

# Real Estate Returns Predictability Revisited:

## Novel Evidence from the US REITs Market

### Abstract<sup>1</sup>

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In this paper we examine the real estate returns predictability employing US Real Estate Investment Trusts (REITs) and a set of possible predictors for the period January 1991 to December 2014. To this end we employ several forecasting models to test for REITs predictability under a flexible framework that captures parameter instability. Apart from the traditional factors examined in relevant studies, we also account for a series of sentiment and uncertainty indicators that may be significant predictors of REITs returns, especially during turbulent times when sentiment determines investment decisions to a greater extent. The empirical results indicate that the good predictors of REITs returns vary over time and over the forecast horizons. Our results suggest that economy-wide indicators, monetary policy instruments and sentiment indicators are among the most powerful predictors of REITs returns. In economic terms an investment strategy that is based on our forecasts outperforms a buy and hold strategy. The issue of the most suitable forecasting method is also discussed in detail. Our results might entail implications for investors and market authorities.

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## 1. Introduction

Real estate market has undoubtedly attracted increasing investment interest, especially after the US 2000 stock market bubble that shook investors' confidence in financial markets and turned their interest to investments that seemed safer and unaffected by financial scandals, such as the real estate (Akerlof and Shiller, 2009). In fact, US real estate prices experienced a prolonged period of impressive returns from 2000 to 2005 (see Figure 1). This period was followed by a dramatic decrease starting from 2006, triggering the global financial crisis.

These unprecedented events place the US real estate market in the centre of investment and research interest as an alternative asset class. Consequently, real estate returns predictability has important implications both for investors (retail or institutional) and market authorities.<sup>2</sup> On one side practitioners as well as individual investors are particularly interested in the possibility of forecasting returns that would directly affect their asset allocation and portfolio formation decisions. On the other side, successful return forecasting directly questions market efficiency with important consequences for all market participants.

However, testing for the real estate market predictability is quite challenging since the real estate market is characterized by high transaction costs, lack of liquidity and low frequency data that are not always observable or systematically collected. In order to surpass these obstacles researchers usually employ Real Estate Investment Trusts (REITs) data to alleviate such problems. According to the National Association of Real Estate Investment Trusts (NAREIT), REITs are exchange-traded funds that earn most of their income from investments in real estate. REITs have been in the epicentre of research interest since their returns do not suffer from measurement error and high transaction costs compared to other real estate investments. In fact, according to Philippas et al. (2013), Ghysels et al. (2013), Lee and Chiang (2010) and Zhou and Lai (2008), REITs constitute a very good proxy for the real estate market, providing at the same time high frequency observable data, since REITs shares trade as common stocks. Moreover, REITs are accessible to all investors irrespective of their portfolios' size making this asset class particularly successful in attracting investment capital. The market capitalisation of the US REITs has increased from \$138,715.4 mil. in 2000 to \$907,425.5 mil. in 2014 marking a remarkable increase of 554% in 14 years.<sup>3</sup>

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<sup>2</sup> Researchers have also focused on investor behaviour in the real estate market trying to identify herd behaviour in real estate market (Lan, 2014; Philippas et al., 2013; Zhou and Anderson, 2013), especially after the recent global financial crisis.

<sup>3</sup> <http://www.reit.com/investing/industry-data-research/us-reit-industry-equity-market-cap>.

In the context of our analysis we test for REITs returns predictability employing a data set of several alternative possible predictors from January 1991 to December 2014. This paper contributes to the existing literature on the predictability of real estate returns in several ways. We provide insight into the generating mechanisms of real estate prices. We examine several different forecasting methods to test for REITs predictability employing the total return FTSE NAREIT all REITs index as a good proxy for the US real estate market. Apart from the traditional factors examined in relevant studies, we also examine for the first time a series of sentiment and uncertainty indicators that may be significant predictors of REITs returns, especially during turbulent times that sentiment determines investment decisions to a greater extent. In this sense, we extend the existing literature both methodologically and conceptually in the examination of real estate market predictability.

Previewing our results, we document that the good predictors of REITs returns vary over time and over the forecast horizons. Overall, during the 2005-2009 sub-period, the Kansas City Financial Stress Index, the relative 3-month Treasury bill, inflation and the term spread have strong predictive ability at all horizons. Most interestingly, monetary policy decisions, as reflected in the short term interest rates, strongly affect the behavior of REITs returns. REITs returns volatility is another important predictor that persists at all horizons except horizon 1. As for model comparisons based on our results, Dynamic Model Averaging (DMA) and Dynamic Model Selection (DMS) models provide acceptable forecasts, while DMS stands out as the best highlighting the importance of accounting for model uncertainty. Both the sum of the log predictive likelihoods and the mean squared forecast error clearly stress the superiority of DMS across all forecast horizons. However, the sum of the log predictive likelihoods and the mean squared forecast error (MSFE) indicate that the time varying parameter model underperforms relative to the DMA and DMS models on average. Finally our models offer an economically viable benefit to investors since an investment strategy that is based on our forecasted REITs returns outperforms a buy and hold strategy.

The rest of the paper is structured as follows: Section 2 provides a brief literature review on real estate returns forecasting, Section 3 presents the employed dataset, Section 4 and 5 report the methodological approach used and the empirical results respectively, and finally, Section 6 summarizes the main empirical findings and concludes the paper.

## 2. Literature review

Forecasting real estate prices has long attracted the interest of researchers. The relevant literature is voluminous focusing on different types of indices including the repeat-sales indices (Case and Shiller, 1987), appraisal indices, such as the National Property Index, the Transaction Based Index by the MIT Centre for Real Estate and stock market based indices, such as the CRSP/Ziman and the FTSE NAREIT US indices. The property type investigated, (residential or commercial real estate) including direct or indirect real estate investment, the econometric method employed in predicting real estate returns including the use of in-sampling or out-sampling forecasting, as well as the market under examination have an impact on the empirical results (Meese and Wallace, 1994; Capozza and Seguin, 1996; Abraham and Hendershott, 1996). Thus, forecasting real estate prices is a complex task to perform due to the heterogeneous nature of real estate assets, being illiquid, and characterised by high transaction costs, information asymmetry and tax considerations. In this section we perform a brief literature review on the predictability of directly measured real estate returns and thereafter we focus on the literature dedicated to the predictability of REITs returns.

The examination of market efficiency in the real estate market is of particular importance for all market participants. The existing literature has largely documented evidence of positive serial correlation of real estate returns (see for example Case and Shiller, 1989; Hill et al., 1997;1999; Schindler et al., 2010; Schindler, 2013), however, the results on whether this finding is exploitable in terms of trading strategies is quite inconclusive.<sup>4</sup>

Hill et al. (1999) tested the random walk hypothesis on the house prices and their results indicated no evidence of a random walk component. Hamilton and Schwab (1985) examined the expected appreciation in house prices in the mid 1970's. Their empirical results did not support the rational expectations hypothesis since households did not accurately incorporate information referring to past appreciation in their expectations. However, the authors argued that the households may have formed "economic rational expectations", i.e. the gains from this information were not worth the relevant cost. As a result, the housing market cannot be considered to be a healthy investing environment for arbitrageurs and the information requirements for individuals cannot justify the effort needed to form economic rational expectations. On the other hand, the real estate forecastability findings provided by Brooks and Tsolacos (2001) are consistent with stock market efficiency, since the excess

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<sup>4</sup> See Gatzlaff and Tirtiroglu (1995), Cho (1996), Maier and Herath (2009) and Ghysels et al. (2013) for a comprehensive review on the real estate market efficiency.

returns of the examined trading strategies do not cover transaction costs, hence they are not exploitable by traders.

In addition, Campbell et al. (2009) examined the housing market in 23 US metropolitan areas using the rent-price ratio. They show that time-dependent and predictable housing premia exist. Several authors have also employed the transaction based Case-Shiller index and provide support that housing returns are predictable. Recently, Schindler (2013) examined the predictability of the Case-Shiller indices computed for 20 cities and his results rejected the random walk hypothesis, indicating strong persistence in the real estate markets under examination. The author concluded that there are exploitable gains in real estate markets and active trading strategies perform better than buy and hold strategies.

A growing strand of literature focuses on the REITs returns predictability. The empirical evidence of REITs superior predictability is rather mixed depending mostly on the employed methodology, the time period and the market under examination. Liu and Mei (1992) analysed the predictability of the equity REITs expected returns employing a multifactor latent variable model with time varying risk premiums, which decomposes excess returns into expected and unexpected. Their results indicated that the expected excess returns of equity REITs move more closely with small-cap stocks and they are more predictable than any other asset examined. In a subsequent study, Mei and Liu (1994) employed various market timing strategies as well as a buy and hold strategy to test the REITs returns predictability. The authors found that real estate predictability results only in moderate success of the market timing strategy, while real estate stocks tend to have higher trading profits and mean adjusted excess returns in comparison to stocks and bonds.

On the other hand, Mei and Lee's (1994) findings did not confirm the higher equity REITs returns predictability, while Li and Wang (1995) indicated that REIT returns have about the same predictability as stocks. Mei and Gao (1995) investigated the return reversals of real estate securities employing an arbitrage portfolio approach at a weekly frequency. The authors identified statistically significant return reversals that can lead to economically significant trading profits for arbitrage traders which, however, disappear taking trading costs and bid-ask spread into consideration. In the same spirit, Nellling and Gyuorko (1998) did not identify any exploitable arbitrage opportunities. Even though the authors found that equity REITs returns are predictable based on past performance, this is not enough to cover for transaction costs. Ling et al. (2000) reported similar findings testing for the excess equity REITs returns predictability compared to the stock market, small-cap stocks and T-bills. Their results reported far less predictability of the excess equity REIT returns out-of-sample

rather than in-sample, also indicating that transactions costs practically eliminate profits from active trading strategies.

Serrano and Hoesli (2007) examined the predictability of REITs returns employing several forecasting methods and compared this to buy and hold strategy. Their findings supported that neural networks provide the best predictions of REITs returns. Brooks and Tsolacos (2003) had also indicated the fact that “analysts should exploit the potential of neural networks”. In a subsequent study, Serrano and Hoesli (2010) examined the difference in the predictability of securitized real estate and stocks returns on a cross-country level and indicated higher predictability for real estate returns in countries that have well established and mature REIT regimes. In fact, United States, the Netherlands and Australia presented the best forecasts using daily data from 1990 to 2007. Moreover, Schindler et al. (2010) examined 14 securitized real estate markets from 1990 to 2006 using relevant indices and indicated that it is possible for investors to gain excess returns in most of the real estate markets of their sample employing strategies that are based on past information. This conclusion is also supported by the recent empirical findings provided by Schindler et al. (2014), employing UK inflation-adjusted house prices from 1974 to 2009. Finally, an de Meulen et al. (2014) examined the role of consumers’ expectations in real estate market forecasting for the German market. Following Rapach and Strauss (2007) and Rouwendal and Longhi (2008) who provided evidence of correlation of consumer confidence with house prices in the US and the Netherlands respectively, an de Meulen et al. (2014) reported that consumer sentiment is in parts important in real estate prices forecasting along with fundamental variables.

### **3. Methodology**

In order to forecast REITs returns, we consider six models namely the Time-Varying Parameter (TVP) model, Dynamic Model Averaging (DMA), Dynamic Model Selection, (DMS), Bayesian Model Averaging (BMA), and an autoregressive model based on recursive Ordinary Least squares (OLS).

The TVP models are often used in empirical macroeconomic research, where their estimates are obtained from state space models such as Kalman filter. Despite their popularity, the predictors are assumed to remain constant over time (Koop and Korobilis, 2012). Moreover, when the number of predictors is large the TVP models tend to over-fit in-sample, thereby leading to poor forecast. Extensions of these models such as the TVP-VAR

models also suffer from constant predictors assumption at each point in time (Koop and Korobilis, 2012). To overcome these problems, the DMA models present a feasible and superior alternative.

Dynamic model averaging (DMA) simply means averaging across various models. Assume that a set of  $K$  models exists and is characterized by having different subsets of  $z_t$  as predictors. Denoting these by  $z^{(k)}$  for  $k = 1, \dots, K$ , the set of models can be written as:

$$\begin{aligned} y_t &= z_t^{(k)} \theta_t^{(k)} + \varepsilon_t^{(k)} \\ \theta_{t+1}^{(k)} &= \theta_t^{(k)} + \eta_t^{(k)} \end{aligned} \quad (1)$$

where  $\varepsilon_t^{(k)}$  is  $N(0, H_t^{(k)})$  and  $\eta_t^{(k)}$  is  $N(0, Q_t^{(k)})$ . Let  $L_t \in \{1, 2, \dots, K\}$  denote which model applies at each time period,  $\Theta_t = (\theta_t^{(1)}, \dots, \theta_t^{(K)})'$  and  $y^t = (y_1, \dots, y_t)'$ . The name ‘‘dynamic model averaging’’ arises from letting different models hold at each point in time and these are subsequently averaged. Specifically, when forecasting time  $t$  variables using information through time  $t-1$ , DMA involves calculating  $Pr(L_t = k / y^{t-1})$  for  $k = 1, \dots, K$ , and averaging forecasts across the  $K$  models, using these probabilities. DMS involves selecting the single model with the highest value for  $Pr(L_t = k / y^{t-1})$  and using this to forecast. However, when  $K$  is large, estimation can take longer time. Thus, a full Bayesian approach to DMA can be quite difficult. To overcome this, we use approximations suggested by Raftery et al. (2010), which involve two parameters  $\lambda$  and  $\alpha$ , for the coefficients and the models, respectively, referred to as the forgetting factors and fix them to numbers slightly below one. In this case standard state space models, such as the Kalman filter which permits real time forecasting, can be employed.

The role of the forgetting factors can be explained by considering first the standard state space model below for  $t = 1 \dots T$ :

$$y_t = z_t \theta_t + \varepsilon_t \quad (2)$$

$$\theta_t = \theta_{t-1} + \eta_t \quad (3)$$

where  $y_t$  is the output vector defined as the growth rate of the real estate investment trusts (REIT) for this study,  $z_t = [1, x_{t-1}, y_{t-1}, \dots, y_{t-p}]$  is an  $1 \times m$  vector of predictors which also includes an intercept and lags of the dependent variable,  $\theta_t = [f_{t-1}, \beta_{t-1}, \gamma_{t-1}, \dots, \gamma_{t-p}]$  is an  $m \times 1$

vector of coefficients (states),  $\varepsilon_t \sim N(0, H_t)$  and  $\eta_t \sim N(0, Q_t)$  are the errors which are assumed to be mutually independent across all leads and lags. For given values of the variance-covariance matrices  $H_t$  and  $Q_t$  the standard filtering and smoothing results can be used to carry out recursive estimation or forecasting. Kalman filtering begins with the result that:

$$\theta_{t-1} / y^{t-1} \sim N(\hat{\theta}_{t-1}, \Sigma_{t/t-1}) \quad (4)$$

where formulae for  $\hat{\theta}_{t-1}$  and  $\Sigma_{t-1|t-1}$  are standard. These formulae depend on  $H_t$  and  $Q_t$ . Then Kalman filtering proceeds, using:

$$\theta_t / y^{t-1} \sim N(\hat{\theta}_{t-1}, \Sigma_{t/t-1}) \quad (5)$$

where

$$\Sigma_{t|t-1} = \Sigma_{t-1|t-1} + Q_t.$$

Raftery et al. (2010) note that the computational burden can be substantially reduced if this latter equation is replaced by:

$$\Sigma_{t|t-1} = \frac{1}{\lambda} \Sigma_{t-1|t-1} \quad (6)$$

or, equivalently,  $Q_t = (1 - \lambda^{-1}) \Sigma_{t-1|t-1}$  where  $0 < \lambda \leq 1$ . The term ‘‘forgetting factor’’ is suggested by the fact that this specification implies that observations  $j$  periods in the past have weight  $\lambda^j$ . It also implies an effective window of  $1/(1 - \lambda)$ . It is common to choose a value of  $\lambda$  near one, which suggests a gradual evolution of coefficients. Raftery et al. (2010) set  $\lambda = 0.99$ . For monthly macroeconomic data, this suggests that observations of five (one) years ago receive approximately 50% (90%) as much weight as the last period’s observation. This would be consistent with fairly stable models where coefficient change is gradual. Values lower than 0.99, for example 0.95, would suggest substantial parameter instability with rapid change in coefficients.

Theoretically, one could specify a transition matrix  $P$ , and obtain the unconditional prediction (i.e not conditional on any specific model)<sup>5</sup>, using MCMC methods. However, to ease the computational burden, we follow Raftery et al. (2010) and Korobilis (2012) and

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<sup>5</sup> See Koop and Korobilis (2012) for technical details on conditional prediction for both single and multi-model cases.



introduce a forgetting factor for the state equation for the models, termed  $\alpha$ . The derivation of Kalman filtering ideas begins with equation (4). For DMA, the result is:

$$P(\Theta_{t-1}, L_{t-1} | y^{t-1}) = \sum_{k=1}^K P(\theta_{t-1}^{(k)} | L_{t-1} = k, y^{t-1}) \Pr(L_{t-1} = k | y^{t-1}), \quad (7)$$

where  $P(\theta_{t-1}^{(k)} | L_{t-1} = k, y^{t-1})$  is given by  $\Theta_{t-1} | L_{t-1} = k, y^{t-1} \sim N(\hat{\theta}_{t-1}^{(k)}, \Sigma_{t-1|t-1}^{(k)})$ . To simplify notations, let  $\pi_{t|s,1} = \Pr(L_t = 1 | y^s)$  and thus, the final term on the right hand side of equation (7) be  $\pi_{t-1|t-1,k}$ . The model prediction equation is:

$$\pi_{t|t-1,k} = \frac{\pi_{t-1|t-1,k}^\alpha}{\sum_{l=1}^K \pi_{t-1|t-1,l}^\alpha}, \quad (8)$$

where  $0 < \alpha \leq 1$  is set to a fixed value slightly less than one and is interpreted in a similar manner to  $\lambda$ , i.e., if  $\alpha = 0.99$  (our benchmark value), for monthly data, the forecast performance five years ago receives 50% as much weight as the forecast performance in the last period, while the forecast performance one year ago receives about 90% as much weight as the performance in the last period. The model updating equation is thus given as:

$$\pi_{t|t,k} = \frac{\pi_{t|t-1,k} P_k(y_t | y^{t-1})}{\sum_{l=1}^K \pi_{t|t-1,l} P_l(y_t | y^{t-1})}, \quad (9)$$

where  $P_l(y_t | y^{t-1})$  is the predictive density for model  $l$ , which is simply a normal density evaluated at  $y_t$ . Recursive forecasting can be done by averaging over predictive results for every model using  $\pi_{t|t-1,k}$ . The DMA point predictions are thus given by:

$$E(y_t | y^{t-1}) = \sum_{k=1}^K \pi_{t|t-1,k} z_t^{(k)} \hat{\theta}_{t-1}^{(k)} \quad (10)$$

DMS proceeds by selecting the single model with the highest value for  $\pi_{t|t-1,k}$  at each point in time and simply using it for forecasting. If we set  $\alpha = 1$ , then  $\pi_{t|t-1,k}$  is simply proportional to the marginal likelihood using data through time  $t-1$ , and gives the standard approaches to BMA. If we also set  $\lambda = 1$ , then we obtain BMA using conventional linear

forecasting models with no time variations in coefficients. We implement the BMA by setting  $\alpha = \lambda = 1$ .<sup>6</sup>

#### 4. Data

We employ monthly data from January 1991 to December 2014 for a series of 13 variables that may be good predictors of REITs returns, while the out-of-sample testing period ranges from August 2005 to December 2014. Note the start and end-points of the sample were purely driven by data availability at the time the paper was being written. The size of the out-of-sample period was however, governed by the first break-date, i.e., July, 2005, for the real returns on REIT, determined by the multiple structural break tests of Bai and Perron (2003). The real REITs returns (RRet) were calculated subtracting the month-on-month CPI-based inflation rate from the FTSE NAREIT All REITs Index (total return), derived from the National Association of Real Estate Investments Trusts official website.<sup>7</sup> This is a market capitalization-weighted index which includes all tax-qualified REITs (equity, mortgage or hybrid) listed on the New York Stock Exchange, the American Stock Exchange or the NASDAQ, providing a very good proxy for the US real estate market.

Our set of conditioning variables captures time variation in the behaviour of the aggregate economy and thus in the current investment opportunity set. Other economic variables that have appeared in the relevant literature include demographic variables, income and employment variables, construction costs, housing starts, tax rates, etc (see Ghysels et al. 2013 for an excellent review of conditioning variables). For example, a demand-driven pressure on house prices might emerge from improved economic conditions and demographic booms. Our set of macroeconomic variables includes the inflation rate (the logarithmic change of the CPI index), the industrial production growth (IPG) based on the Industrial Production Index of the Board of Governors of the Federal Reserve System. As in Ling et al. (2000) we employ the relative 3-month Treasury bill (RTB) calculated as the current rate minus its 12month moving average and the term spread (TS) calculated as the difference between the 5-year and 3-month yields from the U.S. Department of the Treasury. Following Ling et al. (2000) the lagged real US stock market returns using the S&P500 index (RM) is

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<sup>6</sup> Further details on the DMA and DMS methods and implementation can be obtained from Koop and Korobilis (2011, 2012).

<sup>7</sup> See <http://www.reit.com/investing/index-data/ftse-nareit-us-real-estate-index-historical-values-returns>.

included in the models in order to control for potential time-series patterns in stock returns. Moreover the Standard & Poor's dividend-price ratio (DPM) which is a proxy for the state of the equity market was derived from the data segment of Professor Robert J. Shiller's website<sup>8</sup>. Finally we employ the Cochrane and Piazzesi (2005) interest rate factor (CP) defined as "a single tent-shaped linear combination of forward rates"<sup>9</sup> and the real REITs returns volatility (VOL) calculated as the 12-month moving standard deviation (Mele, 2007). It should be noted that these variables have been also used in relevant studies (see for example Ghysels et al., 2013).

We also employ for the first time in the relevant literature a series of sentiment and uncertainty indicators that may convey a superior predictive ability. To this end we include the Kansas City Financial Stress Index (KCFSI), which measures the US financial system's stress based on eleven variables that describe yield spreads and asset prices' behaviour.<sup>10</sup> The Index of Consumer Sentiment (ICS), based on the Thomson Reuters/University of Michigan Surveys of Consumers that provides a good indicator of the future course of the US economy is also included.<sup>11</sup> Moreover, we employ the US Policy Uncertainty Index (USPUN) and the Equity Market Uncertainty Index (EMUI) from the Economic Policy Uncertainty official website.<sup>12</sup> The USPUN index provides a measure of policy-related economic uncertainty, based on 3 components: the policy-related economic uncertainty newspaper coverage, the number of federal tax code provisions expiring in the coming years and the economic forecasters' disagreement. On the other hand, the EMUI index is constructed based on the stock market uncertainty related news articles in US newspapers.<sup>13</sup>

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<sup>8</sup> <http://www.econ.yale.edu/~shiller/data.htm>.

<sup>9</sup> The CP factor was calculated based on the method described in the paper by Cochrane and Piazzesi (2005) using the one to five years Fama-Bliss Discount Bond Yields, with these series being obtained from the Center for Research in Security Prices (CRSP).

<sup>10</sup> Data derived from the official website of the Federal Reserve Bank of the Kansas City, available at <http://www.kc.frb.org/research/indicatorsdata/kcfsi/>.

<sup>11</sup> Data available at <http://www.sca.isr.umich.edu/tables.php>.

<sup>12</sup> Data available at <http://www.policyuncertainty.com/>.

<sup>13</sup> In addition to these 13 predictors, we also analyzed the predictive ability of the four components (news-based, federal-state local expenditure disagreement, CPI disagreement and tax expiration) of the UPUN instead of the aggregate index itself; the debt-ceiling and government shutdown indexes; all of which are available from [www.policyuncertainty.com](http://www.policyuncertainty.com). Barring the news-based component of UPUN, none of the other indices had any predictive ability. Further, we also looked at eight (six on moving average based-rules and 2 on momentum based-rules) technical indicators, which too did not have any predictive ability. In light of this, we decided to

Table 1 reports the descriptive statistics of the real REITs returns and the 13 selected conditioning variables, while Table 2 presents the correlation matrix of all the variables. REITs' returns have low correlations with the rest variables, displaying the highest contemporaneous correlation with the real stock market returns (0.455).

## 5. Empirical Results

The results are presented in two sub-sections. The results in the first sub-section shows which of the variables are good predictors of the REIT returns from the list of the 13 potential variables as listed in the Data section. The forecast performance of the DMA compared to the alternative forecasting models that are nested in the DMA, are discussed in the second sub-section. Five forecast horizons are considered namely: 1-month-ahead ( $h=1$ ), 3-months-ahead ( $h=3$ ), 6-months-ahead ( $h=6$ ), 9-months-ahead ( $h=9$ ), and 12-months-ahead ( $h=12$ ). This is standard practice in the literature using monthly data (see for example Gupta et al., 2014), and corresponds to capturing short-, medium- and long-run horizons. The Schwarz information criterion favors an optimal lag of four. Therefore, we include 4 lags of the independent variable and an intercept in our specifications.

### 5.1. Good predictors for the real estate investment trusts

A key advantage of the DMA framework is that the forecasting model is allowed to vary over time. In other words both the model parameters and the set of predictors are not constant at each point in time. Since we use a set of 13 possible explanatory variables (the intercept and 4 lags of the dependent variable not inclusive, since these are common to all models), we have a total of 8,192 possible models to choose from. The posterior probabilities of inclusion which shed light on the predictive abilities of each predictor for the different forecast horizons over the out-of-sample period 2005:8 to 2014:12, are presented in Figures 2 through 6. It appears that the good predictors of REITs returns vary over time and over the forecast horizons. Particularly, two periods are striking namely 2005-2009 and post 2009. It should be noted that the first period includes the Great Recession period, while the second is the post Great Recession period.

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drop these additional predictors to keep the analysis tractable in terms of the number of predictors. However, details of these results are available upon request from the authors.

During 2005-2009 sub-period, KCFSI, Inflation and RTB, have very strong predictive power for REITs at  $h=1$ . Other good predictors at this horizon but with relatively reduced predictive ability are ICS, IPG, TS, RM and USPUN. At  $h=3$ , KCFSI, RTB, TS and RM are the best predictors while EMUI, USPUN, Inflation, IPG, CP and VOL performed fairly well. At  $h=6$ , we observe that a number of predictors including KCFSI, EMUI, ICS, Inflation, RTB, RM, VOL and TS have strong predictive ability. At  $h=9$ , KCFSI, USPUN, IPG and VOL have the strongest predictive ability while ICS, Inflation, TS and CP faired relatively well. EMUI seemed to be the strongest predictor of REITs at  $h=12$  with Inflation, IPG, RTB and VOL following. Other good predictors at  $h=12$  include KCFSI, ICS, RTB, TS and CP. Overall, during the 2005-2009 sub-period, KCFSI, RTB, Inflation, TS have strong predictive ability at all horizons. VOL is another important predictor that comes through strongly at all horizons except horizon 1.

Variables such as Inflation, ICS, IPG are consistent with a strand of literature (see Ghysels et al. 2013) that attempts to forecast real estate prices through the demand and supply forces in the real estate market. As mentioned earlier the economic activity, demographic trends, construction costs etc are all important factors to be considered. Moreover leverage is another important determinant of real estate prices that might be reflected in the strong predictive ability of RTB and TS. In other words, households' borrowing conditions are tightly linked to real estate values. Finally expectations for future economic and market conditions as reflected in market-wide sentiment indicators are important in explaining real estate price dynamics.

For the post 2009 period, we observe that EMUI, IPG and DPM are the strongest predictors followed by CS and RM at  $h=1$ . At  $h=3$ , ICS featured as the strongest followed by EMUI towards the end of the period and RTB. The strongest predictor at  $h=6$  is RTB whose strong predictive power span throughout this sub-period while KCFSI, IPG, DPM and RM also come through strongly at some points of time for this horizon. At  $h=9$ , ICS, CP and VOL come through strongly, while EMUI is a strong predictor at the beginning of the post 2009 sub-period. At  $h=12$ , EMUI featured very strongly towards the beginning and middle of the sub-period while USPUN, RTB, Inflation, IPG and TS come through strongly during the middle of the sub-period. Overall, it is observed that while EMUI possess strong predictive ability at all horizons except horizon 6, KCFSI shows strong predictive power at horizon 6 only making the later a less good predictor during the post 2009 compared to 2005-2009 sub-period.

In general while there appeared to be many good predictors between 2005-2009 sub-period, the good predictors are fewer for the post 2009 sub-period. There is clearly a large variation over time and over forecast horizons. These results confirm the previously stated advantage of the DMA and DMS that they are capable of picking up good predictors automatically as the forecasting model evolves over time (Koop and Korobilis, 2012).

## 5.2. Forecast evaluation of alternative models

The sum of the log predictive likelihoods, which involves the entire predictive distribution, is usually the best for evaluating the forecast performance of Bayesian models (Geweke and Amisano, 2011). In this study, we use this statistic summed over the out-of-sample period to evaluate the DMA model and all the models nested in the DMA. However, this does not apply to the AR(4) model, which is estimated with recursive OLS. Therefore, in addition to the sum of the log predictive likelihoods, we also report mean squared forecast error (MSFE) in percentages, since this can be computed for all the models.

We present results for six alternative forecasting models. Model 1 is the benchmark dynamic model averaging (DMA), where we set the values for the forgetting factors as  $\alpha = \lambda = 0.99$ . In this case, both the parameters and the set of predictors are allowed to vary over time. Model 2) is the dynamic model selection (DMS) which is also estimated by setting  $\alpha = \lambda = 0.99$ . This however involves selecting the model with the highest probability and using this to forecast. Model 3, the TVP model is a special case of Model 1 where all the predictors are included at all time periods, but parameter values are allowed to change. For implementation purpose, we set  $\alpha = 1$  and  $\lambda = 0.99$ . Model 4 is a also a special case of DMA where the parameters are kept constant but the model evolves over time. Hence, we set  $\alpha = 0.99$  and  $\lambda = 1$  for model 4. Model 5 is the Bayesian model averaging (BMA), where neither the coefficients nor the models vary over time. Thus, we set  $\alpha = \lambda = 1$ . Model 6, is our benchmark AR(4) model, estimated with a recursive OLS method.

Table 3 presents the results from our forecasting exercise for REITs for the five forecasting horizons defined in the previous sub-section. From the results in Table 3, it is clear that DMA and DMS forecast generally well, with DMS being the best overall. The sum of the log predictive likelihoods clearly shows that DMS performs better across all forecast horizons followed by the DMA with parameter and model evolution. The only exception is at horizon 1 where the DMA with constant coefficient forecast better than both DMS and DMA

with model and coefficient evolution. Although DMS and DMA can be interpreted as doing the shrinkage in different ways, however, Koop and Korobilis (2012) noted that DMS puts weight on all models other than the one best model, thus shrinking the contribution of all models except one towards zero. This additional shrinkage appears to have given DMS additional benefits over DMA. This finding is consistent with forecasts obtained by Koop and Korobilis (2012) for inflation and Gupta et al. (2014) for China's foreign exchange reserves using similar models. The results based on the out-of-sample MSFE are somewhat different. While DMS maintained its leading position as the best model for forecasting REITs at all horizons except horizon 3, the DMA performed better than the AR(4) model at horizon 1 only.

Based on the sum of the log predictive likelihoods and the MSFE, the DMA and DMS possess better forecasting ability than the TVP model. The poor performance of the TVP model indicates that the shrinkage offered by DMA and DMS models is of great value in forecasting. Further, model evolution rather than parameter evolution appear to have contributed more to the better forecasting performance of the DMA or DMS. This is because the benchmark DMA and DMS with  $\alpha = \lambda = 0.99$  generally forecast better than the DMA model in which the coefficients assumed to be stable over time (i.e.  $\lambda = 1$ ). These findings demonstrate that allowing for model uncertainty in addition to parameter uncertainty, improves the forecasting ability of the DMA and DMS models.

### 5.3 Trading strategy

Following Serrano and Hoesli (2010), we compare an active trading strategy that is based on our forecasts with a buy and hold strategy<sup>14</sup>. More precisely, we compare the forecasted REIT return with the 12month moving average of the 3-month Treasury yield (adjusted on a monthly basis). If the forecasted REIT return is greater we invest in the relevant REIT index, otherwise we invest in the 3month yield (adjusted on a monthly basis). Starting in August 2005 and for every month until December 2014 we repeat the same procedure using our 1 month horizon and  $\lambda=0.99$  forecasts for all the estimated models.

In the absence of transaction costs the results of the two trading strategies an active and a passive are reported in Table 5. The risk adjusted excess average return expressed by Sharpe

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<sup>14</sup> We would like to thank an anonymous referee for his suggestion to perform a trading strategy.

ratio is greater for a strategy based on forecasted REITs returns rather than for a buy and hold strategy in four out of six cases.

## **6. Conclusions and implications**

The real estate market returns predictability has undoubtedly attracted research interest and REITs definitely provide an appropriate proxy for the market that offers clean, high frequency and observable data. In this paper we examine the real estate returns predictability employing US REITs index and a series of possible predictors for the period 1991-Dec. 2014. To this end we examine several different forecasting methods to test for REITs predictability. Apart from the traditional factors examined in relevant studies, we also examine a series of sentiment and uncertainty indicators that may be significant predictors of REITs returns, especially during turbulent times that sentiment determines investment decisions to a greater extent.

The empirical results indicate that the good predictors of REITs real returns vary over time and over the forecast horizons. In fact, during the 2005-2009 sub-period, the Kansas City Financial Stress Index, the relative 3-month Treasury bill, the inflation, the term spread exhibit strong predictive ability at all horizons, while REITs returns volatility is another important predictor. For the post 2009 period, the Equity Market Uncertainty Index has strong predictive ability at all horizons except horizon 6, while the Kansas City Financial Stress Index has strong predictive power only at horizon 6. Even though there are many good predictors during the 2005-2009 sub-period, these are fewer for the post 2009 sub-period.

With respect to model selection our extensive tests provide evidence that most of the improvements in forecast performance found by Dynamic Model Averaging or Dynamic Model Selection are due to model evolution rather than parameter evolution. Stated differently, allowing for model uncertainty and not only for parameter uncertainty, improves the forecasting performance of these models. Both the sum of the log predictive likelihoods and the mean squared forecast error clearly stress the superiority of Dynamic Model Selection across all forecast horizons.

Our findings entail important implications for all market participants and especially for portfolio managers that indirectly invest in real estate using REITs. The empirical results provide better understanding of the securitized real estate price movements in order to exploit



investment opportunities. Moreover, identifying the key driving forces behind real estate prices could help market authorities to safeguard stability in real estate markets and prevent the creation of future bubbles therein. Future research could place emphasis on the profitability of trading strategies based on the performance of the variables employed. An interesting topic would be to examine the predictive power of the employed variables for REITs sub-sectors returns.

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**Table 1: Descriptive statistics**

	RRet	KCFSI	ICS	USPUN	EMUI	INFL	IPG	TS	RTB	DP	VOL	DPM	RM	CP
Mean	0.892	-0.052	86.213	105.826	92.983	0.196	0.194	1.274	-0.163	0.067	6.278	0.239	0.507	0.066
Median	1.433	-0.395	87.650	94.676	48.026	0.196	0.242	1.320	-0.040	0.053	5.702	0.222	0.769	0.066
Maximum	27.725	5.880	112.000	245.127	1254.199	1.222	2.080	3.120	1.723	0.324	26.192	0.450	11.772	0.067
Minimum	-29.216	-1.060	55.300	57.203	5.058	-1.915	-4.208	-0.900	-2.499	0.008	0.005	0.134	-19.381	0.066
Std. Dev.	5.251	1.007	12.907	34.677	125.310	0.335	0.645	0.879	0.782	0.063	4.422	0.070	3.574	0.000
Skewness	-0.791	2.841	-0.173	1.083	4.330	-1.078	-1.748	-0.158	-0.556	1.595	1.466	0.778	-0.878	0.043
Kurtosis	10.103	13.947	2.471	3.696	32.047	8.978	12.010	2.282	3.573	5.522	6.534	2.740	7.094	2.743
Jarque-Bera	635.510	1825.276	4.796	62.137	11024.430	484.675	1120.858	7.380	18.767	198.433	253.042	29.857	238.165	0.878
Probability	0.000	0.000	0.091	0.000	0.000	0.000	0.000	0.025	0.000	0.000	0.000	0.000	0.000	0.645
Observations	288													

**Notes:** RRet counts for the real REITs return, KCFSI for the Kansas City Financial Stress Index, ICS for the Index of Consumer Sentiment, USPUN for the US Policy Uncertainty Index, EMUI for the Equity Market Uncertainty Index, INFL for inflation, IPG for industrial production growth, TS for term spread, RTB for relative T-bill rate, DP for dividend price ratio, VOL for volatility, DPM for S&P 500 dividend price ratio, RM for S&P500 lagged real returns and CP for the Cochrane-Piazzesi (2005) interest rate factor.

**Table 2: Correlation matrix**

	RRet	KCFSI	ICS	USPUN	EMUI	INFL	IPG	TS	RTB	DP	VOL	DPM	RM	CP
RRet	1.000													
KCFSI	-0.204	1.000												
ICS	0.049	-0.358	1.000											
USPUN	-0.054	0.412	-0.687	1.000										
EMUI	-0.098	0.219	0.026	0.177	1.000									
INFL	-0.016	-0.202	0.055	-0.128	-0.155	1.000								
IPG	-0.041	-0.454	0.245	-0.203	-0.095	0.041	1.000							
TS	0.036	0.014	-0.316	0.228	-0.014	-0.021	0.048	1.000						
RTB	0.075	-0.457	0.354	-0.314	-0.222	0.090	0.330	-0.136	1.000					
DP	0.036	-0.068	0.095	-0.114	0.070	0.078	0.042	0.319	-0.220	1.000				
VOL	0.006	0.367	-0.256	0.214	-0.082	-0.084	-0.142	0.103	-0.134	-0.210	1.000			
DPM	-0.004	0.158	-0.553	0.283	-0.009	-0.060	-0.109	0.497	-0.177	0.598	0.125	1.000		
RM	0.455	-0.311	0.132	-0.176	-0.237	-0.038	0.051	-0.041	0.162	0.053	-0.073	-0.029	1.000	
CP	0.042	-0.257	0.393	-0.413	0.058	0.107	0.162	0.422	-0.083	0.696	-0.209	0.225	-0.021	1.000

Notes: See Table 1 notes.

**Table 3: Comparing different forecasting methods for REIT. Results based on forgetting factors = 0.99**

Forecast Method	Sum of Log predictive likelihood	MSFE
<b>h=1</b>		
DMA ( $\alpha = \lambda = 0.99$ )	-376.321	128.464
DMS ( $\alpha = \lambda = 0.99$ )	-361.118	67.247
TVP( $\alpha=1, \lambda =0.99$ )	-379.741	135.957
DMA ( $\alpha=0.99, \lambda=1$ )	-375.245	100.264
BMA (DMA with $\alpha=\lambda=1$ )	-	102.563
Recursive OLS – AR(4)	-	258.186
<b>h=3</b>		
DMA ( $\alpha = \lambda = 0.99$ )	-389.907	97.460
DMS ( $\alpha = \lambda = 0.99$ )	-377.674	83.545
TVP( $\alpha=1, \lambda =0.99$ )	-392.997	100.411
DMA ( $\alpha=0.99, \lambda=1$ )	-393.465	93.754
BMA (DMA with $\alpha=\lambda=1$ )	-	96.472
Recursive OLS – AR(4)	-	86.467
<b>h=6</b>		
DMA ( $\alpha = \lambda = 0.99$ )	-361.877	96.563
DMS ( $\alpha = \lambda = 0.99$ )	-349.204	61.685
TVP( $\alpha=1, \lambda =0.99$ )	-366.719	100.787
DMA ( $\alpha=0.99, \lambda=1$ )	-364.053	98.727
BMA (DMA with $\alpha=\lambda=1$ )	-	102.548
Recursive OLS – AR(4)	-	154.960
<b>h=9</b>		
DMA ( $\alpha = \lambda = 0.99$ )	-368.777	107.880
DMS ( $\alpha = \lambda = 0.99$ )	-361.128	86.844
TVP( $\alpha=1, \lambda =0.99$ )	-373.037	113.453
DMA ( $\alpha=0.99, \lambda=1$ )	-369.285	105.052
BMA (DMA with $\alpha=\lambda=1$ )	-	147.561
Recursive OLS – AR(4)	-	80.596
<b>h=12</b>		
DMA ( $\alpha = \lambda = 0.99$ )	-345.705	127.199
DMS ( $\alpha = \lambda = 0.99$ )	-333.188	87.620
TVP( $\alpha=1, \lambda =0.99$ )	-348.427	136.306
DMA ( $\alpha=0.99, \lambda=1$ )	-346.564	130.300
BMA (DMA with $\alpha=\lambda=1$ )	-	139.161
Recursive OLS – AR(4)	-	101.737



**Table 4: Comparing different forecasting methods for REIT. Results based on forgetting factors = 0.95**

Forecast Method	Sum of Log predictive likelihood	MSFE
<b>h=1</b>		
DMA ( $\alpha = \lambda = 0.95$ )	-367.149	87.269
DMS ( $\alpha = \lambda = 0.95$ )	-347.786	43.898
TVP( $\alpha=1, \lambda = 0.95$ )	-374.750	125.449
DMA ( $\alpha=0.95, \lambda=1$ )	-370.304	95.511
BMA (DMA with $\alpha=\lambda=1$ )	-379.636	102.563
Recursive OLS – AR(4)	-	258.186
<b>h=3</b>		
DMA ( $\alpha = \lambda = 0.95$ )	-375.730	72.977
DMS ( $\alpha = \lambda = 0.95$ )	-357.120	47.242
TVP( $\alpha=1, \lambda = 0.95$ )	-384.803	82.286
DMA ( $\alpha=0.95, \lambda=1$ )	-383.276	80.892
BMA (DMA with $\alpha=\lambda=1$ )	-397.182	96.472
Recursive OLS – AR(4)	-	86.467
<b>h=6</b>		
DMA ( $\alpha = \lambda = 0.95$ )	-356.912	79.808
DMS ( $\alpha = \lambda = 0.95$ )	-332.550	43.710
TVP( $\alpha=1, \lambda = 0.95$ )	-367.116	90.546
DMA ( $\alpha=0.95, \lambda=1$ )	-355.054	87.334
BMA (DMA with $\alpha=\lambda=1$ )	-368.351	102.548
Recursive OLS – AR(4)	-	154.960
<b>h=9</b>		
DMA ( $\alpha = \lambda = 0.95$ )	-353.875	87.285
DMS ( $\alpha = \lambda = 0.95$ )	-334.285	58.132
TVP( $\alpha=1, \lambda = 0.95$ )	-360.111	96.547
DMA ( $\alpha=0.95, \lambda=1$ )	-362.705	98.112
BMA (DMA with $\alpha=\lambda=1$ )	-373.883	109.927
Recursive OLS – AR(4)	-	147.561
<b>h=12</b>		
DMA ( $\alpha = \lambda = 0.95$ )	-339.965	101.792
DMS ( $\alpha = \lambda = 0.95$ )	-313.324	50.266
TVP( $\alpha=1, \lambda = 0.95$ )	-348.408	132.208
DMA ( $\alpha=0.95, \lambda=1$ )	-340.903	106.662
BMA (DMA with $\alpha=\lambda=1$ )	-349.340	139.161
Recursive OLS – AR(4)	-	101.737

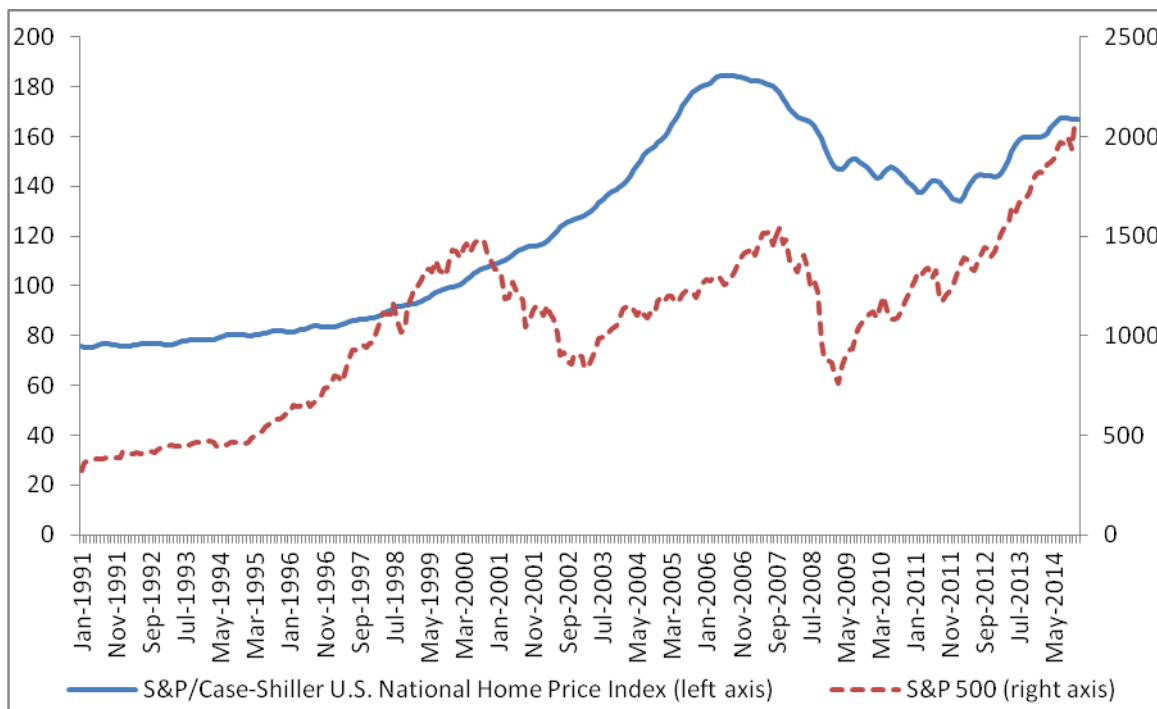
**Table 5. Trading strategy results (8/2005-12/2014)**

	DMA			DMS			DMA_lambda_1		
	REITS	3m Tr. yield	Strategy	REITS	3m Tr. yield	Strategy	REITS	3m Tr. yield	Strategy
<b>Average return (<math>\mu</math>)</b>	0,80%	0,11%	0,49%	0,80%	0,11%	1,23%	0,80%	0,11%	0,95%
<b>Standard deviation (<math>\sigma</math>)</b>	7,05%	0,16%	4,99%	7,05%	0,16%	5,15%	7,05%	0,16%	5,45%
<b>Sharpe ratio</b>	9,77%		7,52%	9,77%		<b>21,71%</b>	9,77%		<b>15,43%</b>

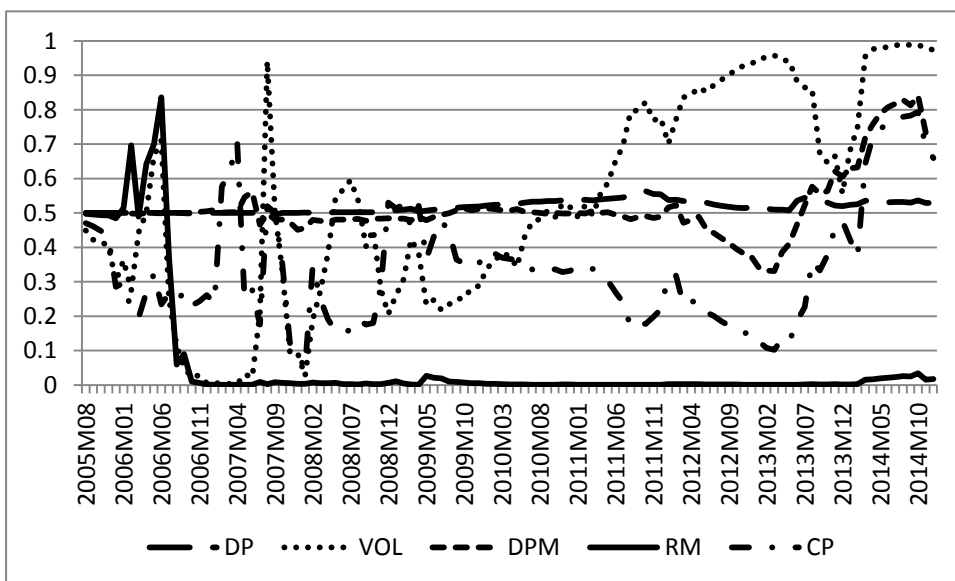
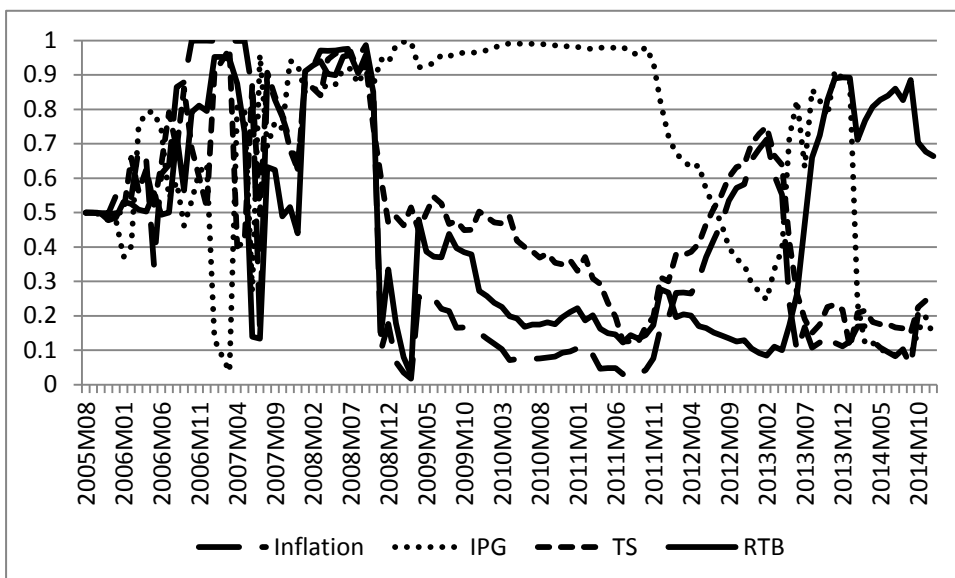
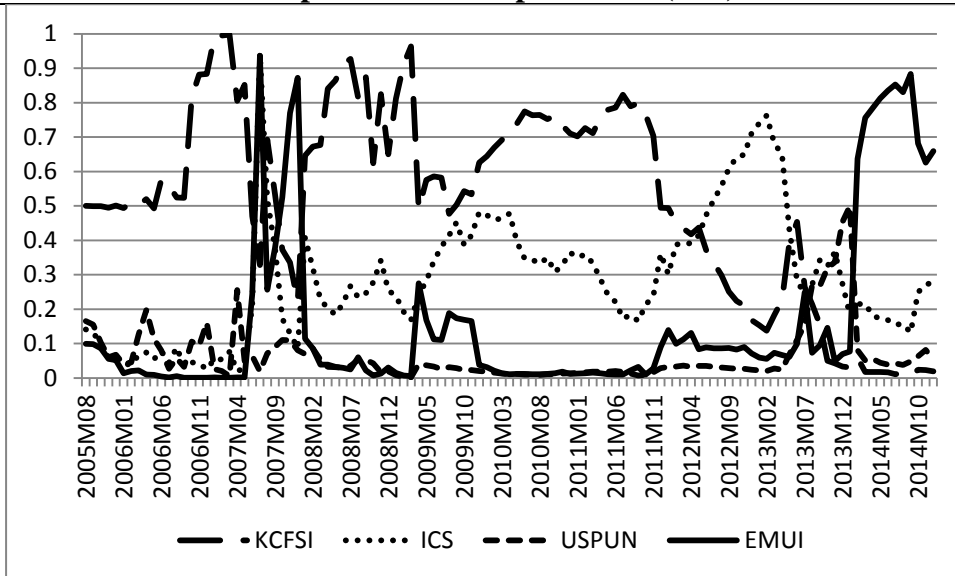
	DMA_alpha_1			BMA			AR(4)		
	REITS	3m Tr. yield	Strategy	REITS	3m Tr. yield	Strategy	REITS	3m Tr. yield	Strategy
<b>Average return (<math>\mu</math>)</b>	0,80%	0,11%	0,78%	0,80%	0,11%	0,96%	0,80%	0,11%	0,60%
<b>Standard deviation (<math>\sigma</math>)</b>	7,05%	0,16%	5,21%	7,05%	0,16%	5,58%	7,05%	0,16%	6,45%
<b>Sharpe ratio</b>	9,77%		<b>12,79%</b>	9,77%		<b>15,21%</b>	9,77%		7,52%

**Figure 1. The evolution of the S&P/Case-Shiller U.S. National Composite Home Price Index and the S&P 500 index (monthly data, Jan.1991 – Dec. 2014)**

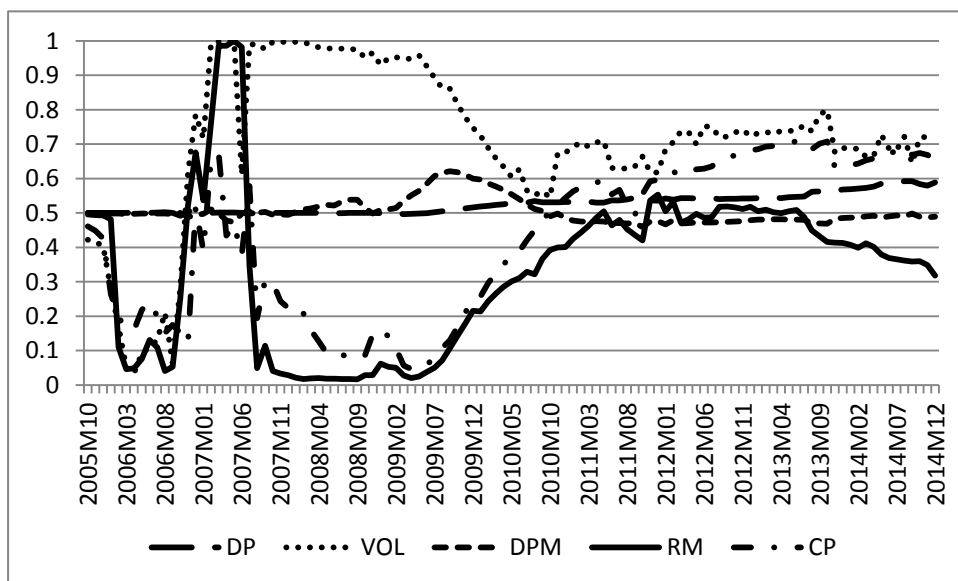
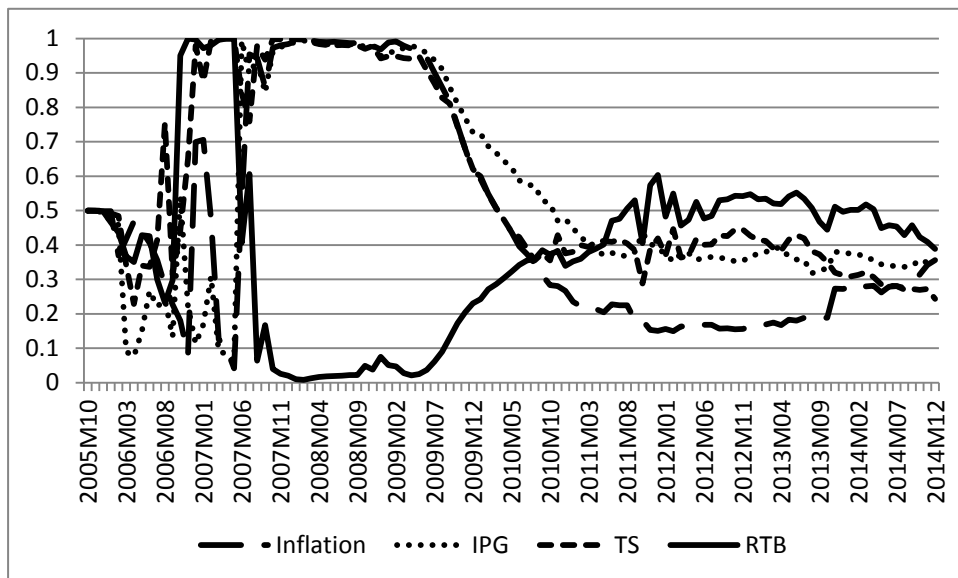
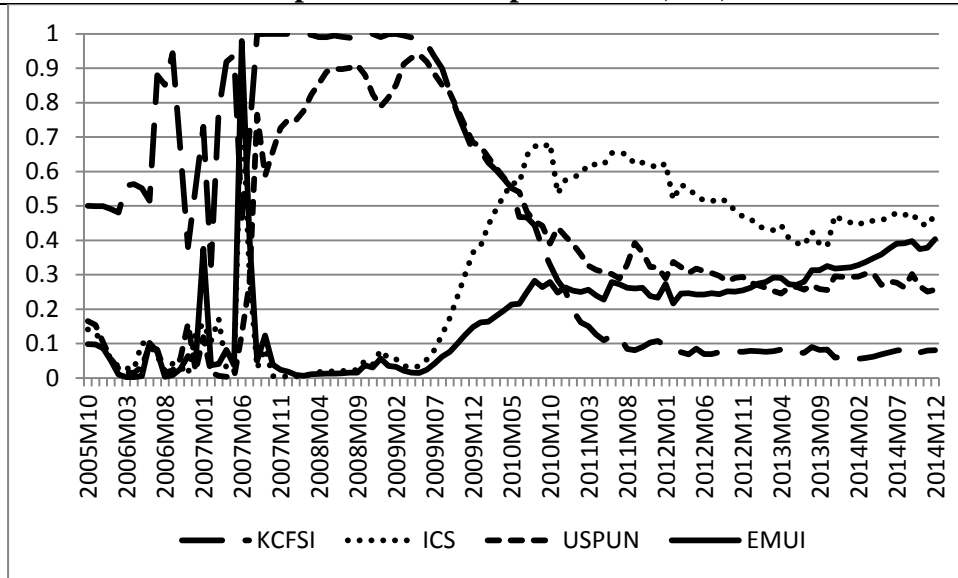


Source: S&P Dow Jones Indices LLC and Prof. R.J. Shiller's website.

**Figure 2: Posterior inclusion probabilities of predictors (h=1)**



**Figure 3: Posterior inclusion probabilities of predictors (h=3)**



**Figure 4: Posterior inclusion probabilities of predictors (h=6)**

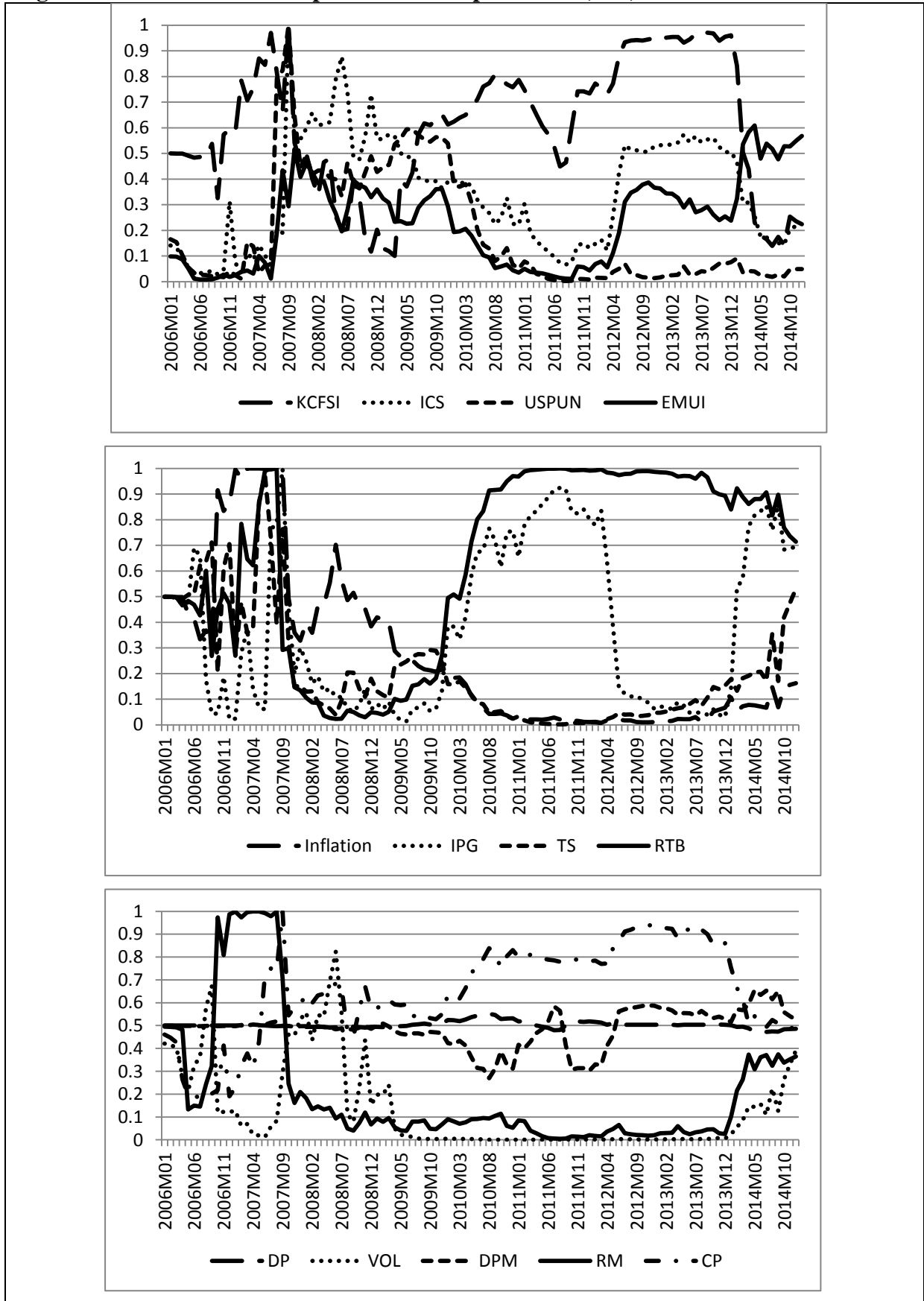


Figure 5: Posterior inclusion probabilities of predictors (h=9)

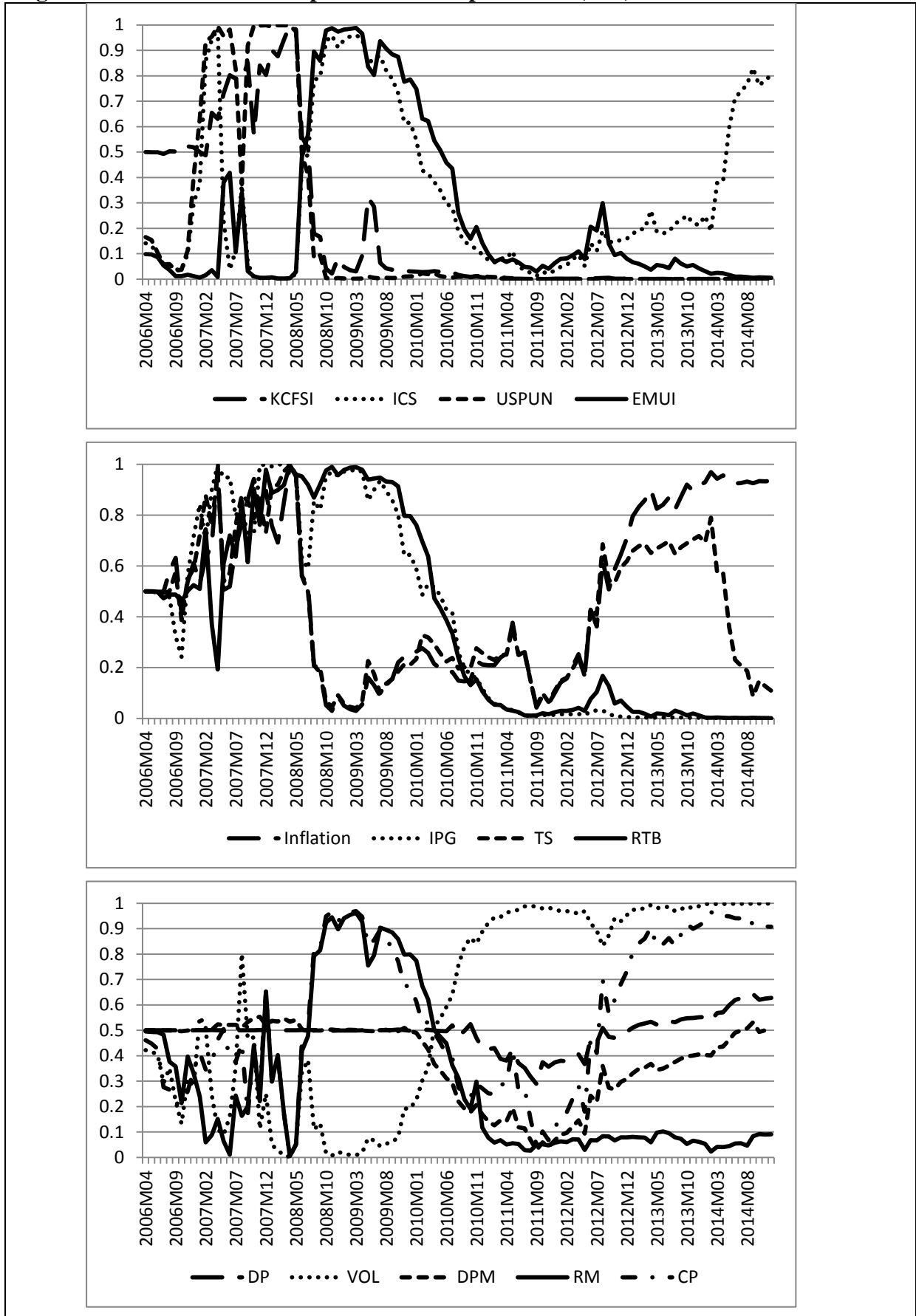


Figure 6: Posterior inclusion probabilities of predictors (h=12)

