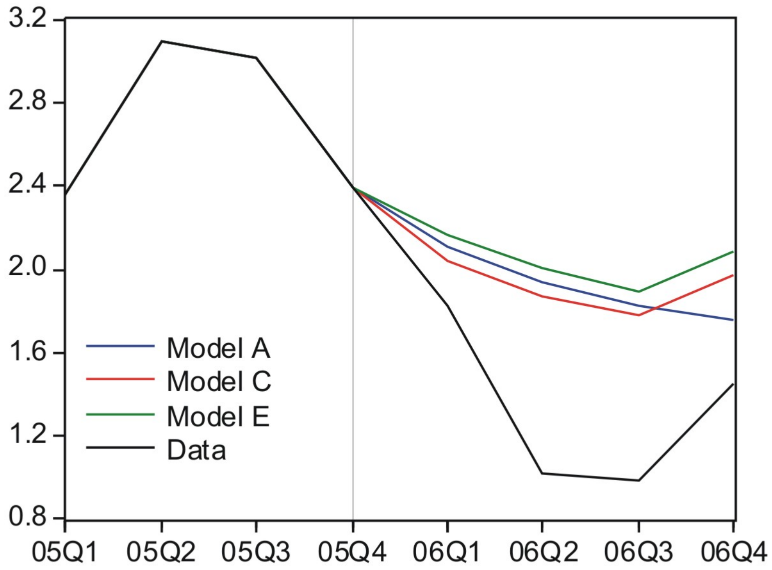


Figure 13 Out-of-Sample Forecasts of Housing Returns from 2006Q1-2006Q4 Based on Information Available at 2005Q4 (Left Panle: Conditional Mean by Conditional-Expectations Method; Right Panel: Median by Simulaton Method)

Model A: Single-Regime (FFR,SPR,GDP,SRET,HRET); Model C: Two-Regime (FFR,GDP,SRET,HRET); Model E: Two-Regime (FFR,SPR,SRET,HRET)



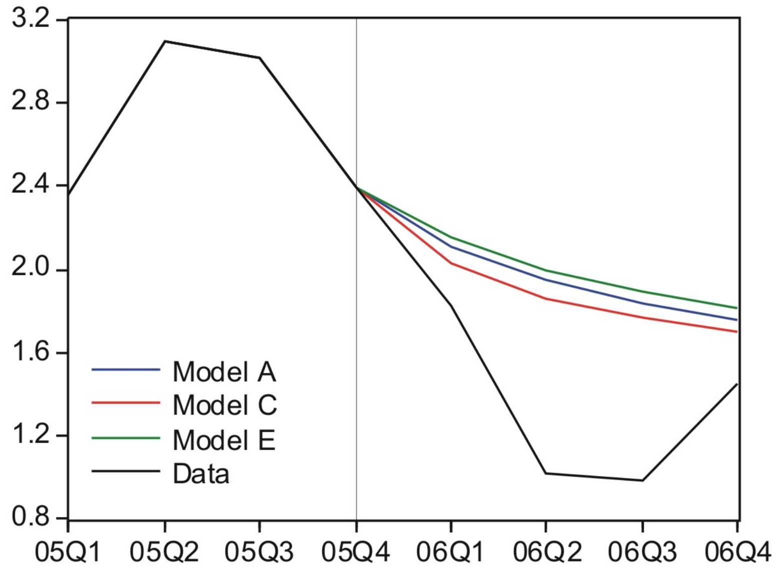
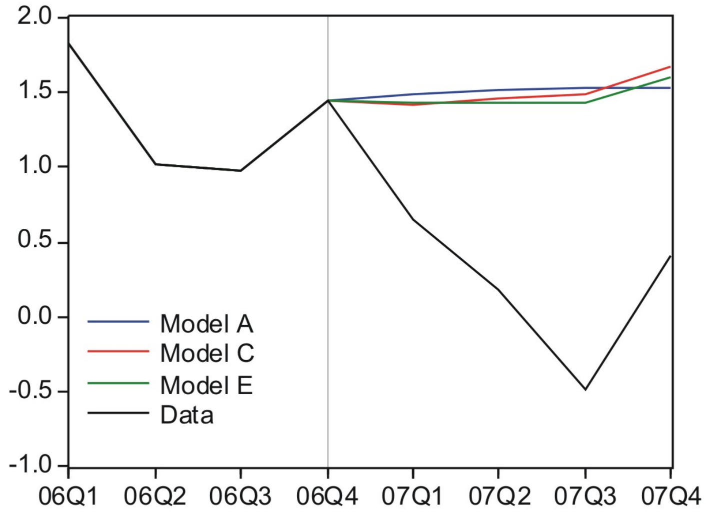


Figure 14 Out-of-Sample Forecasts of Housing Returns from 2007Q1-2007Q4 Based on Information Available at 2006Q4 (Left Panle: Conditional Mean by Conditional-Expectations Method; Right Panel: Median by Simulaton Method)

Model A: Single-Regime (FFR,SPR,GDP,SRET,HRET); Model C: Two-Regime (FFR,GDP,SRET,HRET); Model E: Two-Regime (FFR,SPR,SRET,HRET)



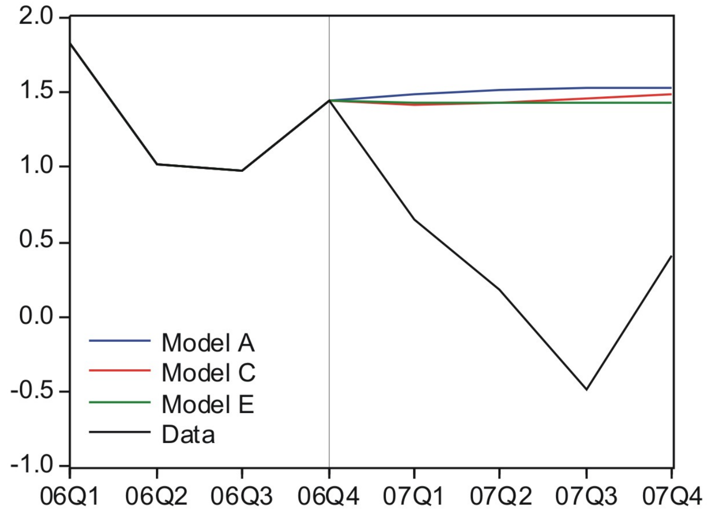


Figure 15 Out-of-Sample Forecasts of Housing Returns from 2008Q1-2008Q3 Based on Information Available at 2007Q4 (Left Panle: Conditional Mean by Conditional-Expectations Method; Right Panel: Median by Simulaton Method)

Model A: Single-Regime (FFR,SPR,GDP,SRET,HRET); Model C: Two-Regime (FFR,GDP,SRET,HRET); Model E: Two-Regime (FFR,SPR,SRET,HRET)