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

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Abstract

This paper empirically investigates the forecasting performances for the housing and stock returns of a series of SVAR models, including various combinations of the federal funds rate, term spread, external finance premium, TED spread, and GDP. Using US data $1975Q2-2008Q3$, we find that, for both the in-sample-fitting and out-of-sample forecasting, the single-regime version always underperforms the regime-switching counterpart. The term spread and TED spread outperform other variables in predicting the stock returns. We also find preliminary evidence that the housing return may help predicting the stock return since 2006. None of the models we examine predict the 2008 downfall of housing returns.

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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

More and more academics and policy makers around the world share the concern of both the determination, as well as the predictability, of asset prices. Such concerns are clearly inspired by the "lost decade" of Japan, the large fluctuations in house price and stock prices in Nordic and east Asian countries during late 1980s and 1990s, the recent subprime crisis, among other similar episodes. Take the recent real estate cycle as 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. Yet the rate of return on housing started to decline around $2006Q1$ and then precipitated in the following quarters when the sub-prime mortgage problem aggravated.[1] According to the estimates of Case-Shiller repeated Sales index, the composite index for the 10-metropolitan areas has dropped from *226* (Jan 2006) to below *160* (Jan 2009).[2] Some authors estimate that millions of house-owners experience negative net worth in their housing investment.

[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.

[2]The figures can be downloaded from http://www2.standardandpoors.com/portal/site/sp/en/us/page.topic/indices_csmahp/

These large-scale reversal movement worry many because large 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 of the USA, 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 of its trade partners. 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 policy-makers to predict the future movement of these asset prices. As a matter of fact, many financial intermediations have failed. 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 a variety of models. To be specific, we use US data $1975Q2 - 2008Q3$, and study various versions of Structural Vector Auto-Regressive ($SVAR$) models, with and without regime-switching. We examine the in-sample forecasts for the period $1975Q1 - 2005Q4$ and the out-of-sample forecasts for the period $2006Q1 - 2008Q3$ of these models. 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. we update the data starting $2006Q1$ and see how these models perform when the growth of US house price began to decline and consequently the subprime crisis unfolded.

Figure 1 provides a visualization of the variables in concern. They include the (3-month) federal funds rates (hereafter FFR) which is a measure of the US monetary policy, the term spreads (SPR) which is the discrepancy of the long term (10 years) interest rate and the short term (3-month) counterpart, external finance premium (EFP) which is equal to corporate bond spread (Baa-Aaa), the TED spread (TED) which is the difference between the 3-month Eurodollar deposit rate and the 3-month T-bill rate, 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 $1975Q1-2008Q3$.[3] The negativity of the housing return in the recent years are clear from the figure. 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)

Our choices of variables can be easily understood. 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 in recent 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.

Similarly, the inclusion of the term spread (SPR) and the GDP growth rate (GDP) in this study are also motivated by earlier literature. The GDP growth rate seems to be a natural choice for a proxy of "economic fundamental." In addition, the aggregate consumption may be "too smooth" to account for the movement of stock return very well.[4] It is well known that the term structure contains information about future inflation, future real economic activities as well as asset returns.[5] Thus, it may be instructive to include the term structure as a (partly) "forward-looking variable" in the regression with-

[3]Notice that this paper uses "asset returns" rather than "asset prices" in the empirical investigation. The reason is clear. "Asset prices" are typically non-stationary while "asset returns" may exhibit mean-reversion.

[4]The literature is too large to be reviewed here. Among others, see Mehra and Prescott (2003).

[5]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 (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.

out taking any stand on the formation of future inflation or interest rate expectation.[6] 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 term spread into the empirical model.

We also consider a measure of the external finance premium (*EFP*) and the TED spread (*TED*). In the literature, EFP is perceived as a measure of the "risk premium," and hence a reflection of the credit market conditions that faced by non-financial firms, while TED as the counterpart faced by banks, and therefore these variables are often included in empirical investigation.[7] In the current context, we include them in the research in an attempt to investigate whether (and if so, how) the credit market conditions would help us to predict the asset return dynamics. The details of selecting the measures of these two variables are explained below.

This paper differs from the literature in several dimensions. First, we use multivariate regime-switching SVAR models, while many existing studies on forecasting either use single-variate (i.e., the variable to be forecasted) model or employ linear VAR (i.e. single regime) models. The former approach may suffer from endogeneity problem,[8] while the latter implicitly rules out the possibility of regime switching.[9] Recently, Chen

[6]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.

[7]The literature is too large to be reviewed here. Among others, see Bernanke and Gertler (1995).

[8]Sims (1980b) makes a strong case why estimating a system of equations, especially in the context of a dynamically interacting system, is econometrically more sensible than single equation estimation.

[9]Again, the literature is too large to be reviewed here. Among others, see Hamilton (1994).

and Leung (2008) show that in the presence of collateral constraint, the bankruptcy possibility and asset price spillover, the relationship between aggregate output and the real estate price may be piece-wise continuous, and hence may not be well captured by widely used linear VAR model. Regime changes may also be an important characteristic of the monetary policy in practice. 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 (such as *"bear versus bull"*) 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 dramatically affect inflation and economic activity (such as oil price shocks). In addition, Chang, Chen and Leung (2010) argue that regime switching model can be consistent with two stylized facts in the asset market: (1) short-run predictability and (2) long-run non-profitability. Thus it may be appropriate to explicitly allow for regime-switching behavior in the study of asset returns and monetary policy.

To further highlight the possible importance of regime-switching, we estimate a linear VAR model which include all 7 variables as a benchmark, and compare its forecasting performance (both in-sample and out-of-sample) with the regime-switching counterparts. Limited by the data availability, all of our regime-switching models can only afford to include 4 variables, which is a much shorter list than the linear model. Obviously, in terms of the ability to predict the asset returns, it puts regime-switching models in a very disadvantageous position. If, however, the regime-switching models still outperform the widely used linear model, it would suggest that regime changes may indeed be very important in the data.

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, it does not really track the regime that occurs for each step of forecasting, and the confidence intervals are not 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 at the same time, namely stock and housing. 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)). On the other hand, recently others find these indicators less conclusive (Bossaerts and Hillion (1999), Goyal and Welch (2003), Lewellen (2004)). The predictability of house prices have also been discussed. 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.

Motivated by some recent research, this paper differentiates itself from earlier efforts by considering both housing and stock returns *simultaneously*. From the investor point of view, since the returns of the two asset are imperfectly correlated, it is natural for agents include both assets under some dynamic portfolio consideration (among others, see Yao and Zhang, 2005; Leung, 2007). Moreover, some 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. Thus, it would be important to take into account the interactions of stock returns and housing returns by studying them at the same time.

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. Section 4 compare forecasting performances across models. Section 5 concludes.

2 The Econometric Analysis

2.1 Data

The empirical analysis of this paper is based on U.S. data, covering the period $1975Q2-2008Q3$. 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 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. Real GDP is taken from the Department of Commerce, Bureau of Economic Analysis. 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 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.[10]

There are a number of available series that have been used as the measure external finance premium. Among these are the prime spread (prime loan rate - federal funds

[10] 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.

rate) and the corporate bond spread (Baa-Aaa), and the high-yield bond spread (Bbb-Aaa). De Graeve (2007) argues that the prime loan spread provides a poor indication of financing conditions of firms which are typically considered vulnerable to credit market frictions, because it focuses on firms of the highest credit quality, to which financial constraints pertain the least. Gertler and Lown (1999) show that the high-yield bond spread is strongly associated with both general financial conditions and the business cycle (as predicted by the financial accelerator). However, the series started only in the early 1980s. Therefore, we choose corporate bond spread (Baa-Aaa) to be our measure of the external finance premium.

The TED Spread is the difference between the interest rate for three-month U.S. T-bills and the three-month Eurodollars contract, represented by the London Interbank Offering Rate (LIBOR). However, the widely-used BBA LIBOR, compiled by the British Bankers' Association, started only from January 1986. Therefore, we replace the 3-month LIBOR rate by 3-month Eurodollar deposit rate. These two series are highly correlated. Both the corporate bond spread and the 3-month Eurodollar deposit rate are from H.15 statistical release ("Selected Interest Rates") issued by the Federal Reserve Board of Governors.

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 several variables are indeed highly correlated: the federal fund rate, the external finance premium, the term spread and the TED spread. On top of the existence of these significant correlations, we also construct the models in a way that would facilitate the comparison. For instance, Model A to D would have FFR involved, which can highlight the potential role of monetary policy in the asset return dynamics. Model F to H differ from the previous ones as the monetary policy variable *FFR* is removed. Instead, an additional financial market variable is introduced to the system. Thus, model F can be interpreted as model C with *FFR* replaced by *EFP*, model G as model E with *FFR* replaced by *EFP*, and model H as model E with *FFR* replaced by *SPR*. As it will become clear, in despite of all these similarities, models which replace one of the these variables by another may have very different performance in forecasting.

(Table 1, 2 about here)

2.2 The Econometric Model

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

$$A_0(s_t)\, y_t = \gamma(s_t) + \sum_{i=1}^{p} A_i(s_t)\, y_{t-i} + u_t(s_t), \tag{1}$$

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.[11] 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:

$$y_t = \delta(s_t) + \sum_{i=1}^{p} \Phi_i(s_t)\, y_{t-i} + \epsilon_t(s_t), \tag{2}$$

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

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

[11] 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

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 probabilities of regime switching for evaluating the forecasting performances of house and stock prices across various models, and then 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.

The first approach is the conventional conditional moment method. 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-step ahead outside the estimation window, using the smoothed transition probabilities. The h-step 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-step 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-step ahead conditional expectations of the variable being predicted. Most existing (non-Bayesian) works follow this method.

The second approach is the simulation method. The idea is simply that 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, $h = 1, ..., 4$.[12] 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. It should be noticed that the regime-switching nature of the model implies that the future forecast is path-dependent and hence the conventional way to construct confidence interval becomes invalid.

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

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

[12]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.

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

where $\widehat{z}_{t+h|t} \equiv E\left(z_{t+h} \mid \Omega_t\right)$. Clearly, the RMSE tends to penalize "big mistakes" more than the MAE. As it will be clear, our main conclusions do not depend on whether RMSE or MAE is used.

3 Estimation Results

Due to limited availability of data, we keep the model as parsimonious as possible to constrict the number of parameters to be estimated. Table 3 list all the models that will be estimated.[13]

(Table 3 about here)

The details of the estimation results for the sampling period $1975Q2-2005Q4$ are presented in the appendix and table 4a provides a summary. In general, a model allowing for regime switching attains a lower value of Akaike's information criterion (*AIC*) and a higher log-likelihood value. Among all these models, the regime switching model (*EFP, TED, SRET, HRET*) has the best goodness of fit, i.e., a significantly lower value of *AIC* than other models, suggesting that the credit market frictions and asset returns are indeed significantly inter-related. To further strengthen this point, table 4b compares the AIC of the single regime (i.e. linear VAR) and the regime switching version for each model. It is clear that for any given set of variables, the regime switching version always attains a significantly lower value of AIC. The difference can sometimes be 10% or more.

(Table 4a, 4b 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. In the

[13]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.

appendix, the figures show that the estimated values of relative 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, almost all 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, we identify two regimes for this monetary policy tool: a high volatility regime (regime 1) and a low volatility regime (regime 2). The transition probability matrix of, for example, (*EFP, TED, SRET, HRET*) is given by

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} = \begin{pmatrix} 0.854 & 0.146 \\ 0.068 & 0.932 \end{pmatrix},$$

which shows that both regimes are *highly persistent*. For example, the expected duration of regime 1 is $1/(1 - p_{11}) = 6.8$ quarters and the expected duration of regime 2 is $1/(1 - p_{22}) = 14.7$ quarters.

Given the estimated parameters, transition probabilities, and variance-covariance matrix, we compute the smoothed probabilities for all from Model B to Model H, as shown in Figure 2. 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).

Basically, these models show similar classifications of the regimes. For those periods identified as regime 1, all models include aftermath of the second oil crises and P. Volcker being appointed as Chairman of the Federal Reserve.[14] Interestingly, when external finance premium (*EFP*) or TED spread (*TED*) is included in Model D to G, the regime 1 also includes the stock market crash in early 2000s, suggesting that *EFP* and *TED* pick up the volatility in the credit market after the stock market crash.

It is also interesting that under model E, which is like model D except that *EFP* is replaced by *TED* spread, the changes in regimes are much more frequent. In general, models that involve TED, such as model G and H, they have regime switching occur much more frequently, suggesting higher variability of the risk premia faced by financial intermediations.

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

(Figure 2 about here)

4 Forecasting

We now proceed to forecast stock and housing returns from 2006Q1 to 2008Q3, given the information from previous years. 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

We compute both *RMSE* and *MAE* of in-sample h-step ahead forecasts, $h = 1, ..., 4$, for each variable across all models. Several findings are in order. First, as shown in table 5a, the in-sample forecasts of asset returns are mixed. For the stock returns, the model C (*FFR, SPR, SRET, HRET*) has the best performance. For housing return, however, it is the model D (*FFR, EFP, SRET, HRET*) which out-perform all others. Notice that both models contain the monetary policy variable *FFR*. It is true whether we use *RMSE* or *MAE* as the criteria. It is interesting to notice that neither the linear model with 7 variables, nor the model B which contains GDP growth, that provide the superior performance. Second, as detailed in the appendix, for the in-sample forecasts of house price, both *RMSE* and *MAE* are in general increasing monotonically in forecasting horizon. That is, the forecasting performances *worsen* as the forecasting horizon is longer. This is true for both criteria and for all models, single-regime or regime-switching model.

(Tables 5a about here)

4.2 Out-of-Sample Forecasting

We now turn to the 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.

First, we conduct out-of-sample forecasting by using the conditional-expectations predictions. The appendix provides details of the *RMSE* and *MAE* of out-of-sample h-step ahead forecasts, $h = 1, ..., 4$, for each variable across all models. Tables 5b summarizes the results.

For out-of-sample forecast, the regime-switching model H (*SPR, TED, SRET, HRET*) is in general very good. In terms of forecasting stock returns, it out-performs all other models under the criteria of *RMSE*. Under the criteria of *MAE*, it is extremely close to the top performer (model A). In terms of forecasting housing returns, it out-performs all other models under the criteria of *MAE*. Under the criteria of *RMSE*, it is extremely close to the top performer (model F). Notice that unlike the case of in-sample forecasting, the model H does not contain neither the monetary policy variable *FFR*, nor the fundamental variable *GDP*. It seems to suggest that the forecasting power of variables for in-sample and for out-of-sample can be quite different.

(Tables 5b about here)

4.3 Diebold and Mariano Test and simulation-based forecasting

On top of the MAE and RMSE statistics we have just calculated, we can also directly measure whether one model predicts (statistically) significantly better than an alternative. Following the literature, we adopt the Diebold-Mariano test to assess the "relative performance" of different models.[15] While Diebold and Mariano (1995), Zivot (2004) provide the details, it may nevertheless be instructive to outline the test here. Let $\{y_t\}$ denote the series to be forecast and let $y^i_{t+h|t}$ be the model i's h-step forecast of y_{t+h} based on the information at time t, $h > 0$, $i = 1, 2$. Let $e^i_{t+h|t}$ be the model i forecast error, $e^i_{t+h|t} \equiv y_{t+h} - y^i_{t+h|t}$. The Diebold-Mariano test is based on the loss differential,

$$d_t = L\left(e^1_{t+h|t}\right) - L\left(e^2_{t+h|t}\right),$$

where $L(.)$ is some loss function. Clearly, if the two models have roughly the same predictive power, the expectation of the loss differential will be zero, $E[d_t] = 0$. If, instead, model 1 predicts better (*worse*) model 2, the expected value of the loss differential will be positive (*negative*).

[15] Diebold and Mariano test has been widely used in the literature. Among others, see Hordahl, Tristani and Vestin (2006) for a review of the literature.

Since model H seems to be the "best performing model" thus far, we use model H as the benchmark and compare different models against it. In terms of the loss function, we follow the literature to use both MSE (which is the square of RMSE) and MAE. The results of in-sample fitting is reported in table 5c and the results of out-of-sample forecasting in table 5d. There is no clear winner for in-sample fitting. For stock return, model A outperforms model H only according to MAE (*5%* significance level). Model H outperforms model G only according to MSE at *10%* significance level. For housing return, no model outperforms any other in a statistically significant manner.

The comparison of out-of-sample forecasting provides a different picture. For stock return, model H outperforms model C (*5%* significance level), model D and model F (both at *10%* significance level) according to MAE. The results for housing return is even more impressive. Model H outperforms model A, B, D, E and G (all at *1%* significance level) according to both MSE and MAE. Model H again outperforms model C (at *5%* significance level) according to MAE. Overall, it seems that model H (with term spread and TED spread) is a good in out-of-sample forecasting for both stock and housing returns. It may be due to the fact that term spread "factors in" the future expectation through the long term interest rate, and TED spread reflects the liquidity of the financial sector, and both are important in determining the post-2005 asset returns. (We will have more discussion on this point in a later section).

(Tables 5c, 5d about here)

To assess the "absolute performance" of different models, we now 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 $2006Q1 - 2006Q4$ 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 *80*-percent confidence intervals can be visualized in Figure 3 for stock returns and Figure 4 for housing returns. Table 5c and 5d provide a summary of the performance of different models

(Figure 3 and 4 about here)

For the predictions of stock returns, the predicted paths of the first two forecasting windows (Figure 3a and 3b) and actual data are well within the boundaries of the 80-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 ($2008Q1 - 2008Q3$ in Figure 3c) performs much worse: except for the regime-switching model H (*SPR, TED, SRET, HRET*), all models have at least one period (i.e. a quarter) which lies outside the confidence region. Notice that for overall out-of-sample forecasting performance (4-quarter ahead forecasts), it is also the model H which performs best overall. While more research are clearly needed, the results here seem to suggest that the interest rate spread (*SPR*) and the TED spread (*TED*) are indeed very important in the forecasting of stock returns.

For the predictions of housing returns, the forecasting performances of all the models in a sense "deteriorate" much faster than the predictions for stock returns. Figure 4a shows that most models basically capture the downward trend of the housing return in 2006 within their 80% confidence intervals, although model A (the linear model with all 7 variables) and model D (*FFR, SPR, SRET, HRET*) are not totally successful even for the forecasting of 2006. Unfortunately, figure 4b 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, except for the *2007Q1*. Figure 4c 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 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. In other words, all models fail, as summarized by table 5d.

(Tables 5e, 5f about here)

5 Is housing important to Stock, and vice versa?

Thus far, we have put the housing return and the stock return together in the regime switching structural vector autoregressive (RSSVAR) models. One may wonder whether it is necessary. To put it in another way, is there any evidence that the inclusion of housing return improve our prediction of the stock return, and vice versa? This section attempts to shed light on this question. In particular, for each model from B to H, we introduce two more sub-models. For instance, model B includes variables (FFR, GDP, SRET, HRET), and model B1 removes the housing return and includes only (FFR, GDP, SRET). Similarly, model B2 removes the stock return and includes only (FFR, GDP, HRET). Thus we can compare the forecasting performance of model B versus model B1 in predicting the stock return, and the difference would highlight the contribution of the housing return in the model. Similarly, model B versus B2 in predicting the housing return, and the difference would highlight the contribution of the stock return in the model. We separate the cases of in-sample fitting and out-of-sample forecasting. In addition, to make our results more robust, we impose the criteria that model B is considered "better" than, say, model B1 only if it produces a lower value of MAE and a lower value of RMSE. And we repeat this procedure for all the RSSVAR models. Table 6a and 6b provide a summary of the results and the details are left in the appendix.

A few results are in order. First, for in-sample fitting, adding housing return does *not* improve the forecasting of the stock return in any model. However, for model E (FFR, TED, SRET, HRET) and model H (SPR, TED, SRET, HRET), the inclusion of housing return does improve the forecasting performance of the stock return. It should be notice that model H is in general the best model for out-of-sample forecasting (see table 5b). One interpretation is that the correlation between the stock return and housing return is weak during the period 1975 to 2005 (the "in-sample" period) and that explains why the housing return does not contribute in forecasting the stock return during in-sample. Since 2006, perhaps due to the financial crisis, the connection between the housing market and the stock market is strengthened. Thus, under some variable combinations (such as model E and H) detect the contribution of the housing return in the prediction of the stock return, and these models also predict better in general. Second, for both in-sample and out-of-sample forecasting, the introduction of stock return does improve the model performance in model C (FFR, SPR, SRET, HRET), model E and model H. It means that stock return does contribute in the forecasting of housing return, and vice versa, if the right model is employed. This interpretation is also consistent with our early finding that according to the Diebold-Mariano test, model H is not superior than other models for in-sample fitting (i.e. 1975-2005 period). On the other hand, model H has a clear edge over most alternatives in predicting asset returns in terms of out-of-sample forecasting (post-2005 period). Overall, our dynamic system approach (which includes both stock return and housing return in the RSSVAR model) seems to be justified, especially for the period post-2005. It even helps us to verify a "structural change" in the relationship between the housing market and the stock market.

(Table 6a, 6b about here)

6 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 policy-makers 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.[16] 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. In terms of "relative performance," we do not find any consistent evidence that any model we consider provides better prediction of asset returns for in-sample fitting (i.e. 1975-2005 period). For out-of-sample forecasting (i.e. 2006 and after), we have clear evidence that our model H (i.e. a regime-switching structural VAR model with term spread and TED spread) outperforms most alternatives, especially in predicting the housing returns. In terms of "absolute performance," our simulation-based estimation shows that given the data from 1975 to 2005, the path of 2006 housing and stock returns are actually within the 80% confidence intervals of our regime switching models. When the model is updated with the 2006 data, the 2007 stock returns are still within the 80% confidence intervals of some of our models. For the year 2008, only model H can successfully contain the

[16]For instance, 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."

actual time path of the stock return. For the housing return, most of our models fail in the year 2007, and all of them fail for the year 2008. Thus, there is a possibility that the U.S. asset returns experience two "structural changes," one in 2006 and one in 2008. Clearly, more research efforts are needed to verify a such speculation.

Methodologically, we also demonstrate a few things. First, the widely used linear VAR model (i.e. single regime) with 7 variables can actually under-perform than the regime-switching counterparts with only 4 variables most of the time. In addition, we show that for the same combinations of variables (model B to H), the regime-switching version always outperforms the linear version. It shows that a carefully selected subset of variables with the consideration of non-linearity (regime-switching in the current context) could provide a better characterization as well as forecasting performance of the data. We also demonstrate that the simulation-based method used by Sargent, Williams and Zha (2006), Sims and Zha (2006) can provide useful guidance in the performance comparison of different regime switching models. Lastly, we show that the inclusion of the stock return does improve the forecasting of the housing return, and vice versa, provided that the right model is chosen. Future research may want to further explore along these lines.

Clearly, this research can be extended in several dimensions. First, it would be interesting to apply the current econometric framework to other economies. Earlier studies (e.g. Davis and Fagan, 1997) suggest that the predictive power in European Union countries may be different from that of the United States. Second, it would be interesting to incorporate higher frequency variables and study the (potential) price discovery processes among different asset markets. Finally, it would be interesting to develop a theoretical framework which can mimic the stylized facts found in this paper, which will further enhance our understanding of the interactions between the real economy and the asset markets.[17]

[17] Among others, see Amisano and Tristani (2009) for related studies.

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

	FFR	SPR	GDP	EFP	TED	SRET	HRET
Mean	6.397	1.502	0.759	1.087	0.883	1.968	1.344
Median	5.563	1.604	0.731	0.957	0.637	2.263	1.313
Maximum	17.780	3.611	3.865	2.513	3.307	18.952	45.11
Minimum	0.997	-2.182	-20.38	0.560	0.097	-26.431	-2.713
Std. Dev.	3.508	1.335	0.750	0.422	0.742	7.659	1.040
Skewness	1.037	-0.627	-0.127	1.220	1.552	-0.664	-0.040
Kurtosis	4.283	2.941	6.150	4.229	4.917	4.070	4.691
Observations	134.000	134.000	134.000	134.000	134.000	134.000	134.000

Note: FFR denotes the federal funds rate, SPR denotes the term spread, GDP means the gross domestic production growth rate, EFP means the external finance premium, TED means the market liquidity, SRET means stock index return, and HRET means housing market return.

Table 2 Correlation Coefficients (1975Q2-2008Q3)

	FFR	SPR	GDP	EFP	TED	SRET	HRET
FFR	1.000	**-0.557**	-0.104	**0.544**	**0.833**	0.009	0.015
SPR		1.000	0.145	0.037	**-0.437**	0.021	-0.115
GDP			1.000	-0.179	-0.165	0.030	0.111
EFP				1.000	**0.650**	0.057	-0.151
TED					1.000	-0.049	-0.076
SRET						1.000	0.055
HRET							1.000

Table 3 List of Models

Model	Model Structure	Variables
A	Linear	FFR, SPR, TED, EFP, GDP, SRET, HRET
B	Two-regime	FFR, GDP, SRET, HRET
C	Two-regime	FFR, SPR, SRET, HRET
D	Two-regime	FFR, EFP, SRET, HRET
E	Two-regime	FFR, TED, SRET, HRET
F	Two-regime	EFP, SPR, SRET, HRET
G	Two-regime	EFP, TED, SRET, HRET
H	Two-regime	SPR, TED, SRET, HRET

Key: (unless specified, all variables refer to quarterly data) FFR, Federal Fund Rate; SPR, term spread, which is equal to (10-year bond rate – FFR); TED, TED spread, which is equal to (3-month Eurodollar deposit rate - 3-month T-bill rate), a measure of market liquidity; EFP, External Finance Premium, which is equal to corporate bond spread (Baa-Aaa), a measure of External Finance Premium; GDP, GDP growth rate; SRET, Stock Market Return; HRET, Housing Market Return.

Table 4a A Summary of Goodness of Fit for All Eight Models

Models		AIC
Model A	Single-regime model (FFR, SPR, TED, EFP, GDP, SRET, HRET)	11.230
Model B	Two-regime model (FFR, GDP, SRET, HRET)	13.472
Model C	Two-regime model (FFR, SPR, SRET, HRET)	12.450
Model D	Two-regime model (FFR, EFP, SRET, HRET)	10.159
Model E	Two-regime model (FFR, TED, SRET, HRET)	11.134
Model F	Two-regime model (EFP, SPR, SRET, HRET)	9.747
Model G	Two-regime model (EFP, TED, SRET, HRET)	**8.404**
Model H	Two-regime model (SPR, TED, SRET, HRET)	11.274

Table 4b A Comparison of Goodness of Fit between linear versus regime-switching VAR: AIC (model; linear VAR) / AIC (model; regime-switching VAR)

Models		Ratio of AIC
Model B	(FFR, GDP, SRET, HRET)	1.062 (14.306/13.472)
Model C	(FFR, SPR, SRET, HRET)	1.066 (13.2177/12.450)
Model D	(FFR, EFP, SRET, HRET)	**1.126** **(11.444/10.159)**
Model E	(FFR, TED, SRET, HRET)	**1.122** **(12.489/11.134)**
Model F	(EFP, SPR, SRET, HRET)	**1.105** **(10.773/9.747)**
Model G	(EFP, TED, SRET, HRET)	**1.112** **(9.346/8.404)**
Model H	(SPR, TED, SRET, HRET)	1.082 (12.201/11.274)

Table 5a A Summary of In-sample Forecasting Performances (4-Quarter Ahead Forecasts)

		Stock Returns		Housing Returns	
		RMSE	MAE	RMSE	MAE
Model A	Single-regime model (FFR, SPR, TED, EFP, GDP, SRET, HRET)	7.5842	5.6699	0.8226	0.6499
Model B	Two-regime model (FFR, GDP, SRET, HRET)	7.6411	5.6640	0.8286	0.6508
Model C	Two-regime model (FFR, SPR, SRET, HRET)	**7.5103**	**5.5922**	0.7974	0.6361
Model D	Two-regime model (FFR, EFP, SRET, HRET)	7.6460	5.6561	**0.7801**	**0.6129**
Model E	Two-regime model (FFR, TED, SRET, HRET)	7.6232	5.6959	0.7984	0.6207
Model F	Two-regime model (EFP, SPR, SRET, HRET)	7.7767	5.7204	0.7940	0.6331
Model G	Two-regime model (EFP, TED, SRET, HRET)	7.7917	5.8092	0.8397	0.6468
Model H	Two-regime model (SPR, TED, SRET, HRET)	7.6169	5.7064	0.8161	0.6313

Table 5b A Summary of Out-of-Sample Forecasting Performances (4-Quarter Ahead Forecasts)

		Stock Returns		Housing Returns	
		RMSE	MAE	RMSE	MAE
Model A	Single-regime model (FFR, SPR, TED, EFP, GDP, SRET, HRET)	7.9841	**5.6808**	2.1292	1.8424
Model B	Two-regime model (FFR, GDP, SRET, HRET)	7.2027	5.8760	2.1303	1.8739
Model C	Two-regime model (FFR, SPR, SRET, HRET)	7.3392	6.0156	1.9161	1.7198
Model D	Two-regime model (FFR, EFP, SRET, HRET)	7.3122	5.9867	1.9977	1.7797
Model E	Two-regime model (FFR, TED, SRET, HRET)	7.0037	5.7126	2.0761	1.7754
Model F	Two-regime model (EFP, SPR, SRET, HRET)	8.2423	6.7808	**1.8184**	1.6078
Model G	Two-regime model (EFP, TED, SRET, HRET)	7.2071	5.7972	2.0430	1.7617
Model H	Two-regime model (SPR, TED, SRET, HRET)	**6.9225**	**5.6933**	**1.8284**	**1.5201**

Table 5c A Summary of Diebold and Mariano (1995) Statistics
(In-sample 4-Quarter Ahead Forecasts)

		Stock Returns		Housing Returns	
		MSE	MAE	MSE	MAE
Model A	Single-regime model (FFR, SPR, TED, EFP, GDP, SRET, HRET)	0.7318	2.478**	-0.1621	-0.4963
Model B	Two-regime model (FFR, GDP, SRET, HRET)	-0.1614	0.6655	-0.3220	-0.5398
Model C	Two-regime model (FFR, SPR, SRET, HRET)	1.1722	1.2627	0.5635	-0.1613
Model D	Two-regime model (FFR, EFP, SRET, HRET)	-0.2795	0.6718	1.3709	0.8491
Model E	Two-regime model (FFR, TED, SRET, HRET)	-0.2855	0.3332	0.9024	0.4998
Model F	Two-regime model (EFP, SPR, SRET, HRET)	-1.1219	-0.1338	0.7738	-0.0715
Model G	Two-regime model (EFP, TED, SRET, HRET)	-1.8132*	-1.2011	-0.9156	-0.7527

Note: The DM test is used to compare the forecasting ability for model H and the competing model. * Significant at 10% level of significance. ** Significant at 5% level of significance. A positive number indicates that model H is not as good as the alternative while a negative number indicates that model H out-performs the alternative model.

Table 5d A Summary of Diebold and Mariano (1995) Statistics
(Out-of-sample 4-Quarter Ahead Forecasts)

		Stock Returns		Housing Returns	
		MSE	MAE	MSE	MAE
Model A	Single-regime model (FFR, SPR, TED, EFP, GDP, SRET, HRET)	-1.1363	0.1264	-3.3408***	-32.7923***
Model B	Two-regime model (FFR, GDP, SRET, HRET)	-1.3610	-1.5920	-4.3774***	-17.4304***
Model C	Two-regime model (FFR, SPR, SRET, HRET)	-1.5381	-2.2680**	-1.1721	-2.4465**
Model D	Two-regime model (FFR, EFP, SRET, HRET)	-1.2888	-1.8064*	-5.6608***	-5.7929***
Model E	Two-regime model (FFR, TED, SRET, HRET)	-1.0822	-0.2802	-2.8926***	-30.1051***
Model F	Two-regime model (EFP, SPR, SRET, HRET)	-1.5901	-1.8569*	0.1079	-1.1512
Model G	Two-regime model (EFP, TED, SRET, HRET)	-1.0213	-0.6897	-3.5273***	-11.1494***

Note: The DM test is used to compare the forecasting ability for model H and the competing model. * Significant at 10% level of significance. ** Significant at 5% level of significance. *** Significant at 1% level of significance.

Table 5e Is the forecasted Stock return within the 80% confidence interval?

Models		Predicting 2006 based on 1975-2005	Predicting 2007 based on 1975-2006	Predicting 2008 based on 1975-2007
Model A	Single-regime model (FFR, SPR, TED, EFP, GDP, SRET, HRET)	Yes	Yes	Partly
Model B	Two-regime model (FFR, GDP, SRET, HRET)	Yes	Yes	Partly
Model C	Two-regime model (FFR, SPR, SRET, HRET)	Yes	Yes	Partly
Model D	Two-regime model (FFR, EFP, SRET, HRET)	Yes	Yes	Partly
Model E	Two-regime model (FFR, TED, SRET, HRET)	Yes	Yes	Partly
Model F	Two-regime model (EFP, SPR, SRET, HRET)	Yes	Yes	Partly
Model G	Two-regime model (EFP, TED, SRET, HRET)	Yes	Yes	Partly
Model H	Two-regime model (SPR, TED, SRET, HRET)	**Yes**	**Yes**	**Yes**

Table 5f Is the forecasted Housing return within the 80% confidence interval?

Models		Predicting 2006 based on 1975-2005	Predicting 2007 based on 1975-2006	Predicting 2008 based on 1975-2007
Model A	Single-regime model (FFR, SPR, TED, EFP, GDP, SRET, HRET)	Partly	Partly	No
Model B	Two-regime model (FFR, GDP, SRET, HRET)	Yes	Partly	No
Model C	Two-regime model (FFR, SPR, SRET, HRET)	Yes	Partly	No
Model D	Two-regime model (FFR, EFP, SRET, HRET)	Partly	Partly	No
Model E	Two-regime model (FFR, TED, SRET, HRET)	Yes	Partly	No
Model F	Two-regime model (EFP, SPR, SRET, HRET)	Yes	Partly	No
Model G	Two-regime model (EFP, TED, SRET, HRET)	Yes	Partly	No
Model H	Two-regime model (SPR, TED, SRET, HRET)	Yes	Partly	No

Table 6a: Do models forecast stock return better in the presence of housing return?

	In-sample	Out-of-sample
Model B predicts stock return better than B1	No	No
Model C predicts stock return better than C1	No	No
Model D predicts stock return better than D1	No	No
Model E predicts stock return better than E1	No	**Yes**
Model F predicts stock return better than F1	No	No
Model G predicts stock return better than G1	No	No
Model H predicts stock return better than H1	No	**Yes**

Table 6b: Do models forecast housing return better in the presence of stock return?

	In-sample	Out-of-sample
Model B predicts housing return better than B2	No	No
Model C predicts housing return better than C2	**Yes**	**Yes**
Model D predicts housing return better than D2	No	No
Model E predicts housing return better than E2	**Yes**	**Yes**
Model F predicts housing return better than F2	No	No
Model G predicts housing return better than G2	No	No
Model H predicts housing return better than H2	**Yes**	**Yes**

Key: “YES” means the model is better in both RMSE and MAE criteria.

Figure 1a Federal Funds Rate (FFR), Term Spread (SPR), Percentage Changes in Gross Domestic Production (GDP), External Finance Premium (EFP)

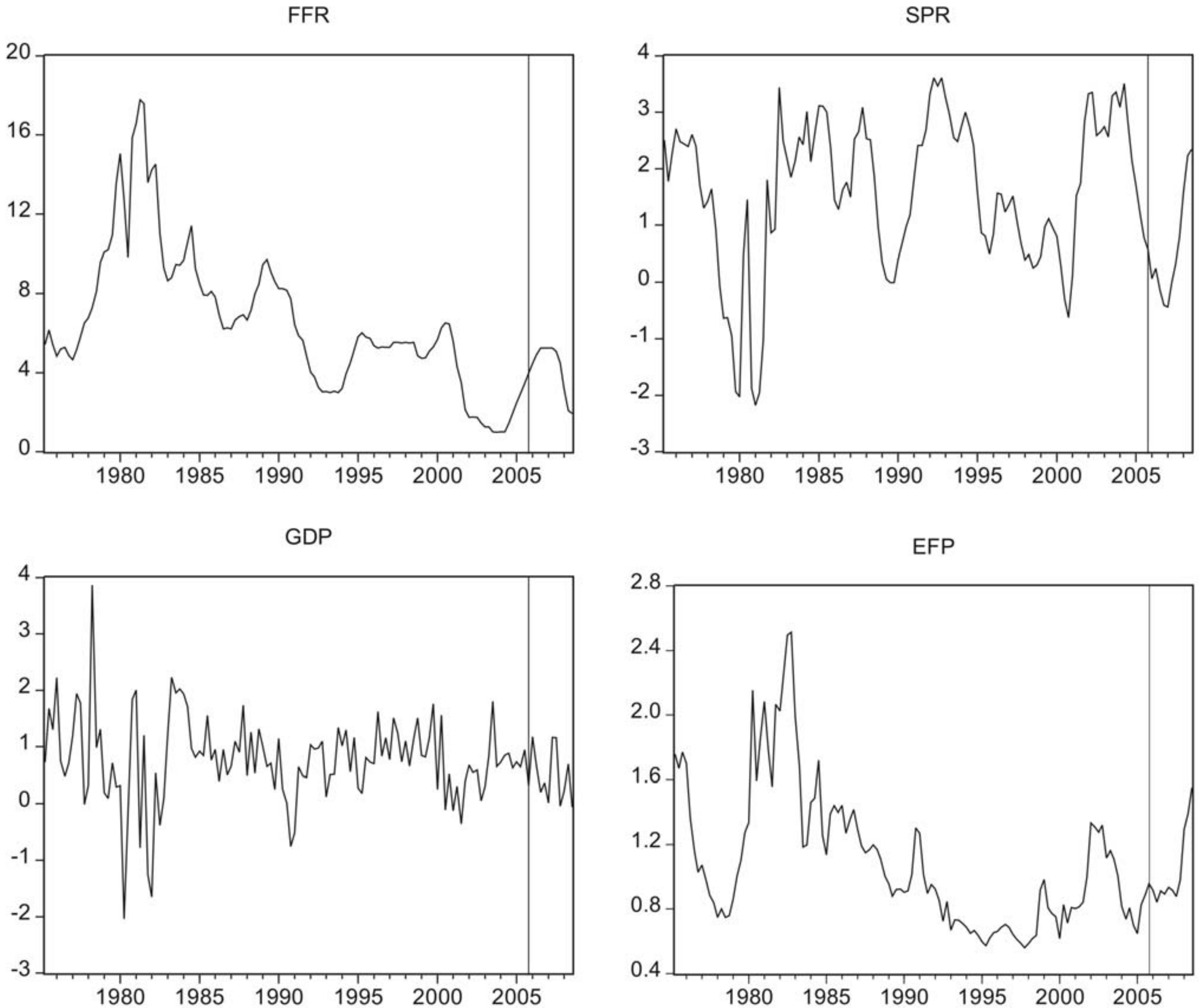

Figure 1b Market Liquidity (TED), Stock Index Return (SRET), Housing Market Return (HRET)

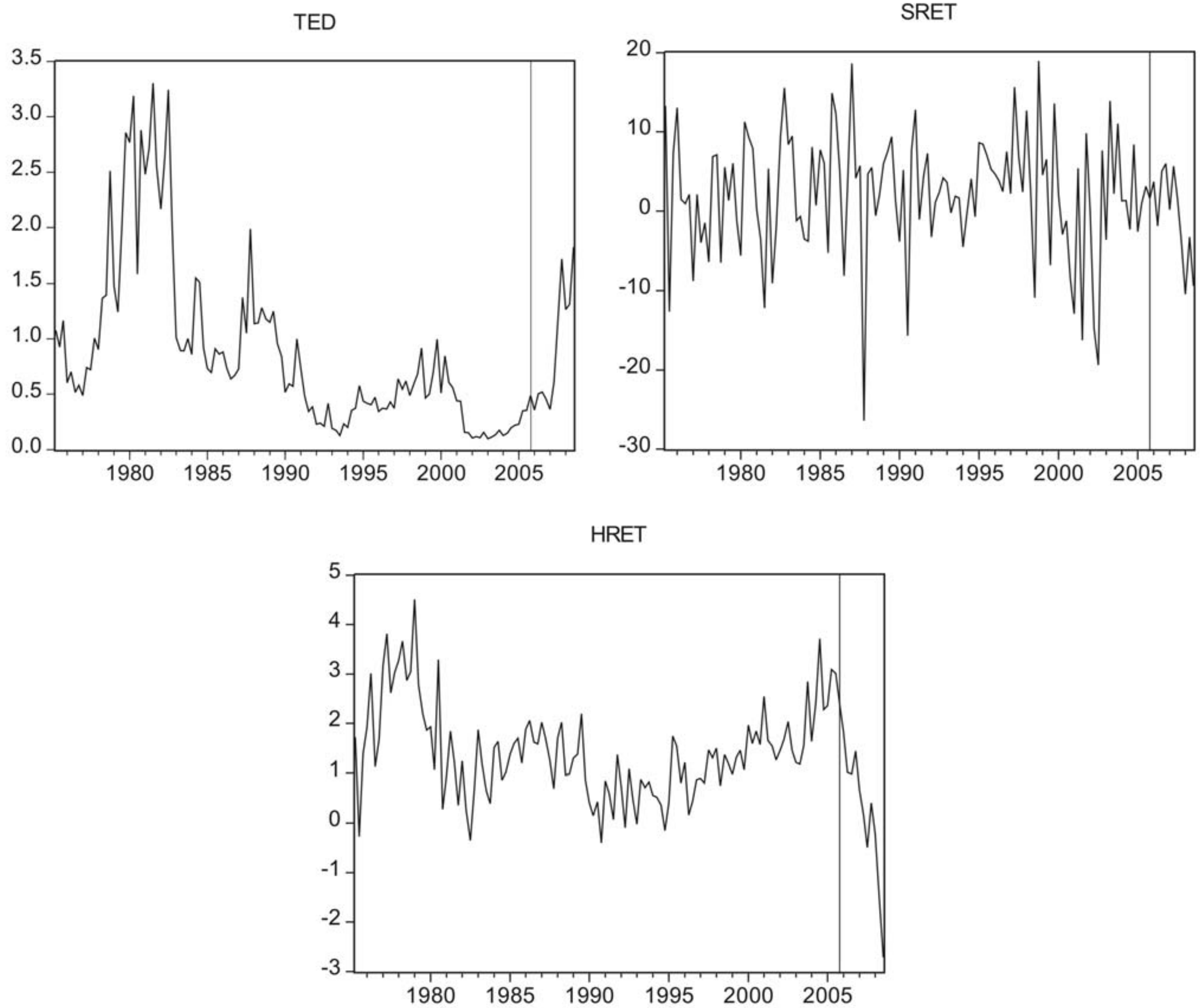

Figure 2a Smoothed Probabilities for Model B (FFR,GDP,SRET,HRET)

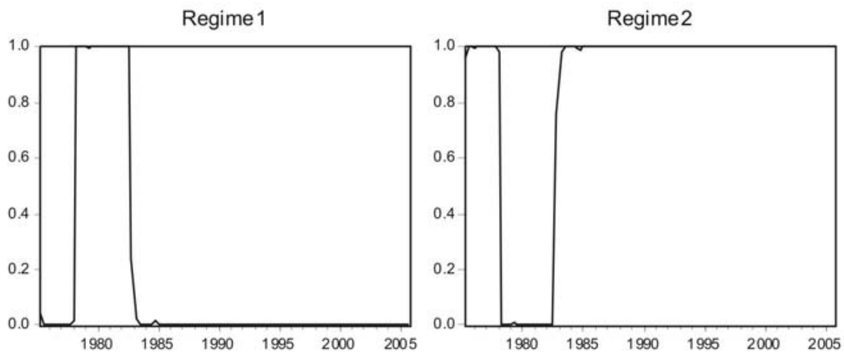

Figure 2b Smoothed Probabilities for Model C (FFR,SPR,SRET,HRET)

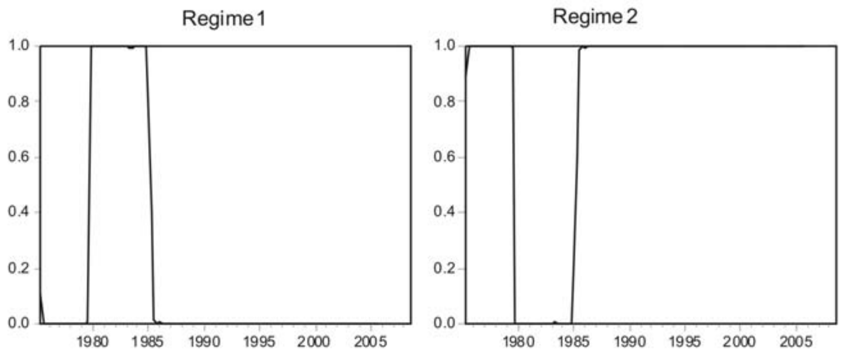

Figure 2c Smoothed Probabilities for Model D (FFR,EFP,SRET,HRET)

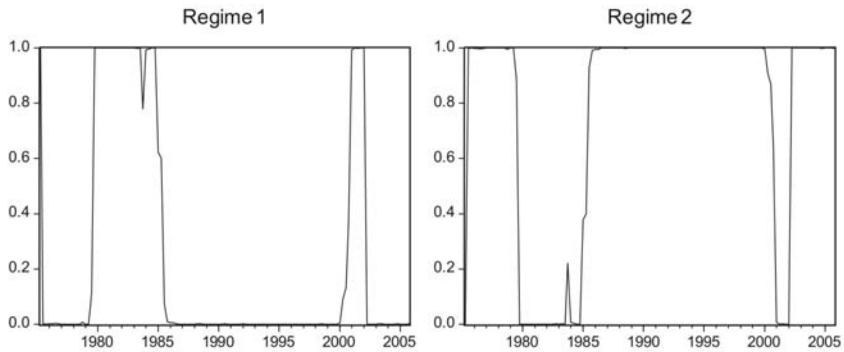

Figure 2d Smoothed Probabilities for Model E (FFR,TED,SRET,HRET)

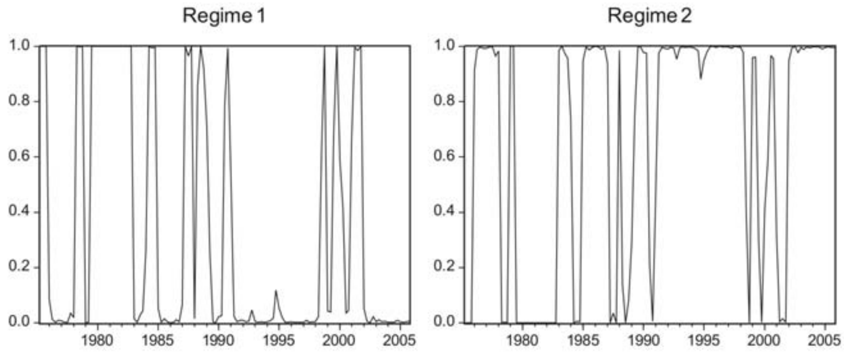

Figure 2e Smoothed Probabilities for Model F (EFP,SPR,SRET,HRET)

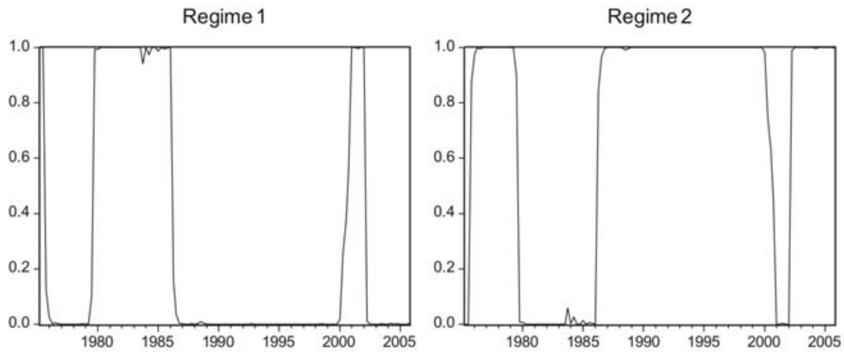

Figure 2f Smoothed Probabilities for Model G (EFP,TED,SRET,HRET)

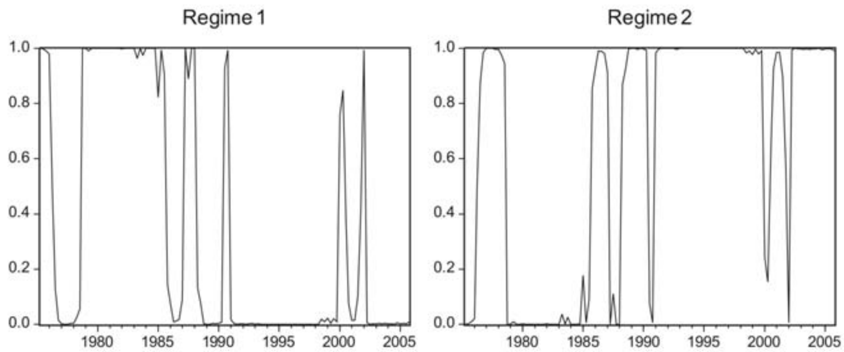

Figure 2g Smoothed Probabilities for Model H (SPR,TED,SRET,HRET)

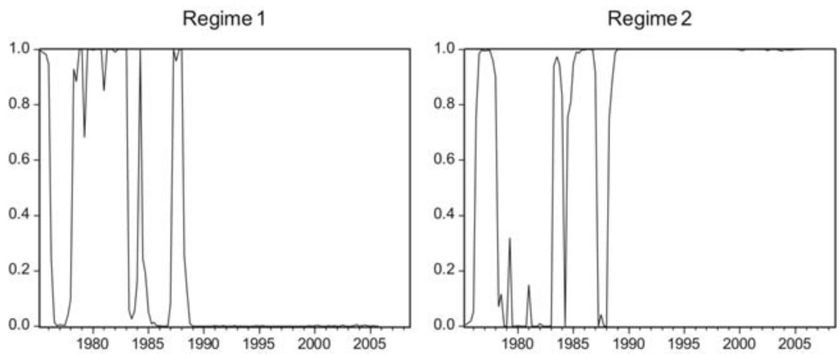

Figure 3a Simulation-Based Out-of-Sample Forecasts of Stock Returns with 80-Percent Confidence Interval (CI) from 2006Q1-2006Q4 Based on Information Available at 2005Q4

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

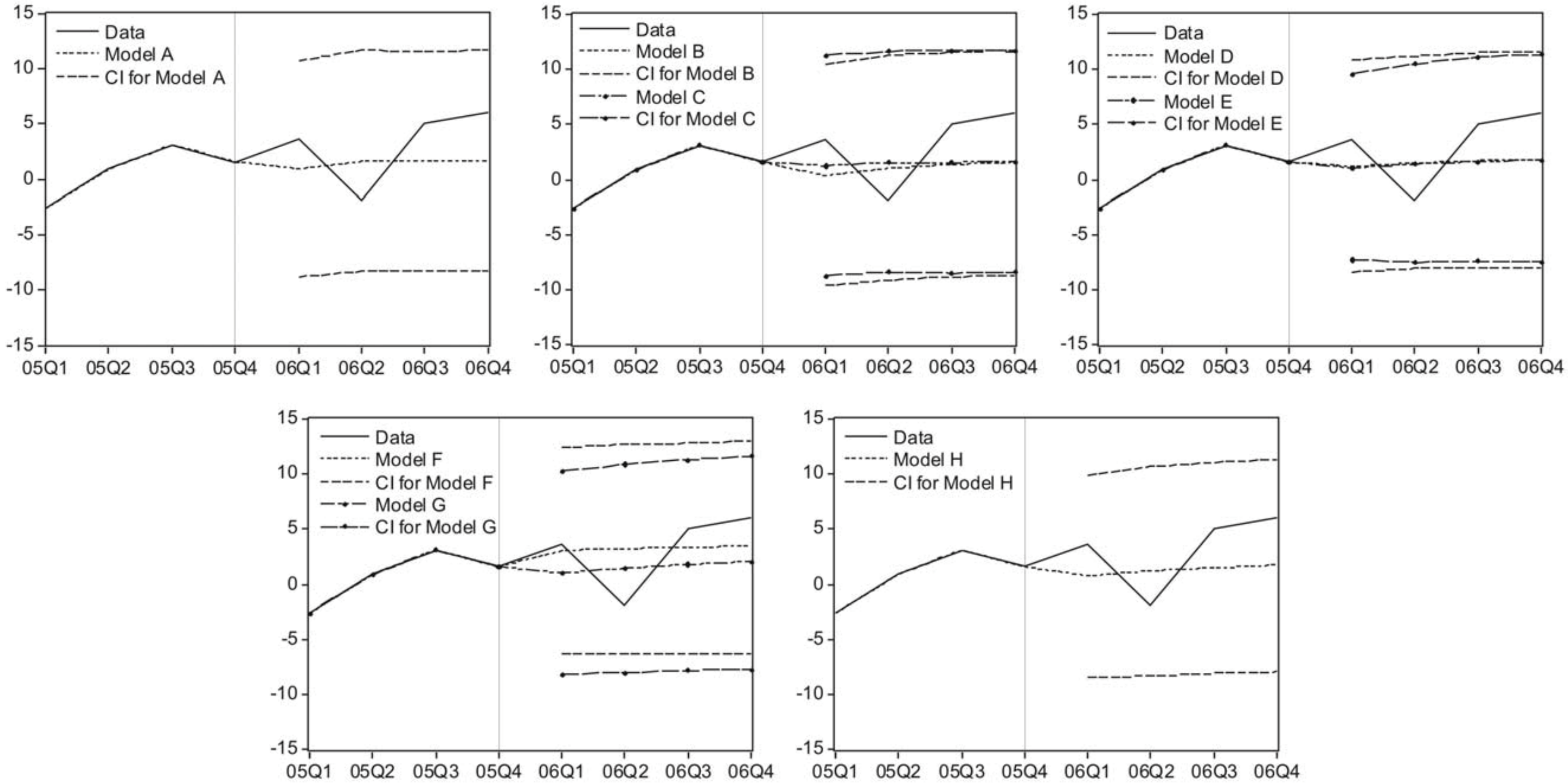

Figure 3b Simulation-Based Out-of-Sample Forecasts of Stock Returns with 80-Percent Confidence Interval (CI) from 2007Q1-2007Q4 Based on Information Available at 2006Q4

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

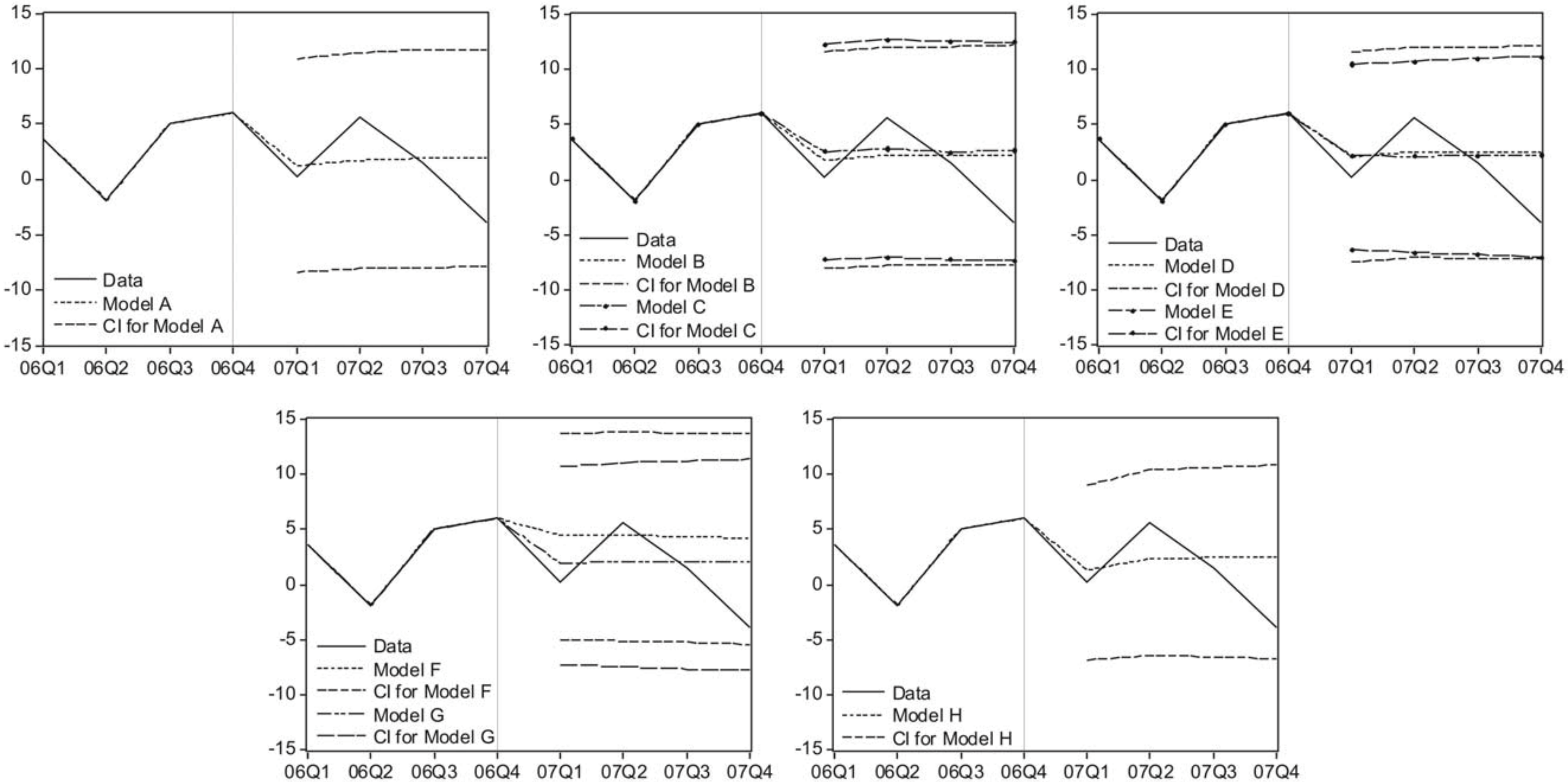

Figure 3c Simulation-Based Out-of-Sample Forecasts of Stock Returns with 80-Percent Confidence Interval (CI) from 2008Q1-2008Q3 Based on Information Available at 2007Q4

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

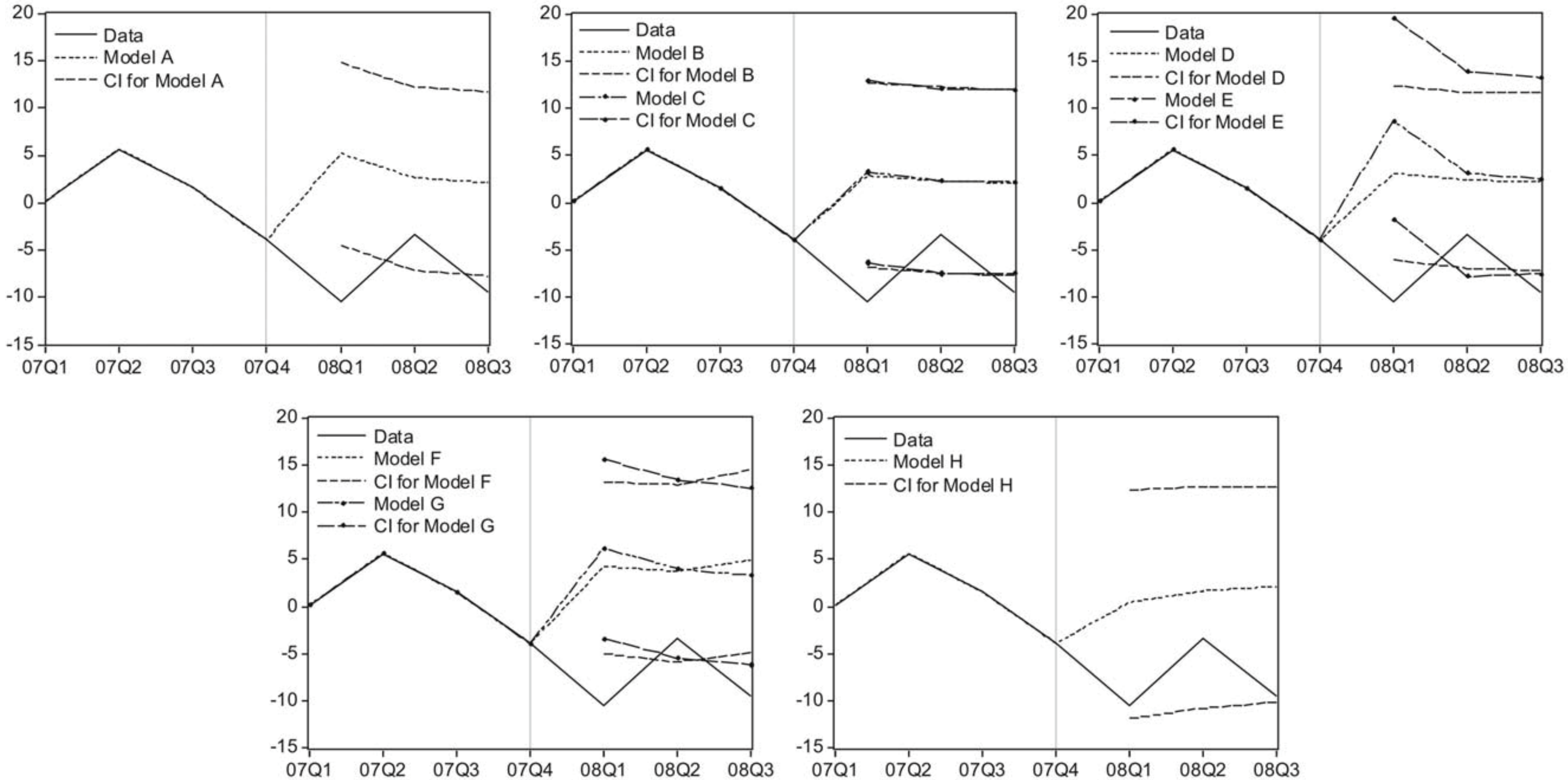

Figure 4a Simulation-Based Out-of-Sample Forecasts of Housing Returns with 80-Percent Confidence Interval (CI) from 2006Q1-2006Q4 Based on Information Available at 2005Q4

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

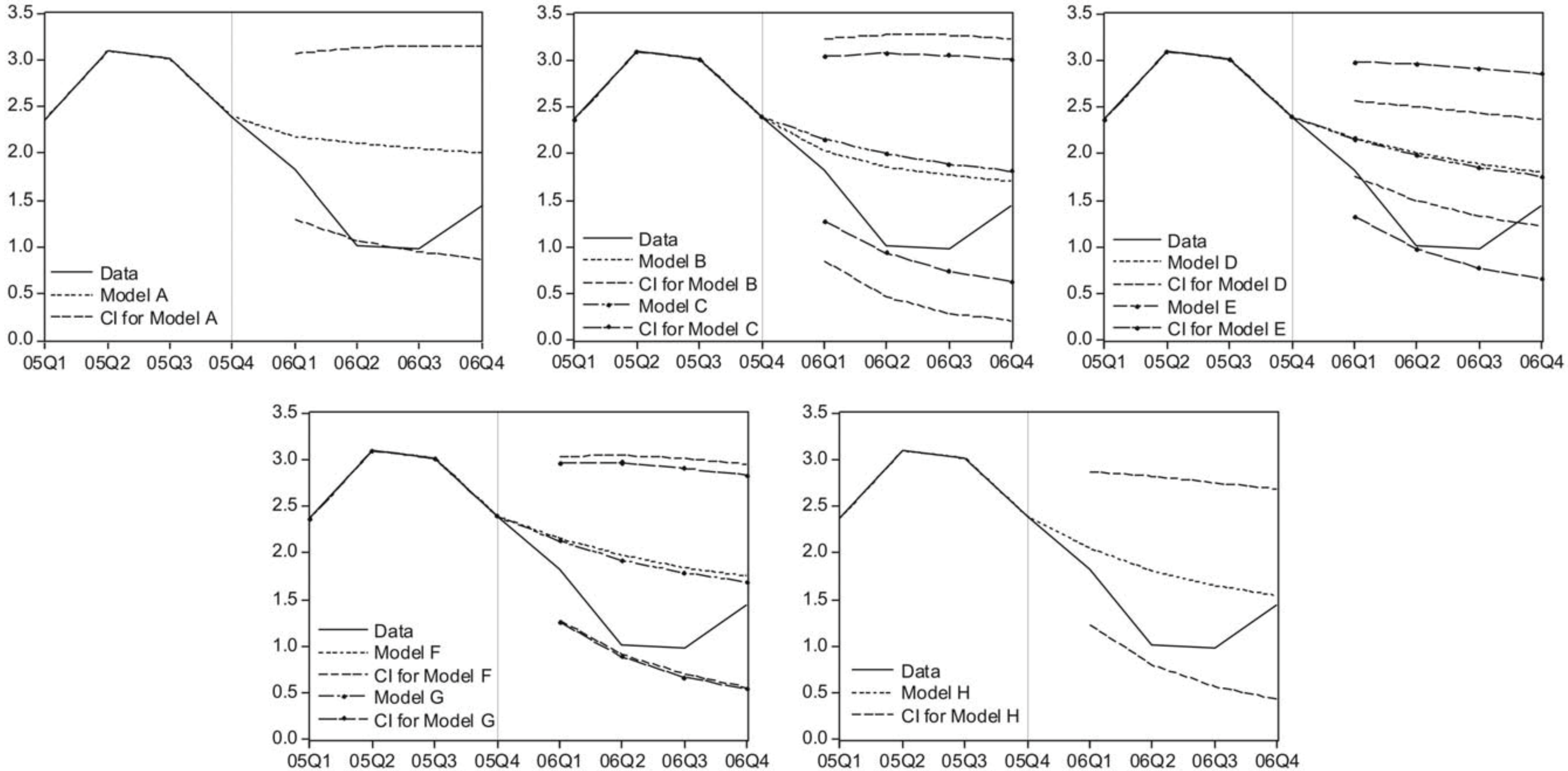

Figure 4b Simulation-Based Out-of-Sample Forecasts of Housing Returns with 80-Percent Confidence Interval (CI) from 2007Q1-2007Q4 Based on Information Available at 2006Q4

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

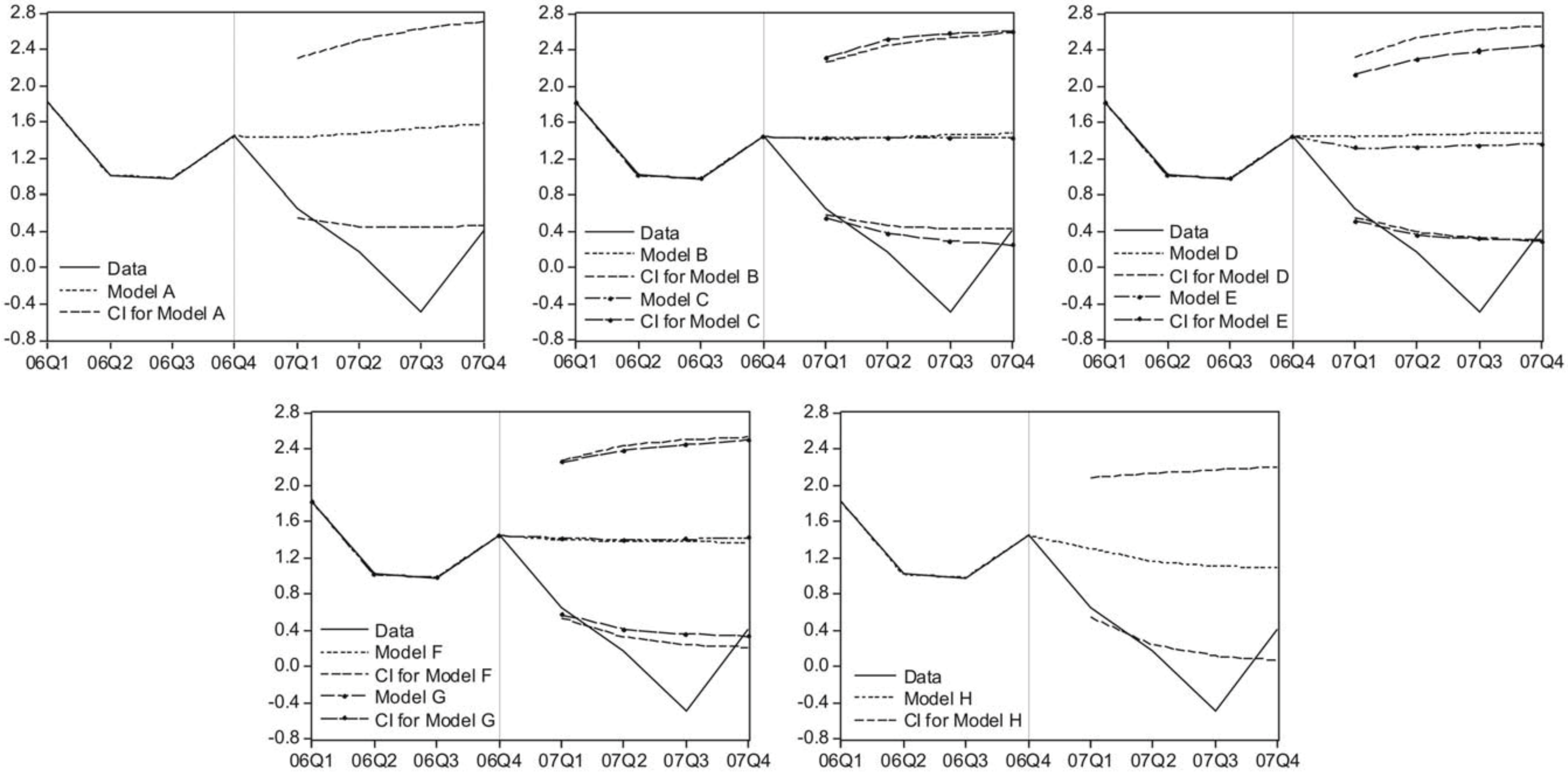

Figure 4c Simulation-Based Out-of-Sample Forecasts of Housing Returns with 80-Percent Confidence Interval (CI) from 2008Q1-2008Q3 Based on Information Available at 2007Q4

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