Maximizing Equity Market Sector Predictability in a Bayesian Time Varying Parameter Model*

Lorne D. Johnson**
Caxton Associates
New York, U.S.A.

Georgios Sakoulis
J.P Morgan Fleming Asset Management
London, U.K.

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Abstract

A large body of evidence has emerged in recent studies confirming that macroeconomic factors play an important role in determining investor risk premia and the ultimate path of equity returns. This paper illustrates how widely tested financial and economic variables from these studies can be employed in a time varying dynamic sector allocation model for U.S. equities. The model developed here is evaluated using Bayesian parameter estimation and model selection criteria. We find that using the Kalman filter to estimate time varying sensitivities to predetermined risk factors results in significantly improved sector return predictability over static or rolling parameter specifications. A simple trading strategy developed here using Kalman filter predicted returns as input provides for potentially robust long run profit opportunities.

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**Corresponding author, Caxton Associates, 667 Madison Avenue, New York, New York, 10021, E-mail: ljohnson@caxton.com, Tel.: 212-303-6118

1. Introduction

As the field of finance has struggled to find a successor model to the benchmark CAPM specification, the role conditional macroeconomic factors play in determining investor risk premia and ultimately equity return predictability has come into greater focus. One of the earliest and most straightforward investigations on the role macroeconomic factors play in determining equity returns is that of Chen, Roll and Ross (1986). Using cross-sectional analysis, Chen et al. find that a number of macroeconomic risk factors are significantly priced in the stock market. In another application, Lo and MacKinlay (1997) derive predictive portfolios based on lagged macroeconomic variables that lend themselves to dynamic trading strategies. A further indication of the importance of lagged macroeconomic variables is presented in Ferson and Harvey (1999), where conditional lagged fundamental information included in a risk pricing model renders sorted portfolio attributes in the popular Fama and French (1993) three factor model insignificant.

In addition to the available empirical tests suggesting an important role for conditional macroeconomic information in asset pricing, a pricing model based strictly on prior macroeconomic information has intuitive and theoretical appeal. As pointed out by Roll (1977), any empirical examination of the standard CAPM is theoretically suspect if the chosen proxy for the market portfolio is not truly representative of the entire market. Even providing for a reasonable proxy for the market portfolio, Cochrane (1996) notes that explanations of changes in returns over the business cycle based on expected market returns are hardly useful in establishing what risk factors cause returns of individual portfolios to vary. What is surely of greater interest over the business cycle are what particular macroeconomic forces drive expected returns.

The other obvious advantage of a factor model incorporating strictly lagged information is the potential application to return predictability. In one such exercise, Lo & MacKinlay (1997) find that up to 50% of the variation in returns can be explained by lagged economic factors introduced through what they term a Maximally Predictable Portfolio. Any evidence of systematic predictability naturally lends itself to questions of market efficiency, however, a model based on return reaction to fundamental information is much easier to reconcile with a future cash flow model than much of what is currently in the anomaly literature. A broad competing class in the predictability literature has focused on non-fundamental momentum effects that provide some predictability over sorted portfolios. Jegadeesh and Titman (1993) and Lee and Swaminathan (2000) report to find consistent profit opportunities on the order of 1% per month employing a basic strategy of buying past winners and selling past losers.

Another question of interest in testing a factor model based on fundamental information is the extent to which tangible fundamentals actually drive the stock market. The late 1990's is a notable period in which the valuation of broad classes of equities de-coupled from traditional pricing measures. The classic dividend discount model of Gordon (1962) extended by Campbell and Shiller (1989) posits that the value of an individual equity or broad market index is a function of future anticipated cash payments. Changes in price should move in tandem with growth in dividends and expectations of higher dividends in the future. Pairing this model with the experience of the late 1990's required extraordinary future dividend income growth to explain the rapid increase in equity valuations. Even an extension of the Campbell and Shiller model using earnings as a proxy for dividends struggles to account for the run up in equity valuations without allowing for substantial future earnings growth significantly greater than trend GDP growth. Despite record 7.5% real earnings growth in the 1990's, as documented in Fama and French (2002), the non-fundamental equity premium, calculated here as real capital gains net of real earnings growth, was a substantial 5.22% per year. The dividend yield by the end of the 1990's fell to as low as 1.1%, indicating a very high level of expected dividend growth in the future or a new regime of near zero discount rates. Therefore, a further question of interest is the degree to which observable fundamentals even matter in determining equity returns over different stages of the business cycle, or in the case of the late 1990's, during a possible speculative boom.

One of the primary motivating factors in the development of the conditional pricing models of Ferson and Harvey (1999), Wu (2001) and Cochrane (1996) is the strong empirical evidence that equity market risk premia are time varying. Each of these conditional beta representations use lagged macroeconomic factors to capture time variation. Another approach to addressing time variation in risk factors is to allow the evolution of risk sensitivities to evolve in a Bayesian manner. Such an approach is made available through application of the Kalman filter with a time varying parameter specification. An example of a time varying parameter model using the Kalman filter can be found in Kim and Nelson (1989).

Our interest here is to develop a robust dynamic trading model for economic sectors using factors identified as significant in the preceding literature. Further, the model we develop assumes time-variation in factor sensitivities to capture changing risk premia over time. Time variation in factor betas is approached using dynamic updating in the Kalman filter. The result is a highly responsive model that significantly outperforms comparable static and rolling parameter specifications. Employing this methodology, we would like a model that is particularly prescient at business cycle turning points. Such a model may provide an important hedge against more passive models optimized over the most recent economic regime or long term samples. The model developed here also appears to have important risk pricing properties when contrasted with the benchmark CAPM.

The balance of this paper is organized as follows: In Section 2 a time varying parameter factor model (TVPFM) using lagged economic factors and industry sectors as portfolios is motivated and developed. Section 3 describes the full Bayesian estimation and model selection criteria employed for evaluating the model. Some preliminary indications from the model output are also discussed. Section 4 investigates the behavior of out of sample risk premia on the predicted model sector returns. In Section 5, the potential profitability of a simple trading strategy using the predicted returns of the TVPFM is investigated and discussed. Section 6 concludes.

2. A Time Varying Parameter Factor Model

2.1. General Model Specification

We begin with a time series factor model of equity returns. The factors are assumed to be lagged fundamental macroeconomic variables. The return generating process for each portfolio i is expressed as

$$r_{i,t+1} = f_t'\beta_{t+1} + u_{i,t+1} \tag{1}$$

$$u_{i,t} \sim N(0, \sigma^2_{u_{i,S_t}}),$$

where for each portfolio return $r_{i,t+1}$, β_{t+1} is a Kx1 vector of K-1 time varying factor loadings and a time varying intercept term, f_t is a Kx1 vector of unity and K-1 lagged macroeconomic factors and $u_{i,t+1}$ is a normally distributed disturbance term with conditional variance to allow for heteroskedasticity. From here forward in this section, for simplified notation, the portfolio subscript *i* is dropped.

We incorporate time variation in the factor sensitivities by modeling each factor sensitivity, or beta, as a random walk such that each can be expressed as

$$\begin{aligned} \beta_{k,t} &= \beta_{k,t-1} + v_{k,t} \\ v_{k,t} &\sim N(0, \sigma^2_{v_k}). \end{aligned} \tag{2}$$

Assuming the variance parameters are known, the evolution of risk factor sensitivities can be estimated in state space form. Prediction and updating for the state vector of factor loadings using the Kalman filter proceeds as follows:

Prediction:

$$\begin{aligned} \beta_{t|t-1} &= \beta_{t-1|t-1} \\ P_{t|t-1} &= P_{t-1|t-1} + Q \\ \eta_{t|t-1} &= r_t - f'_{t-1}\beta_{t|t-1} \\ \xi_{t|t-1} &= f'_{t-1}P_{t|t-1}f_{t-1} + \sigma^2_{u_{S_t}} \end{aligned} \tag{3}$$

Updating:

$$\begin{aligned} \beta_{t|t} &= \beta_{t|t-1} + K_t\eta_{t|t-1} \\ P_{t|t} &= P_{t|t-1} - K_t f'_{t-1}P_{t|t-1} \end{aligned}$$

where $K_t = P_{t|t-1}f_{t-1}\xi^{-1}_{t|t-1}$ is the Kalman gain. In (3), $\beta_{t|t-1}$ is the expectation of β_t given information up to time *t-1*, $P_{t|t-1}$ is the covariance matrix of $\beta_{t|t-1}$, $\eta_{t|t-1}$ is the prediction error,

$\xi_{t|t-1}$ is the variance of the prediction error and Q is the diagonal matrix of the variances of the shocks to the factor loadings, $\sigma^2_{v_k}$, for k = 1 to K. If $(\sigma^2_{u_{S_t}}, Q)$ are known, we can make inferences about the behavior of the state vector. If unknown, $(\sigma^2_{u_{S_t}}, Q)$ can be estimated using Bayesian inference as described in Carter and Kohn (1994) and Kim and Nelson (1999). Bayesian parameter estimation and model selection criteria are described in greater detail in Section 3.

While some conditional pricing models use lagged macroeconomic variables to model variation in economic risk premia on sorted portfolio attributes or the market portfolio, we are interested in investigating a related but different question. Given the strong evidence for the importance of lagged economic information in pricing equities, we would like to measure time variation in equity risk sensitivities to macroeconomic factors directly.

The case for persistent time varying second moments in returns on equity market portfolios has been discussed in French, Schwert and Stambaugh (1987) and Schwert and Seguin (1990). To address this property of equity returns, a Markov-switching process in the variance of the portfolio return error terms is also provided for in the model. Attention is limited to two discrete states over a state variable, S_t, where a high variance state exists when $S_t = 1$ and a low variance state prevails when $S_t = 0$. The error term in (1) follows the distribution:

$$\begin{aligned} &u_t \sim N(0, \sigma^2_{u_{S_t}}) \\ &\sigma^2_{u_{S_t}} = \sigma^2_{u_0}(1 - S_t) + \sigma^2_{u_1} S_t \qquad (4) \\ &\sigma^2_{u_1} > \sigma^2_{u_0}. \end{aligned}$$

As such, u_t will be heteroskedastic with conditional variance determined by the unobserved state variable S_t. The state variable S_t evolves based on the following transition probabilities:

$$\begin{aligned} &P(S_t = 1 \mid S_{t-1} = 1) = p \\ &P(S_t = 0 \mid S_{t-1} = 1) = 1 - p \\ &P(S_t = 0 \mid S_{t-1} = 0) = q \\ &P(S_t = 1 \mid S_{t-1} = 0) = 1 - q. \end{aligned}$$

The specification for Markov switching variance presented here closely follows that of Turner, Startz and Nelson (1989).

2.2.1. The Data: The Sectors

The financial instruments used in this study as dependent variables are the ten sector total return indices as defined by the Global Industry and Classification Standard (GICS), jointly developed by Morgan Stanley Capital International and Standard and Poor's. The series were downloaded through FACTSET. Returns are constructed by taking the difference in the logs of two consecutive index levels. The frequency of the series is weekly and the period we examine starts on the first week of January 1990 and ends the second week of January 2003. Table 1 presents descriptive statistics for the sample period under consideration.

(Insert Table 1 here)

Figure 1 presents the evolution of an initial $100 investment in each of the 10 GICS sector indices starting on January 12, 1990. The technology sector experienced the highest return up until April 14, 2000, after which point the sector index collapsed. Over the entire sample, the highest return was in the Healthcare sector, while the lowest return was found for the Utilities sector.

2.2.2. The Data: The Factors

The factors chosen for the model are done so to maintain a parsimonious framework and to be consistent with previous advances in the literature. The chosen factors are:

$\Delta divyield$ - The change in the dividend yield on the S&P 500 composite index

$\Delta spread$ - The change in the spread between the 10 year treasury note yield and the 90 day treasury bill yield.

Δoil - The percent change in the near month crude oil contract.

$\Delta junk$ - The change in the default spread, defined as the difference between the Moody's Baa and Aaa corporate yield.

The dividend yield, corporate spread and term spread have been standard features of prior studies investigating the contribution of lagged macroeconomic information in pricing equities.[1] The price of oil is also of interest to us as a factor, given the strong role oil shocks have played at turning points of postwar business cycles. An investigation by Hamilton (2000), allowing for a non-linear response function between GDP and oil disruptions, finds a clear link between petroleum supply disruptions and lower GDP. In an explicit examination of the impact of oil prices on equity markets, Jones and Kaul (1996) find that timely oil price information that precedes other economic series has a significant effect on real stock returns.

Although our factor model follows no specific theoretical model, it is well grounded in the ICAPM of Merton (1973) given that all our chosen variables are anticipated to forecast changes in future wealth and consumption flows. As will be discussed in Section 4, the lagged macroeconomic factor model also appears far better at pricing risk than the benchmark two parameter CAPM.

2.3. Testing Time-Variation

Pesaran and Timmermann (2002) argue that despite the empirical evidence indicating a time varying relationship between state variables and returns, research concentrating on the prediction of stock returns, still, to a large extent, employs models with time invariant parameters. Pesaran and Timmermann employ a simple reversed CUSUMQ test to identify structural change points and proceed to estimate a model relating S&P 500 monthly returns to a pre-specified set of lagged macroeconomic variables using only data after the most recent break has occurred. They find that the forecasting ability of their model greatly improves upon a comparable static specification, as well as a variety of alternative structural change models. Our proposed conditional model for predicting sector returns based on lagged fundamentals, although similar in spirit to theirs, explicitly accounts for time variation in the exposures to the state variables as well as the error variance in a dynamic Bayesian regression framework.

[1] Chen, Roll and Ross (1986) use the level of the term spread in a cross sectional analysis of economic factors and stock returns. Lo and MacKinlay (1997) use the dividend yield, term spread and default spread in a predictive model

Before we estimate and evaluate the model in detail, we proceed with an exploratory investigation of the time varying properties of the data. We are interested in making some general statements regarding the stability of a static version of our model with respect both to the exposures to the macroeconomic state variables and the error variance. A sufficient condition for proposing a dynamic model that explicitly incorporates time-variation in the parameters relating financial returns to macroeconomic variables is to show that its static counterpart is unstable, i.e., the parameters are subject to structural change. Thus, our purpose is to test for regression stability without explicitly estimating the timing of the breaks or the value of the parameters. A variety of means for testing and estimating structural break models have been proposed in the literature. We concentrate on the testing frameworks developed by Hansen (1992) and Bai and Perron (1998, 2001), BP hereafter. Bayesian model selection techniques are explored in a later section.

Hansen's Lc statistic is a Lagrange multiplier test of the null hypothesis of constant parameters against the alternative that parameters follow a martingale. The test relies on the assumption of stationary regressors and is able to test constancy for both the β's and σ_u^2 in the model presented at the beginning of this section. As in Hansen (1992), we are interested in testing the stability of each parameter individually, as well as the joint stability of the parameters in each of the sector regressions. Hansen provides the critical values for these tests.

BP developed a method for estimating multiple structural breaks in linear regression models. Their testing procedure allows for differentiation in the regression errors, but does not provide methods for parametrically estimating this heterogeneity. The determination of break points depends on both the distance allowed between break points, as well as the upper bound imposed in the number of breaks to be considered. The latter point is less of a drawback in the present context as we are only interested in testing for the presence of parameter instability. In BP's methodology there is not a unique test that determines the number of breaks. The statistical determination of structural change depends on the values of various test statistics. The first one is the sup$F_T(l)$ test which tests the null hypothesis of no breaks for all the parameters, against the

of future returns. Ferson and Harvey (1999) use the term spread, dividend yield and default spread as instruments in alternative of *l* breaks, where *l*<=*ub,* and *ub* is the upper bound in the number of breaks imposed a priori. Another version of this statistic is what BP call the Wdmax which applies weights to $\sup F_T(l)$ so that the marginal *p*-values are equal across values of *l*. Alternatively, the number of breaks can be determined based on the values of F-statistics that explicitly test the null of *l* breaks against the alternative of *l+1* breaks. In other words, this statistic tests whether further structural change is present in the data, given that some break points have already been identified. As in the previous case, the tests used have non-standard asymptotic distributions. The critical value tables are provided by BP.

Table 2 presents results for the individual and joint Lc tests applied to the ten economic sectors. For each of the 10 sectors, constancy in the variance of the error terms is rejected, with the individual Lc statistic significant at the 1% level. This result is consistent with the extensive literature on time-varying variances in financial and economic time-series. The individual test results are less clear for the β_k parameters in equation (2). Specifically, the null of constant exposure to changes in the dividend yield is not accepted at the 5% level for the Financials or Utilities sectors. Similarly, the null hypothesis is rejected at the same significance level for constancy of exposure to the yield spread for the Health Care sector and for the change in the price of oil for the Technology sector. The null of parameter stability is also rejected for the intercept of the Technology and Telecommunications sectors.

(Insert Table 2 here)

An important result in Table 2 is that the joint Lc statistic rejects stability at the 1% significance level for all sectors with the exception of Consumer Staples, for which the null is rejected at the 5% level. Given these results, it is relevant to consider Hansen's own observation that joint significance tests may be more reliable than single parameter tests, especially when *"…the shifting error variance induces too much noise into the series for the test to be able to distinguish parameter variation from sampling variation*".

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a conditional factor model.

Table 3 presents results based on BP's testing methodology. We have defined the upper bound to be 5 breaks. In the construction of the tests, we have allowed for heterogeneity and autocorrelation in the residuals, as well as different moment matrices for the regressors across segments. The Wdmax(1%) test, which tests the null hypothesis of no breaks against an unspecified number of breaks at the 99% level, is significant for all sectors except Consumer Staples. The $\sup F_T(l)$ test, evaluating a specified number of breaks versus the null of no breaks gives similar results. In particular the null of parameter constancy for all *l* breaks is rejected at the most conservative significance levels for all sectors with the exception of Consumer Staples, where once again no break is identified. The sequential tests also reject parameter constancy, although they give a mixed picture about the number of potential breaks. In particular, for the Consumer Discretionary, Technology, and Materials sectors the $\sup F_T(5|4)$ test rejects the null of 4 breaks, in favor of the 5 break alternative. The Industrials, Financials, and Utilities sectors are subject to 4 breaks, Healthcare to 3 breaks, while the Energy and Telecommunications sectors are subject to 2 breaks. Consumer Staples is the only sector where BP's result points to the existence of a very stable relationship between our set of regressors and the sector's returns.

(Insert Table 3 here)

While the above discussion is by no mean exhaustive, the instability of factor loadings and return variances for the chosen data is statistically established. We propose a model that we believe captures the dynamic nature of financial returns and their interaction with a pre-specified set of fundamental factors.

3. Bayesian Empirical Tests of the TVPFM

3.1. Specifications for Tested Models

With the factors for the TVPFM defined, the return generating process for each sector portfolio can now be presented as

$$r_{i,t+1} = \beta_{0,t+1} + \beta_{1,t+1}\Delta divyield_t + \beta_{2,t+1}\Delta spread_t + \beta_{3,t+1}\Delta oil_t + \beta_{4,t+1}\Delta junk_t + u_{i,t+1} \quad (5)$$

$$u_{i,t} \sim N(0, \sigma^2_{u_{i,S_t}}) .$$

The specification in (5) allows for time variation in factor sensitivities and return variances consistent with the sector parameter stability diagnostics discussed in the previous section. To further investigate the appropriateness of the specification in (5) to capture these return dynamics, we also consider three alternative specifications to independently evaluate the importance of time variation in the factor sensitivities and return variances. The capability of each model to describe the data is evaluated by calculating marginal likelihood values for each model and computing Bayes factors. The methodology for calculating Bayes factors employed here follows that in Chib (1995) and is discussed in further detail below.

The first of the alternative model specifications is a simple factor model with fixed unconditional factor sensitivities and fixed unconditional variance. The first alternative specification is

$$r_{i,t+1} = \beta_0 + \beta_1 \Delta divyield_t + \beta_2 \Delta spread_t + \beta_3 \Delta oil_t + \beta_4 \Delta junk_t + u_{i,t+1} \quad (5a)$$

$$u_{i,t} \sim N(0, \sigma^2_{u_i}).$$

The model in (5a) is intended to serve as a benchmark case.

The second alternative specification is designed to test the importance of the introduction of time variation in factor sensitivities while holding the variance term constant. The second alternative specification is given by

$$r_{i,t+1} = \beta_{0,t+1} + \beta_{1,t+1} \Delta divyield_t + \beta_{2,t+1} \Delta spread_t + \beta_{3,t+1} \Delta oil_t + \beta_{4,t+1} \Delta junk_t + u_{i,t+1} \quad (5b)$$

$$u_{i,t} \sim N(0, \sigma^2_{u_i}).$$

Finally, the third alternative specification is intended to evaluate the importance of incorporating heteroskadacticity into the model, holding factor sensitivities fixed. The third alternative specification is

$$r_{i,t+1} = \beta_0 + \beta_1 \Delta divyield_t + \beta_2 \Delta spread_t + \beta_3 \Delta oil_t + \beta_4 \Delta junk_t + u_{i,t+1} \quad (5c)$$

$$u_{i,t} \sim N(0, \sigma^2_{u_{i,S_t}}).$$

Estimation of each model is performed using Gibbs sampling Markov chain Monte Carlo (MCMC) integration. A brief outline of the Gibbs sampling sequence for the model in (5) is presented in Appendix A. Details of the output of the Gibbs sampler for the model in (5) are presented in greater detail in a later section. Each of the alternative models presented in this section are simplified versions of that in (5) with fewer components. We choose the Bayesian methodology for evaluating our model for two primary reasons. First, the Gibbs sampling methodology allows for more stable estimation of multi-parameter non-linear models than does typical maximum likelihood estimation. Secondly, model comparison using marginal likelihood values provides a way to compare alternative non-nested model specifications not available in the classical framework. From here forward in this section, for simplified notation, the portfolio subscript *i* is dropped.

3.2 Calculating Bayes Factors for Model Comparison

To assess which model explains the data best, marginal likelihood values are calculated for each of the models presented in the previous section. From these marginal likelihood values, Bayes factors comparing any of the two models can then be computed as the ratio of the marginal likelihood values.

$$BF_{l,j} = \frac{m_l(Y_t)}{m_j(Y_t)}. \tag{6}$$

where $BF_{l,j}$ is the Bayes factor of the posterior odds in favor of model *l* over model *j*.

The marginal likelihood values for each model are calculated from

$$m(Y_t) = \frac{f(Y_t \mid \theta^*)\pi(\theta^*)}{\tilde{\pi}(\theta^* \mid Y_t)}. \tag{7}$$

Here the numerator on the right side of (7) is the product of the likelihood value of the data at θ^* and the prior density at θ^*. Here, $\theta = \theta^*$ indicates that the parameter space is evaluated at the posterior mean from the initial Gibbs sampling runs as presented in Appendix A. The denominator is the simulated posterior density of θ^*. For computational efficiency, the relation in (7) can be rewritten in log form as

$$\ln m(Y_t) = \ln f(Y_t \mid \theta^*) + \ln \pi(\theta^*) - \ln \tilde{\pi}(\theta^* \mid Y_t). \tag{8}$$

The log likelihood value for the model in (5) is calculated as

$$\ln f(Y_t \mid \theta^*) = \sum_{t=1}^{T} \ln(p(S_t = 0 \mid Y_{t-1,} \theta^*) f(y_t \mid \sigma_v^2, \sigma_{u_0}^2) + p(S_t = 1 \mid Y_{t-1,} \theta^*) f(y_t \mid \sigma_v^2, \sigma_{u_1}^2)), \quad (9)$$

where $\sigma_v^2 = [\sigma_{v_1}^2 \ \ \sigma_{v_2}^2 \ \ \sigma_{v_3}^2 \ \ \sigma_{v_4}^2 \ \ \sigma_{v_5}^2]'$.

The prior log density can be expressed as

$$\ln \pi(\theta^*) = \ln \pi(\sigma_v^2 *) + \ln \pi(\sigma_u^2 *) + \ln \pi(p^*, q^*), \quad (10)$$

where $\sigma_u^2 = [\sigma_{u_0}^2 \ \ \sigma_{u_1}^2]'$.

The posterior density is calculated using the method described in Chib (1995) to simulate marginal conditional densities. The log posterior density can be expressed as

$$\ln \tilde{\pi}(\theta^* \mid Y_t) = \ln \tilde{\pi}(\sigma_v^2 * \mid Y_t) + \ln \tilde{\pi}(\sigma_u^2 * \mid Y_t, \sigma_v^2 *) + \ln \tilde{\pi}(p^*, q^* \mid Y_t, \sigma_v^2 *, \sigma_u^2 *). \quad (11)$$

Derivation of the posterior density for the model in (5) is presented in Appendix B.

Marginal likelihood values for each of the economic sector portfolios for each of the four model specifications are presented in Table 4. For each model, the priors are non-informative and the Gibbs sampler is run 8,000 times after 2,000 initial Gibbs runs to realize some convergence for the parameters for each step of the simulation. To evaluate the relative strength of each model, we use the guidelines for model comparison in Kass and Raftery (1995). The guidelines for interpreting the log Bayes factors for model *l* and model *j* are

$\ln B_{l,j}$	Evidence against model *j*
0 to 1	Not worth more than a bare mention
1 to 3	Positive
3 to 5	Strong
>5	Very Strong

In comparing the model in (5b), allowing for time variation in the factor sensitivities, and the static specification in (5a), for each economic sector, the model with time variation is strongly preferred over the model with static unconditional factor sensitivities. For each case, the Bayes factor exceeds 4, and for 9 of the 10 sectors, the Bayes factor exceeds 5, indicating very strong evidence in favor of model (5b) over model (5a). Based on the marginal likelihood values, it is also clear that allowing for heteroskedastic errors in (5c) results in a much more probabilistic model for each sector than that of the unconditional variance model in (5a). In this case, the Bayes factor favoring model (5c) over model (5a) exceeds 28 for each of the economic sectors.

(Insert Table 4 here)

Finally, it is also shown in table 4 that the model in (5), incorporating both time varying factor sensitivities and Markov switching heteroskedastic errors, is preferred to all other models by a Bayes factor of at least 3 for eight of the ten economic sectors. For Consumer Staples and Health Care, model (5c) is preferred to model (5).

3.3 Empirical Results for the Fully Specified Model

Table 5 summarizes results from the Bayesian Gibbs sampling estimation of the parameters in model (5). The sample period for the simulation is January 12, 1990 to June 10, 2002. For each model for each parameter, the posterior mean, median and standard deviation are reported. For each sector there is strong evidence for persistent volatility regimes as indicated by the values for p and q greater than 0.9 for each of the tested portfolios. The standard error terms, σ_{v_k} , are generally of small size, indicating a slow evolution process for the factor loadings.

(Insert Table 5 here)

Given the estimated parameters, inference and prediction of the state vector, β_T, can proceed. Because we are ultimately interested in the predictability of portfolio returns, we would like to focus on the behavior of out of sample factor loadings as opposed to the backward looking path of factor loadings once parameters for the full sample are estimated. To accomplish this, we begin generating β_T at observation 250 based on model parameters estimated through observation 250. For β_{250} to β_{299}, β_T is generated based on the parameters estimated for the sample ending at t = 250. To capture any additional parameter instability, the parameters are estimated again for the sample ending at t = 300. β_{300} to β_{349} are then generated based on the parameters estimated for the sample ending at t = 300. This sequence of re-estimating the parameters every 50 periods is then repeated through t = 650. Ultimately a sample of β_T is estimated for β_{250} to β_{678}.

Examples of the paths of the factor loadings are presented in Figure 2. In the Energy, Industrials, and Materials sectors, the change in the price of oil would be anticipated to be an important determinant of expected returns. Figure 2a shows the time path of the 'real time' sensitivity of the Energy sector's expected return to the oil factor. The figure indicates that the energy sector does not always respond to lagged changes in the price of oil in the same fashion. There are three distinct regimes over the past eight years in its evolution. The loading was negative and almost constant until the fall of 1997, when it turned and remained on a positive trend until the start of 2000. A positive sensitivity, in terms of our forecasting model would imply that a positive change in the lagged price of oil would, ceteris paribus, signal a higher conditional expected return for the Energy sector. Since then, the loading has once again turned negative and its magnitude has increased.

The change in the dividend yield would be expected to play some role in forecasting 'cyclical' sectors, such as Consumer Discretionary, Financials, Industrials, and Materials. Figure 2b shows the time path of the sensitivity to the dividend yield factor for the Financials sector. The sector has had a consistently positive exposure to the factor, which increased in magnitude following the market breakdown in 2000. The positive return sensitivity to changes in the dividend yield with respect to the Financials sector 'peaked' in April 2002, and while the exposure to the factor has come down since, it is still higher than the level observed prior to 1999.

For the Utilities sector, the loading on the default spread factor is negative for most of the estimation period, as can be seen in Figure 2c. The sensitivity reversed signs for a brief period leading up to the end of the bull market. Since then the sensitivity has turned negative, and the absolute level has increased substantially. The behavior is consistent with the sector's under-performance. Utility firms had large exposure to the credit market following the 1990's. After 2000, default spreads widened with adverse effects for the sector. Although Bayes factor tests prefer the constant sensitivity specification to the dynamic one, the time-variation in the loading on changes in the yield curve, show an interesting evolution when considering the forecast of expected returns in the Healthcare sector. A shift from a negative sensitivity regime to a positive one is evident in early 1999. Since then, a positive change in the slope of the curve is associated with higher conditional expected returns.

Time variation of the intercept terms is displayed in figures 2e and 2f for the Technology and Telecommunications sectors respectively. The path of the intercept terms in both sectors, and especially in Technology, mirrors the fate of the sector, pre and post the market collapse in mid-2000. The variation of the intercept term could be explained by either the omission from our model of additional factors that help forecast expected returns, or the existence of momentum effects in the market. This issue is addressed in more detail in a later section.

4. Cross Sectional Regression Results

As a general test of how well the time varying parameter model describes return behavior across portfolios, we propose a series of cross-sectional tests against the benchmark Sharpe-Lintner-Black Capital Asset Pricing Model (CAPM). Despite the many shortcomings of the CAPM, some discussed earlier in Section 1, in its basic form, it should be expected to explain a significant component of the variation in returns across sector portfolios. In contrast to a model estimated using lagged information, one might entertain the prior that a model with only lagged information would be at a disadvantage to a model such as the CAPM that incorporates contemporaneous information.

We consider the cross-sectional regression

$$r_{i,t+1} = \lambda_{0,t+1} + \lambda_{1,t+1}\beta_{i,t} + \lambda_{2,t+1}M_{i,t} + u_{i,t+1} \ , \quad (12)$$

where $\beta_{i,t}$ is the time series regression coefficient for each sector *i* from the CAPM estimated through time *t*. $M_{i,t}$ is the predicted return for each sector *i* at time *t* estimated by the time varying parameter model (TVPFM) in (5) using factors and parameters through time *t*. $\lambda_{0,t}$ is the intercept and $\lambda_{1,t}$ and $\lambda_{2,t}$ are slope coefficients on the estimated market betas and the predicted returns of the time varying parameter model. This form of cross-sectional regression is comparable to that performed by Ferson and Harvey (1999) where a predicted return calculated with lagged macroeconomic factors is included in a cross-sectional test of the Fama and French three factor model. Results of a number of cross-sectional regressions are presented in Table 6 using the method presented in Fama-MacBeth (1973).

(Insert Table 6 here)

In Panel A, estimates for the CAPM betas and predicted returns from OLS regressions on lagged macro factors are generated using expanding samples from the first week in January 1990 through time *t*. Cross-sectional regressions are performed for each time *t,* from the week ending October 14, 1994 to the week ending January 10, 2003, for a total of 429 regressions. These expanding sample estimates represent the full unconditional estimates for the CAPM betas and factor model predicted returns through time *t*. In the regression including only market betas, there is little evidence supporting the proposition that the CAPM significantly explains the cross-section of returns for the selected sector portfolios. In the second regression in Panel A, the predicted returns from the expanding sample OLS factor model do little better describing the cross-section of returns, with an insignificant coefficient of similar magnitude to that on the market portfolio.

Given the strong evidence presented here for time varying risk sensitivities in the TVPFM, it is also of interest to test if the sector CAPM can be improved by allowing for time variation in the market beta. A number of studies of late have attempted to prop up the CAPM in the face of relentless attack by models that incorporate portfolio attributes as well as the market portfolio.

Most well developed are those models incorporating conditional factors, including those presented here, to capture time varying risk. Ferson and Harvey (1991) use conditional information in the estimation of parameters in cross-sectional regression tests of the CAPM and later use conditioning information to calculate parameters in time series regressions in Ferson and Harvey (1999). Jaganathan & Wang (1996) augment the CAPM by including human capital in addition to the market portfolio. A CAPM model with time varying random walk coefficients estimated using the Kalman filter can be interpreted as a truly agnostic dynamic model with no preference as to which exogenous macroeconomic variables govern the time varying risk premium on the market portfolio. For consistency the Bayesian beta CAPM proposed also allows for heterodkedastic errors.

As presented in Panel B, allowing for Bayesian time variation in the market beta does little to improve the explanatory power of the market portfolio in the cross-section. For both regressions in Panel B, there is only weak evidence of a positive market risk premium. As in Panel A, results when the predicted returns from an expanding sample OLS factor model are included provide little support for the notion that lagged macro factors describe a significant amount of the variation of sector returns in the cross section either.

An initial attempt to test the influence of parameter time variation in a predicted returns model in the cross-section is examined in Panel C. Here, time series regressions for the CAPM and the lagged macroeconomic factor predicted returns are performed using rolling regressions over the previous 50 weeks of data. In the first cross-sectional regression, again, time variation introduced by rolling regressions does nothing to improve the ability of the CAPM betas to describe sector returns. Allowing for time variation in the predicted return regressions, however, increases the apparent risk premium and improves the significance of the predicted returns in explaining the cross section of portfolio returns.

In Panels D and E, cross sectional regressions are performed using the TVPFM predicted returns from (5) as regressors. In each case the size of the apparent risk premium is greater than that observed in the rolling regression example at a similar level of significance. In each case the *t*-

score on λ_2 is greater than 2. The contribution of the market portfolio in the regressions in panels D and E is smaller and less significant than that of the TVPFM predicted returns.

These tests lead to two initial conclusions. First, for the sample period of weekly returns examined, there is little evidence that the CAPM provides a good measure of the variation in sector returns. Second, failure to allow for time variation in return sensitivity to macroeconomic information can lead to the spurious conclusion that lagged macroeconomic information is not priced either. These tests provide further evidence that sector returns have a significant predictive component that can be captured in part by the TVPFM model developed here.

5. A Dynamic Trading Strategy Based on the TVPFM

5.1. Description of Trading Strategy

Given the strong evidence of a predictable component in sector returns priced by the TVPFM, it is of interest to see if the step ahead model forecasts can be exploited profitably. To test for this possibility, we propose a basic trading strategy of sorting the ten S&P 500 sectors based on the predicted returns of the TVPFM. At the end of each period *t*, a long position will be purchased in the weighted constituents of the sector with the highest predicted positive return. Like wise, a short position is taken in the weighted constituents of the portfolio with the lowest predicted negative return. We impose the constraint that no long position will be taken in a sector portfolio with a negative predicted return and no short position will be taken in a sector portfolio with a positive predicted return.

Returns for the dynamic sector allocation strategy are calculated assuming available capital at each period *t* is evenly distributed between a long portfolio that is purchased, and in collateral against the portfolio of shares being sold short. In the event of a vector of all positive (negative) predicted returns, only a long (short) strategy will be pursued with one half the amount of capital at risk as in the case of balanced long and short portfolios.

In addition to testing the trading strategy on the model developed in Section 2, we also investigate the profitability of four additional lagged factor model specifications. The alternative strategies are chosen in part to simulate different rates of parameter responsiveness to new information. The first of the alternative strategies is an expanding sample beta estimation in which unconditional model parameters are estimated by OLS at each time *t* based on the full sample up to time *t* beginning at *t* = 250 and continuing through the end of the sample. For the second strategy, estimates of unconditional model parameters are re-estimated every 50 periods using the full sample. The final two additional strategies are rolling beta specifications, the first using a sample from *t*-249 to *t* at each time *t* and the second using a shorter sample of *t*-49 to *t* at each time *t*. For each case, predicted returns for each portfolio at each time *t* are generated by

$$E_{i,t}[r_{i,t+1}] = f_t'\beta_{i,t|t}\,, \qquad (13)$$

where $\beta_{i,t|t}$ is the latest vector of portfolio factor loadings conditional only on information through time *t.*

Geometric returns and Sharpe ratios for the five strategies are presented in Table 7. For each of the strategies, with the exception of the TVPFM generated positions, there is at least one negative year. The discrete rolling OLS strategy has the poorest yearly return and Sharpe ratio while the Kalman filter estimated TVPFM has the highest return and Sharpe ratio. The TVPFM outperforms the other strategies most dramatically in the last three years of the sample, following the March 2000 market peak. A comparative look at the cumulative returns for each strategy is presented in Figure 3.

(Insert Table 7 here)

5.2. Transaction Costs

A crucial issue that needs to be addressed in the evaluation of model profitability is the drag of transaction costs. Given the specific set of portfolios we are trading, a reasonable estimate of these costs can be addressed and is done so here. From the simulation discussed earlier in this section, the average portfolio holding period was 1.48 weeks resulting in approximately 35 annual liquidations and initiations for the long and short strategies. To quantify approximate costs, we propose a strategy of simulating the sector index by buying constituents comprising

75% of the value weighted portfolio. The average weighted constituent price per sector for January 1, 2002 is presented in Table 8.

(Insert Table 8 here)

Assuming an average price of $45 per share, (slightly lower than that for the average portfolio), broker commissions of 3 cents per share and one cent of slippage per transaction, we arrive at an average transaction cost per week of 0.104%. The annual drag is approximately 5% per year. Once transaction costs are accounted for, the simulated strategy using the Kalman filter estimated TVPFM still has a final cumulative return of 177.34% and an annualized Sharpe ratio of 0.92. The next best strategy, using 250 period rolling OLS betas, posted a total cumulative return of 69.73% and a Sharpe ratio of 0.44 after accounting for transaction costs. The poorest performing strategy after accounting for transaction costs, with a final arithmetic return of –10.94%, is the discrete rolling beta strategy.

5.3. Monte Carlo Simulations

To investigate the possibility that the results of our simulation were the result of fortuitous random sampling, we conduct a simple Monte Carlo experiment. Following Lander, Orphanides, and Douvogiannis (1997), we implement parametric bootstrapping techniques in order to obtain a distribution of random returns, which in turn could be compared with the ones from our econometric specifications. In our original trading rules design, we allowed the possibility to invest in long-short, long only, and short only positions. Most often, when the portfolio was not invested in a neutral fashion, it would assume a long only position. For example, in the Kalman strategy, out of the 155 weeks that the portfolio was invested in only one leg of the long-short strategy, in 153 cases, the portfolio was long only. The results are very similar for the other specifications as well. Since we need to get comparable returns from the random portfolios, we specify a number of weeks, which are randomly selected, when we form long only portfolios. The rest of the time we assume a balanced long-short position.

The solid line in Figure 4 graphs the annualized geometric average return from 5,000 random rule replications for each design. The dotted lines represent the 5th and 95th percentile of the distribution of these returns. Although all the econometric specifications had actual returns above the average random return, it is only the 5yr rolling OLS and the Kalman specifications that achieve returns consistent with rejecting the hypothesis of randomness at the 5% level.

5.4. Interpreting the Results of the Trading Strategy

Our results may indicate that increasing uncertainty increases investor focus on observable fundamentals. In addition to the precipitous drop in equities beginning in March 2000, volatility increased substantially and remained high through the end of 2002. In contrast, during a period of greater optimism about future dividend growth prospects, signaled by falling earnings and dividend yields, lagged or even contemporaneous fundamental data may be discounted in favor of a focus on more forward looking measures.

To investigate this hypothesis further, we conduct another series of cross-sectional regressions identical to those in Section 4. In this case, however, the sample is split between the period prior and the period following the March 2000 stock market peak. This follows the recommendation of Kan and Zhang (1999) to run split sample regressions to test the stability of risk premia. Instability in factor premiums may indicate the presence of useless factors. As presented in Table 9, the results of additional cross sectional regressions indicate a larger risk premium on the predicted returns in the second subset following March 2000 than in the initial sample from 1994 to 2000. The larger risk premium estimate is consistent with the conjecture that following the market peak, a greater focus was put on fundamental information. Lack of certainty about earnings and future economic prospects results in a higher level of surveillance of economic news by investors.

(Insert Table 9 here)

The far more striking result for the cross-sectional regressions in Table 9 is the instability of the risk premium on market betas. In Panels A and B, the CAPM beta risk premia are both large and significant for those regressions without the TVPFM predicted returns, consistent with the theory underlying the CAPM model. In the presence of the TVPFM predicted returns, the market risk premia are still positive and somewhat less significant. In Panels C and D the market risk premium becomes negative and mostly insignificant with the exception being a near significant negative risk premium for Bayesian market betas in the presence of the TVPFM predicted returns. On the criteria suggested by Kan and Zhang, the return on the value weighted market return could be considered a useless factor.

6. Conclusion

The work presented here lends support to previous work laying out the importance of lagged macroeconomic information in determining expected investor returns. Further, we find these same macroeconomic factors useful in forecasting returns directly. The information derived from recently observed macroeconomic fundamentals appears particularly important at business cycle turning points and periods of high economic uncertainty such as the period immediately following the equity market peak in March 2000. Those following the stock market just prior to the peak in 2000 no doubt recall an emphasis on new non-traditional measures of valuation quite distinct from the macroeconomic and financial factors investigated here. As noted in Campbell and Shiller (1989), a rising P/D ratio is indicative of higher expected returns in the future. Therefore, the instruments driving returns in the 1994 to early 2000 sample may have been more forward looking measures that are difficult to quantify, and as such cannot be easily introduced into a macroeconomic model such as this. Despite this possible shortcoming, the model does at least as well as the traditional CAPM at pricing risk during our weekly sample period, even prior to 2000.

Appendix A
Gibbs sampling algorithm for model specified in (5)

Posterior densities of the parameters in (5) are estimated using Gibbs-sampling simulations. The parameters to be estimated are $\theta = \{\sigma^2_{v_k} \text{ for } k = 1 \text{ to } 5, \sigma^2_{u_0}, h, p, q\}$, where h is a parameter for identifying $\sigma^2_{u_1}$ such that $\sigma^2_{u_1} = \sigma^2_{u_0}(1+h)$. Given that each of the density functions for each of the parameters has a conjugate prior density, the unsolved parameters of the model can be drawn directly from the conditional posterior distributions. To simplify the notation, portfolio subscripts are dropped. The parameters to be estimated have the following posterior distributions:

$$\sigma^2_{v_k} \sim InverseGamma(\frac{a_1}{2}, \frac{b_1}{2}) \tag{A1}$$

for $k = 1$ *to* 5

$$a_1 = a_0 + T_1$$
$$b_1 = b_0 + (\beta_{k,T} - \beta_{k,T-1})'(\beta_{k,T} - \beta_{k,T-1})$$

where a_0 and b_0 are non-informative priors, $\beta_{k,T}$ is the vector of Kalman filter generated factor loadings for factor loading k from (3) and T_1 is the number of rows in $\beta_{k,T}$.

$$\sigma^2_{u_0} \sim InverseGamma(\frac{a_2}{2}, \frac{b_2}{2}) \tag{A2}$$
$$a_2 = a_0 + T_2$$
$$b_2 = b_0 + (Z^*)'(Z^*)$$

where a_0 and b_0 are non-informative priors, Z^* is the vector of the state dependent disturbance terms z_t^*, where $z_t^* = \frac{r_t - f'_{t-1}\beta_t}{\sqrt{1+hS_t}}$. T_2 is the size of Z^*.

$$h \sim InverseGamma(\frac{a_3}{2}, \frac{b_3}{2}) \tag{A3}$$
$$a_3 = a_0 + T_3$$
$$b_3 = b_0 + (Z^{**})'(Z^{**})$$

where a_0 and b_0 are non-informative priors, Z^{**} is the vector of the state dependent disturbance terms z_t^{**}, where $z_t^{**} = \frac{r_t - f'_{t-1}\beta_t}{\sigma_{u_0}}$. T_3 is the size of Z^{**}.

$$p \sim Beta(u_{11} + n_{11}, u_{10} + n_{10}) \tag{A4}$$

where u_{11} and u_{10} are non-informative priors and n_{11} and n_{10} are the number of transitions from state 1 to state 1 and state 1 to state zero respectively.

$$q \sim Beta(u_{00} + n_{00}, u_{01} + n_{01}) \tag{A5}$$

where u_{00} and u_{01} are non-informative priors and n_{00} and n_{01} are the number of transitions from state zero to state zero and state zero to state 1 respectively.

The algorithm for one iteration of the Gibbs sampler for the model in (5) proceeds as follows:

(i) Generate β_T from $\pi(\beta_T \mid \sigma_{v,}^2 \sigma_u^2, S_T, Y_T)$ by running the Kalman filter described in (3), where conditional on S_T, β_T is independent of p and q.

(ii) Generate S_T from $\pi(S_T \mid \sigma_u^2, \beta_T, p, q, Y_T)$ where conditional on β_T, S_T is independent of σ_v^2.

(iii) Generate $\sigma_{v_k}^2$ for $k = 1$ to 5 from $\pi(\sigma_{v_k}^2 \mid \beta_{k,T})$ where conditional on $\beta_{k,T}$, $\sigma_{v_k}^2$ is independent of σ_u^2, p, q, Y_T and $\sigma_{v_j}^2$ for all $j \neq k$.

(iv) Generate $\sigma_{u_0}^2$ from $\pi(\sigma_{u_0}^2 \mid h, S_T, \beta_T, Y_T)$ where conditional on h, S_T and β_T, $\sigma_{u_0}^2$ is independent of p, q and σ_v^2.

(v) Generate h from $\pi(h \mid \sigma_{u_0}^2, S_T, \beta_T, Y_T)$ where conditional on $\sigma_{u_0}^2, S_T$ and β_T, σ_u^2 is independent of p, q and σ_v^2.

(vi) Generate p from $\pi(p \mid S_T)$ where conditional on S_T, p is independent of all other conditioning information.

(vii) Generate q from $\pi(q \mid S_T)$ where conditional on S_T, q is independent of all other conditioning information.

Here $\sigma_v^2 = [\sigma_{v_1}^2 \;\; \sigma_{v_2}^2 \;\; \sigma_{v_3}^2 \;\; \sigma_{v_4}^2 \;\; \sigma_{v_5}^2]'$ and $\sigma_u^2 = [\sigma_{u_0}^2 \;\; \sigma_{u_1}^2]'$.

Appendix B
Estimation of the posterior density for model in (5)

Simulation of the joint posterior density

$$\ln\tilde{\pi}(\theta^* \mid Y_t) = \ln\tilde{\pi}(\sigma_v^2{*} \mid Y_t) + \ln\tilde{\pi}(\sigma_u^2{*} \mid Y_t, \sigma_v^2{*}) + \ln\tilde{\pi}(p^*, q^* \mid Y_t, \sigma_v^2{*}, \sigma_u^2{*}) \qquad \text{(B1)}$$

is performed by generating conditional marginal densities through additional runs of the Gibbs sampler, where θ^* is the posterior mean from the initial Gibbs sampling runs. The conditional densities are the terms on the right hand side of (B1). The sequence of additional Gibbs runs to simulate the densities is

$$\tilde{\pi}(\sigma_{v_1}^2{*} \mid Y_t) = \frac{1}{G}\sum_{g=1}^{G}\tilde{\pi}(\sigma_{v_1}^2{*} \mid \sigma_{v_2}^{2(g)}, \sigma_{v_3}^{2(g)}, \sigma_{v_4}^{2(g)}, \sigma_{v_5}^{2(g)}, \sigma_u^{2(g)}, p^{(g)}, q^{(g)}, S_t^{(g)}, Y_t) \qquad \text{(B2)}$$

then

$$\tilde{\pi}(\sigma_{v_2}^2{*} \mid Y_t, \sigma_{v_1}^2{*}) = \frac{1}{G}\sum_{g=1}^{G}\tilde{\pi}(\sigma_{v_2}^2{*} \mid \sigma_{v_1}^2{*}, \sigma_{v_3}^{2(g)}, \sigma_{v_4}^{2(g)}, \sigma_{v_5}^{2(g)}, \sigma_u^{2(g)}, p^{(g)}, q^{(g)}, S_t^{(g)}, Y_t) \qquad \text{(B3)}$$

then

$$\tilde{\pi}(\sigma_{v_3}^2{*} \mid Y_t, \sigma_{v_1}^2{*}, \sigma_{v_2}^2{*}) = \frac{1}{G}\sum_{g=1}^{G}\tilde{\pi}(\sigma_{v_3}^2{*} \mid \sigma_{v_1}^2{*}, \sigma_{v_2}^2{*}, \sigma_{v_4}^{2(g)}, \sigma_{v_5}^{2(g)}\sigma_u^{2(g)}, p^{(g)}, q^{(g)}, S_t^{(g)}, Y_t) \qquad \text{(B4)}$$

then

$$\tilde{\pi}(\sigma_{v_4}^2{*} \mid Y_t, \sigma_{v_1}^2{*}, \sigma_{v_2}^2{*}, \sigma_{v_3}^2{*}) = \frac{1}{G}\sum_{g=1}^{G}\tilde{\pi}(\sigma_{v_4}^2{*} \mid \sigma_{v_1}^2{*}, \sigma_{v_2}^2{*}, \sigma_{v_3}^2{*}, \sigma_{v_5}^{2(g)}\sigma_u^{2(g)}, p^{(g)}, q^{(g)}, S_t^{(g)}, Y_t) \qquad \text{(B5)}$$

then

$$\tilde{\pi}(\sigma_{v_5}^2{*} \mid Y_t, \sigma_{v_1}^2{*}, \sigma_{v_2}^2{*}, \sigma_{v_3}^2{*}, \sigma_{v_4}^2{*}) = \frac{1}{G}\sum_{g=1}^{G}\tilde{\pi}(\sigma_{v_5}^2{*} \mid \sigma_{v_1}^2{*}, \sigma_{v_2}^2{*}, \sigma_{v_3}^2{*}, \sigma_{v_4}^2{*}, \sigma_u^{2(g)}, p^{(g)}, q^{(g)}, S_t^{(g)}, Y_t) \qquad \text{(B6)}$$

then

$$\tilde{\pi}(\sigma_{u_0}^2{*} \mid Y_t, \sigma_v^2{*}) = \frac{1}{G}\sum_{g=1}^{G}\tilde{\pi}(\sigma_{u_0}^2{*} \mid \sigma_v^2{*}, p^{(g)}, q^{(g)}, h^{(g)}, S_t^{(g)}, Y_t) \qquad \text{(B7)}$$

Where $\sigma_v^2{*} = [\sigma_{v_1}^2{*}\,\sigma_{v_2}^2{*}\,\sigma_{v_3}^2{*}\,\sigma_{v_4}^2{*}\;\sigma_{v_5}^2{*}]$

then

$$\tilde{\pi}(h^* \mid Y_t, \sigma_v^2{*}, \sigma_{u_0}^2{*}) = \frac{1}{G}\sum_{g=1}^{G}\tilde{\pi}(h^* \mid \sigma_{u_0}^2{*}, \sigma_v^2{*}, p^{(g)}, q^{(g)}, S_t^{(g)}, Y_t) \qquad \text{(B8)}$$

then

$$\tilde{\pi}(p^*, q^* \mid Y_t, \sigma_v^2{*}, \sigma_u^2{*}) = \frac{1}{G}\sum_{g=1}^{G}\tilde{\pi}(p^*, q^* \mid \sigma_v^2{*}, \sigma_u^2{*}, S_t^{(g)}, Y_t)\,. \qquad \text{(B9)}$$

where the superscript (*g)* refers to the *g*-th draw of the current Gibbs run and indicates that the conditioning item is variable. Conditioning items with a * superscript are fixed posterior mean values from the initial Gibbs run.

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Table 1

Summary Statistics for Sector Returns

Summary statistics for the returns of the 10 GICS sectors are presented. All sector returns are in log difference weekly rates. The sample period for the statistics is January 12, 1990 through January 10, 2003.

Summary Statistics

	Mean	Median	S.D.	Min	Max
CONS DISCR	0.151	0.262	2.645	-15.074	9.833
CONS STAPLE	0.187	0.242	2.280	-13.617	10.414
ENERGY	0.109	0.199	2.665	-13.897	9.634
FINANCIALS	0.216	0.171	3.105	-12.501	14.729
HEALTHCARE	0.223	0.165	2.720	-11.553	9.151
INDUSTRIALS	0.147	0.273	2.543	-19.129	10.838
TECHNOLOGY	0.197	0.398	4.158	-24.197	14.583
MATERIALS	0.073	0.145	2.776	-15.054	13.345
TELECCOMS	0.035	0.195	2.848	-14.190	14.331
UTILITIES	0.007	0.039	2.330	-14.881	7.988

Table 2

Parameter Constancy Tests

$$r_{i,t+1} = \beta_0 + \beta_1 \Delta divyield_t + \beta_2 \Delta spread_t + \beta_3 \Delta oil_t + \beta_4 \Delta short_t + u_{i,t+1}$$

Results are presented for testing the null of parameter constancy using Hansen's Lc statistic. All data are in weekly frequency. The sample period over which the statistics are estimated is January 12, 1990 through January 10, 2003.

		β_0	β_1	β_2	β_3	β_4	σ_u^2
CONS DISCR	**Individual Lc**	0.212	0.075	0.094	0.116	0.031	3.840***
	Joint Lc	4.321***					
CONS STAPLE	**Individual Lc**	0.257	0.025	0.126	0.104	0.106	1.344***
	Joint Lc	1.875**					
ENERGY	**Individual Lc**	0.107	0.076	0.116	0.311	0.117	3.551***
	Joint Lc	4.586***					
FINANCIALS	**Individual Lc**	0.144	0.4701**	0.156	0.149	0.038	3.183**
	Joint Lc	3.999**					
HEALTH CARE	**Individual Lc**	0.223	0.025	0.670**	0.089	0.054	1.226***
	Joint Lc	2.136***					
INDUSTRIALS	**Individual Lc**	0.249	0.118	0.153	0.292	0.017	2.456***
	Joint Lc	3.437***					
TECHNOLOGY	**Individual Lc**	0.355*	0.093	0.059	0.483**	0.069	6.583***
	Joint Lc	7.303***					
MATERIALS	**Individual Lc**	0.084	0.139	0.060	0.150	0.035	4.010***
	Joint Lc	4.628***					
TELECOMMS	**Individual Lc**	0.452**	0.019	0.242	0.073	0.127	5.177***
	Joint Lc	6.011***					
UTILITIES	**Individual Lc**	0.233	0.571**	0.090	0.033	0.291	6.512***
	Joint Lc	8.571***					

, **, *, reject stability at the 10%, 5%, and 1% asymptotic significance levels respectively.*

Table 3

Parameter Constancy Tests

$$r_{i,t+1} = \beta_{0,t} + \beta_{1,t}\Delta divyield_t + \beta_{2,t}\Delta spread_t + \beta_{3,t}\Delta oil_t + \beta_{4,t}\Delta short_t + u_{i,t+1}$$

Results are presented for testing the null of parameter constancy using Bai and Perron's testing procedure. The Wdmax(1%) test denotes the F-statistic for testing the null of no breaks against the alternative of l breaks subject to a pre-specified upper bound in the possible number of breaks (here the upper bound is set to 5). In particular the Wdmax test applies appropriate weights to each F-statistic so that the marginal p-values are equal across values of l. Each of the SupFT(l) statistics tests the null of 0 against l breaks where l=1,2,…,5. The SupFT(l+1|l) statistic tests the null of l breaks (where l is given), against the alternative of one additional structural break. All data are in weekly frequency. The sample period over which the statistics are estimated is January 12, 1990 through January 10, 2003.

	Wdmax(1%)	$SupF_T(1)$	$SupF_T(2)$	$SupF_T(3)$	$SupF_T(4)$	$SupF_T(5)$	$SupF_T(2\|1)$	$SupF_T(3\|2)$	$SupF_T(4\|3)$	$SupF_T(5\|4)$
CONS DISCR	73.497***	48.591***	61.824***	43.751***	23.746***	33.683***	54.830***	4.486	10.916	58.4531***
CONS STAPLE	17.520	17.520*	12.348	12.441	13.128	11.970	8.474	14.996	14.996	14.4506
ENERGY	26.755***	11.301	20.086**	18.993***	22.562***	19.548***	24.729***	11.294	20.539*	8.803
FINANCIALS	31.335***	31.335***	10.137	14.952*	16.916**	19.334***	11.617	24.946**	24.946**	19.588
HEALTH CARE	28.359***	19.553**	18.453**	20.383***	18.661***	19.079***	22.765**	22.380**	14.701	9.979
INDUSTRIALS	65.883***	36.979***	40.587***	29.727***	35.693***	44.325***	40.131***	4.960	38.229***	15.331
TECHNOLOGY	34.267***	34.267***	23.830***	22.409***	23.409***	19.052***	12.047	28.859***	28.859***	46.827***
MATERIALS	37.648***	25.678***	19.362**	24.536***	21.680***	25.329***	13.249	26.642***	14.766	23.517**
TELECOMMS	43.981***	25.239***	31.191***	33.348***	29.746***	25.459***	35.182***	16.921	16.921	21.027
UTILITIES	46.313***	11.529	21.907***	33.263***	32.993***	28.115***	57.383***	10.462	31.038***	11.514

, **, *, reject stability at the 10%, 5%, and 1% asymptotic significance levels respectively.*

Table 4

Log Marginal Likelihood Results for Tested Models

Log marginal likelihood values for four alternative model specifications are presented for ten industry sectors below.

SECTOR	Model (5)	Model (5a)	Model (5b)	Model (5c)
CONS DISCR	-1509.16	-1561.00	-1546.66	-1516.65
CONS STAPLE	-1441.81	-1482.44	-1459.90	-1421.54
ENERGY	-1526.62	-1577.42	-1553.16	-1530.91
FINANCIALS	-1624.57	-1681.40	-1653.84	-1631.14
HEALTH CARE	-1557.21	-1593.43	-1570.48	-1545.39
INDUSTRIALS	-1486.91	-1551.76	-1526.59	-1494.67
TECHNOLOGY	-1790.64	-1856.57	-1838.03	-1822.00
MATERIALS	-1545.43	-1605.36	-1583.89	-1552.33
TELECOMM	-1547.12	-1579.09	-1574.32	-1550.19
UTILITIES	-1374.16	-1448.24	-1429.48	-1401.57

Table 5

Bayesian Gibbs Sampling Estimation Results for the Model in (5)

Results of Gibbs sampling simulations for ten economic sector portfolios for the model in (5) are presented. For each portfolio the sample period is January 12, 1990 through June 14, 2002. For each portfolio the number of runs of the Gibbs sampler is 10,000 with the first 2,000 runs discarded for calculation of descriptive statistics. The first item for each sector for each parameter is the posterior mean of the simulation. The median of the posterior sample is presented below in italics and the standard deviation of the posterior sample is presented in parenthesis.

	σ_{u_0}	σ_{u_1}	σ_{v_1}	σ_{v_2}	σ_{v_3}	σ_{v_4}	σ_{v_5}	p	q
CONS DISCR	1.9883	3.0165	0.00974	0.00002	0.00033	0.00063	0.00007	0.9912	0.9865
	1.9869	*3.0150*	*0.00703*	*0.00001*	*0.00021*	*0.00023*	*0.00004*	*0.9925*	*0.9888*
	(0.0687)	(0.0783)	(0.00888)	(0.00003)	(0.00051)	(0.00104)	(0.00006)	(0.0061)	(0.0098)
CONS STAPLE	1.7946	2.6813	0.00003	0.00002	0.00004	0.00004	0.00001	0.9710	0.9375
	1.7900	*2.6767*	*0.00002*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.9763*	*0.9527*
	(0.0852)	(0.0945)	(0.00004)	(0.00002)	(0.00008)	(0.00080)	(0.00001)	(0.0218)	(0.0531)
ENERGY	2.0511	3.0897	0.00002	0.00012	0.00023	0.00003	0.00055	0.9923	0.9923
	2.0507	*3.0883*	*0.00002*	*0.00001*	*0.00009*	*0.00002*	*0.00011*	*0.9937*	*0.9943*
	(0.0808)	(0.0908)	(0.00003)	(0.00024)	(0.00039)	(0.00003)	(0.00089)	(0.0058)	(0.0078)
FINANCIALS	2.4424	3.6886	0.00002	0.00011	0.00032	0.00036	0.00019	0.9867	0.9788
	2.4377	*3.6838*	*0.00001*	*0.00005*	*0.00011*	*0.00026*	*0.00007*	*0.9887*	*0.9827*
	(0.1083)	(0.1214)	(0.00004)	(0.00014)	(0.00045)	(0.00027)	(0.00039)	(0.0092)	(0.0158)
HEALTH CARE	2.1204	3.1749	0.00081	0.00011	0.19069	0.00001	0.00097	0.9464	0.9076
	2.1149	*3.1702*	*0.00017*	*0.00006*	*0.17111*	*0.00001*	*0.00005*	*0.9660*	*0.9520*
	(0.1233)	(0.1359)	(0.00167)	(0.00013)	(0.08705)	(0.00003)	(0.00122)	(0.0667)	(0.1393)
INDUSTRIALS	1.9359	2.9386	0.00003	0.00074	0.00019	0.00003	0.00024	0.9898	0.9880
	1.9350	*2.9377*	*0.00002*	*0.00014*	*0.00007*	*0.00003*	*0.00003*	*0.9913*	*0.9902*
	(0.0663)	(0.0759)	(0.00004)	(0.00132)	(0.00028)	(0.00003)	(0.00035)	(0.0067)	(0.0092)
TECHNOLOGY	3.3343	4.9890	0.00005	0.00088	0.00033	0.02595	0.00010	0.9945	0.9929
	3.3298	*4.9860*	*0.00002*	*0.00004*	*0.00028*	*0.00091*	*0.00008*	*0.9955*	*0.9952*
	(0.1097)	(0.1250)	(0.00007)	(0.00168)	(0.00023)	(0.04832)	(0.00009)	(0.0041)	(0.0074)
MATERIALS	2.1700	3.2698	0.00318	0.00007	0.00143	0.00050	0.00017	0.9905	0.9874
	2.1676	*3.2669*	*0.00185*	*0.00004*	*0.00115*	*0.00003*	*0.00003*	*0.9923*	*0.9899*
	(0.0952)	(0.1064)	(0.00511)	(0.00008)	(0.00132)	(0.00127)	(0.00035)	(0.0073)	(0.0105)
TELECOMM	2.2645	3.3547	0.00002	0.00030	0.00033	0.01216	0.00164	0.9935	0.9887
	2.2857	*3.3759*	*0.00001*	*0.00005*	*0.00028*	*0.00991*	*0.00093*	*0.9949*	*0.9924*
	(0.1204)	(0.1323)	(0.00002)	(0.00070)	(0.00023)	(0.00990)	(0.00212)	(0.0051)	(0.0119)
UTILITIES	1.7988	2.6694	0.00027	0.00112	0.00041	0.00092	0.00045	0.9954	0.9913
	1.7978	*2.6690*	*0.00014*	*0.00008*	*0.00001*	*0.00053*	*0.00007*	*0.9962*	*0.9940*
	(0.0521)	(0.0600)	(0.00036)	(0.00291)	(0.00141)	(0.00112)	(0.00084)	(0.0035)	(0.0086)

Table 6

Cross Sectional Regression Results

Cross sectional regression results for tests of the importance of the market portfolio and predicted returns based on lagged macroeconomic indicators on S&P 500 sector portfolio returns are summarized. The OLS regression coefficients are expressed as percentage per week. For each cross-sectional regression at time *t*, the regressors are a constant term, the betas from a contemporaneous time series regression on the return on the S&P 500 index at time *t-1* and a forecasted return estimated with lagged macroeconomic factors through period *t-1*. Expanding betas for the market portfolio and predicted returns are estimated using data beginning in January 1990. Rolling CAPM betas and predicted returns are estimated using the most recent 50 weeks of data. Bayesian betas and predicted returns are estimated in the time varying parameter model described in section 2. The out of sample forecast period is the week ending October 14, 1994 to the week ending January 10, 2003. The number of cross sectional regressions is 429. Fama-MacBeth standard errors are underneath the coefficients in parentheses.

Panel A. Expanding CAPM Betas and Expanding Predicted Returns

λ_0	λ_1 (market)	λ_2 (macro)
-0.0563	0.1874	-
(0.1975)	(0.2292)	-
-0.0849	0.1571	0.1502
(0.1916)	(0.2464)	(0.3814)

Panel B. Bayesian CAPM Betas and Expanding Predicted Returns

λ_0	λ_1 (market)	λ_2 (macro)
-0.0601	0.1977	-
(0.1656)	(0.2035)	-
-0.0925	0.1651	0.1285
(0.1736)	(0.2176)	(0.3714)

Panel C. Rolling CAPM Betas and Rolling Predicted Returns

λ_0	λ_1 (market)	λ_2 (macro)
-0.0141	0.1464	-
(0.1534)	(0.1708)	-
-0.0670	0.1119	0.2562
(0.1440)	(0.1877)	(0.0983)

Panel D. Expanding CAPM Betas and Bayesian Predicted Returns

λ_0	λ_1 (market)	λ_2 (macro)
-0.0086	-0.1546	0.6330
(0.1935)	(0.2566)	(0.2706)

Panel E. Bayesian CAPM Betas and Bayesian Predicted Returns

λ_0	λ_1 (market)	λ_2 (macro)
-0.0649	0.0142	0.5611
(0.1729)	(0.2258)	(0.2650)

Table 7

Strategy Performance Summary

Annualized geometric returns and Sharpe ratios for a dynamic sector allocation model using 5 different econometric specifications are presented. For each case, total available capital is split evenly between a long portfolio based on the highest predicted sector return and a short portfolio based on the lowest predicted sector return. For the expanding sample strategy, parameters are updated by OLS every period beginning at T = 250 using the full available sample through time *t*. For the discrete rolling strategy, parameters are updated by OLS every 50 periods for the sample from *t-T* to *t*. For the 5yr rolling sample strategy, parameters are updated by OLS weekly using a sample from *t-T* to *t*. For the 1yr rolling sample strategy, parameters are updated by OLS weekly using a sample from *t-49* to *t*. For the Bayesian beta strategy, variance parameters are estimated every 50 periods and the beta parameters are updated using the Kalman filter. All results are based on forecasts for period *t+1* using parameters and data estimated through period *t*. The total sample is 678 observations. Estimation results for each strategy begin in period 250 (October 14, 1994). The starting capital level for each strategy is normalized at 100.

Year	Expanding Sample	Discrete Rolling OLS	1yr Rolling OLS	5yr Rolling OLS	Kalman
1995	17.02%	14.88%	15.42%	23.92%	8.20%
1996	7.77%	14.89%	-10.88%	3.54%	7.33%
1997	7.67%	6.94%	17.62%	11.87%	20.97%
1998	25.17%	0.92%	13.83%	10.22%	20.07%
1999	12.47%	8.10%	24.98%	9.54%	18.59%
2000	-7.21%	-20.00%	-0.34%	-2.93%	31.52%
2001	-8.99%	5.23%	11.95%	27.15%	25.50%
2002	5.60%	-5.14%	3.91%	10.07%	13.42%
Average Geometric Return For Period 1995-2002	6.68%	2.53%	8.41%	10.83%	17.95%

Sharpe Ratios Per Year

Year	Expanding Sample	Discrete Rolling OLS	1yr Rolling OLS	5yr Rolling OLS	Kalman
1995	1.5	1.59	1.41	2.47	0.85
1996	0.78	1.38	-1.12	0.33	0.65
1997	0.91	0.85	2.01	1.35	2.58
1998	1.84	0.07	1.10	0.94	1.83
1999	0.75	0.51	1.77	0.63	1.26
2000	-0.43	-1.01	-0.01	-0.13	1.62
2001	-0.47	0.28	0.62	1.36	1.36
2002	0.3	-0.27	0.24	0.55	0.73
Average Sharpe Ratios For Period 1995-2002	0.46	0.17	0.55	0.72	1.24

Table 8

Price Per Share of Value Weighted Sector Constituents

The value weighted constituent price per share for the ten S&P 500 GICS primary industry sectors on January 1, 2002 are presented. Prices are calculated as the sum of prices for the constituents comprising 75% of the sector valuation multiplied by their corresponding weights in the sector portfolio scaled such that the weightings sum to unity.

Sector Weighted Price Per Share
January 1, 2002

Consumer Discretionary Index	$46.23
Consumer Staples Index	$52.58
Energy Index	$51.94
Financial Index	$53.74
Health Care Index	$53.15
Industrials Index	$50.81
Information Technology Index	$50.53
Materials Index	$39.87
Telecommunication Services Index	$36.75
Utilities Index	$39.23

Table 9

Split Sample Cross Sectional Regression Results

Cross sectional regression results for tests of the importance of the market portfolio and predicted returns based on lagged macroeconomic indicators on S&P 500 sector portfolio returns are summarized for the period of October 14, 1994 to March 10, 2000 and from March 11, 2000 to January 10, 2003. The OLS regression coefficients are expressed as percentage per week. For each cross-sectional regression at time *t*, The regressors are a constant term, the betas from a contemporaneous time series regression on the return on the S&P 500 index at time *t-1* and a forecasted return estimated with lagged macroeconomic factors through period *t-1*. Rolling CAPM betas and predicted returns are estimated using the most recent 50 weeks of data. Bayesian betas and predicted returns are estimated in the time varying parameter model described in section 2. The number of cross sectional regressions is 280 in the first sample and 149 in the second sample. Fama-MacBeth standard errors are underneath the coefficients in parentheses.

Sample I: October 14, 1994 to March 10, 2000

Panel A. Rolling CAPM Betas and Rolling Parameter Predicted Returns

λ_0	λ_1 (market)	λ_2 (macro)
-0.0177	0.3364	-
(0.1460)	(0.1797)	-
-0.1048	0.3813	0.2320
(0.1556)	(0.2057)	(0.1281)

Panel B. Bayesian CAPM Betas and Bayesian Predicted Returns

λ_0	λ_1 (market)	λ_2 (macro)
-0.0947	0.4419	-
(0.2018)	(0.2452)	-
-0.0219	0.3167	0.3769
(0.2121)	(0.2770)	(0.3428)

Sample II: March 11, 2000 to January 10, 2003

Panel C. Rolling CAPM Betas and Rolling Predicted Returns

λ_0	λ_1 (market)	λ_2 (macro)
-0.0383	-0.2359	-
(0.2751)	(0.3570)	-
0.0267	-0.4202	0.2697
(0.2952)	(0.3757)	(0.1460)

Panel D. Bayesian CAPM Betas and Bayesian Predicted Returns

λ_0	λ_1 (market)	λ_2 (macro)
0.0383	-0.2814	-
(0.2985)	(0.3607)	-
-0.1125	-0.5648	0.8515
(0.3029)	(0.3881)	(0.4062)

Figure 1

Sector Index Evolution

We assume an initial investment of $100 in each of the GICS indices and present the evolution of a buy and hold investment for each sector portfolio.

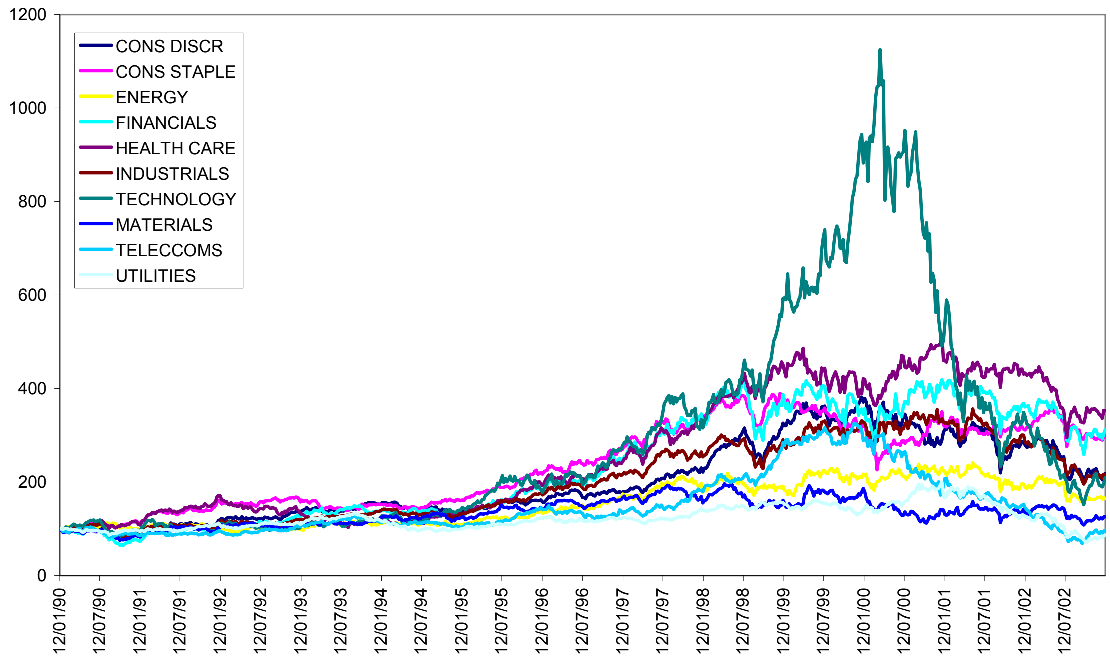
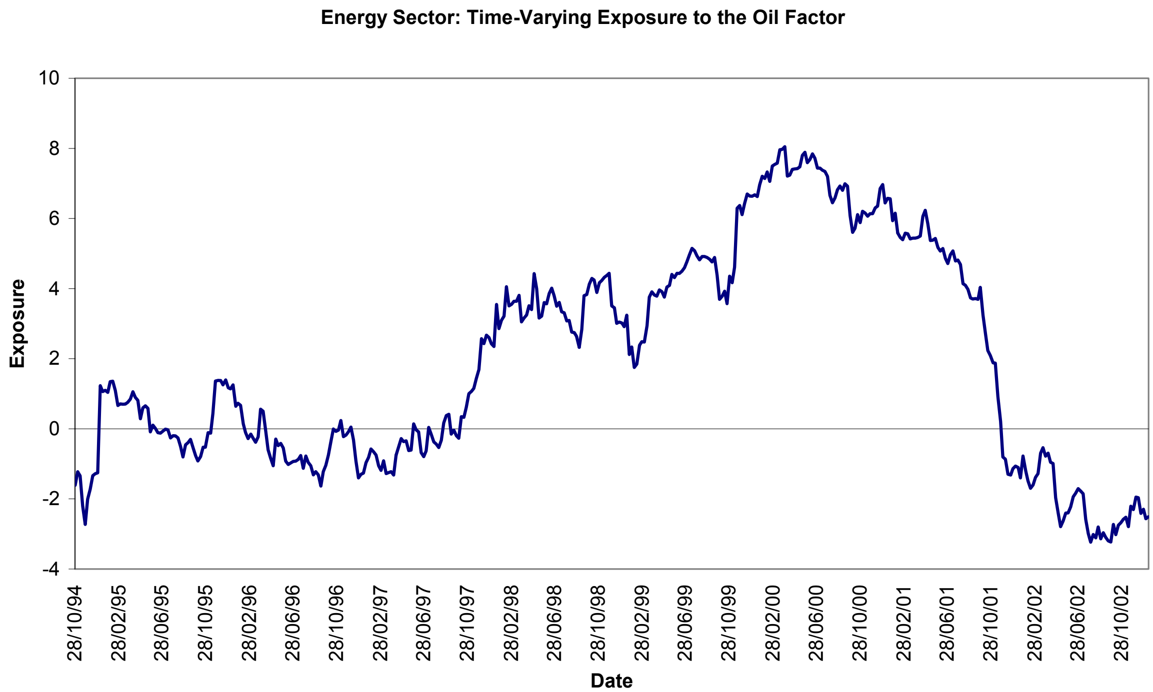


Figure 2

Factor Loadings for Selected Economic Sectors

The graphs below present the time varying sensitivities for some of the factors in some of the sectors discussed in the paper. The complete set of these graphs, is available upon request from the authors.

2a



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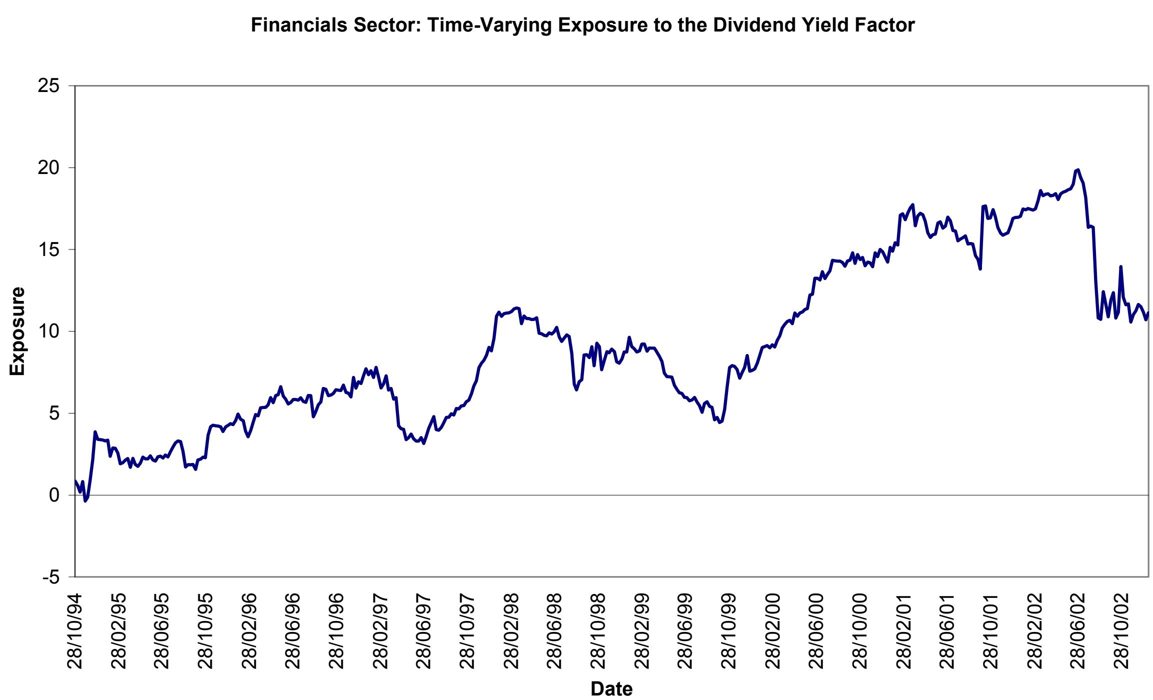
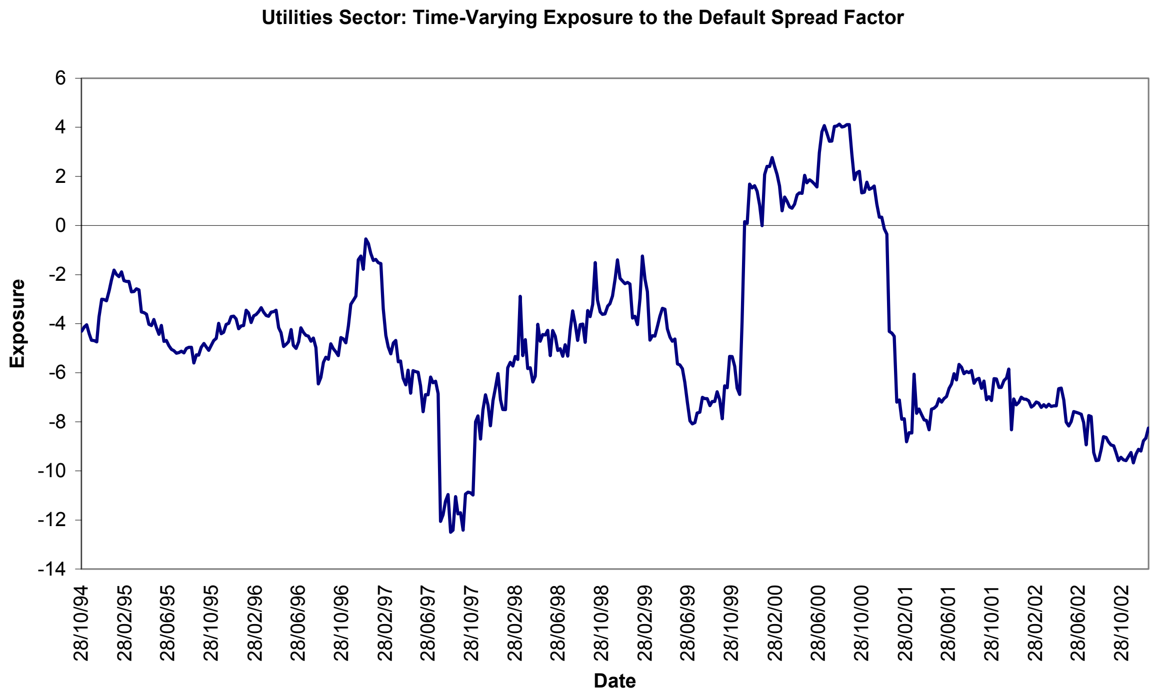


Figure 2 continued

Factor Loadings for Selected Economic Sectors

The graphs below present the time varying sensitivities for some of the factors in some of the sectors discussed in the paper. The complete set of these graphs, is available upon request from the authors.

2c



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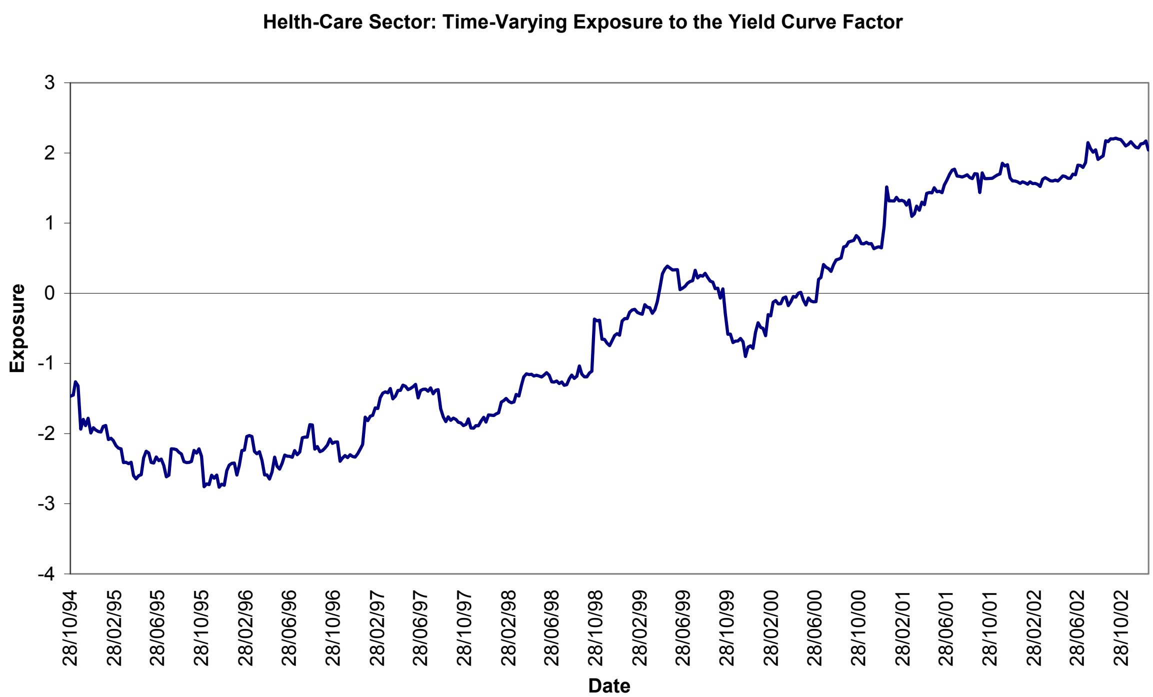
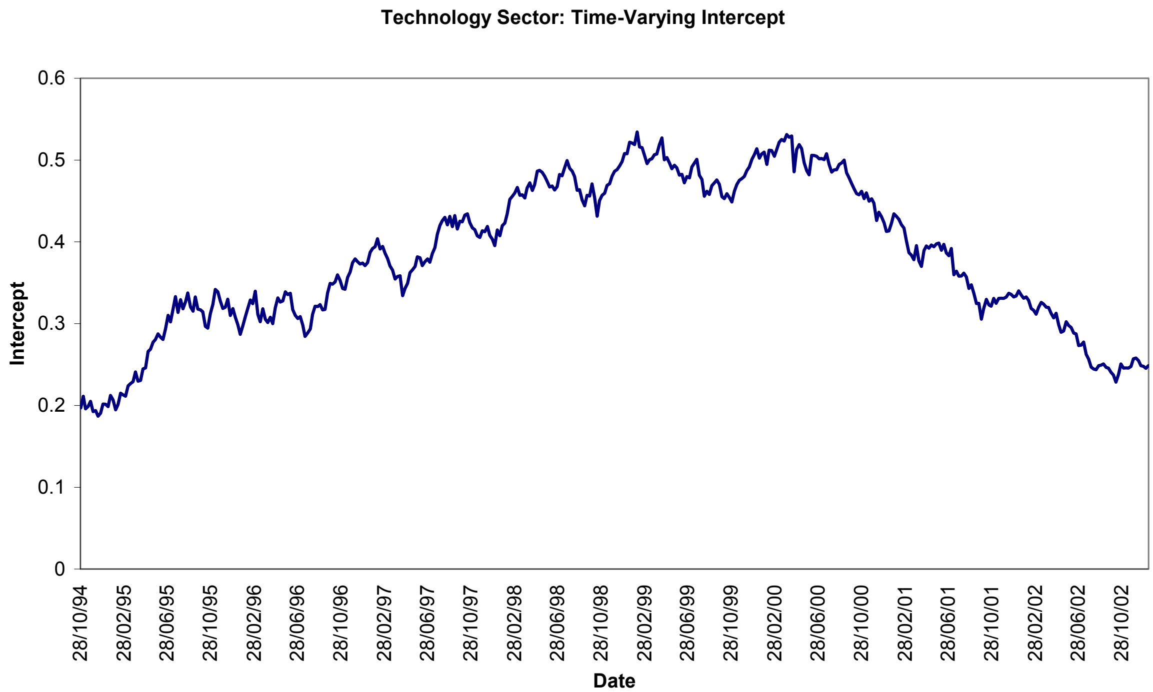


Figure 2 continued

Factor Loadings for Selected Economic Sectors

The graphs below present the time varying sensitivities for some of the factors in some of the sectors discussed in the paper. The complete set of these graphs, is available upon request from the authors.

2e



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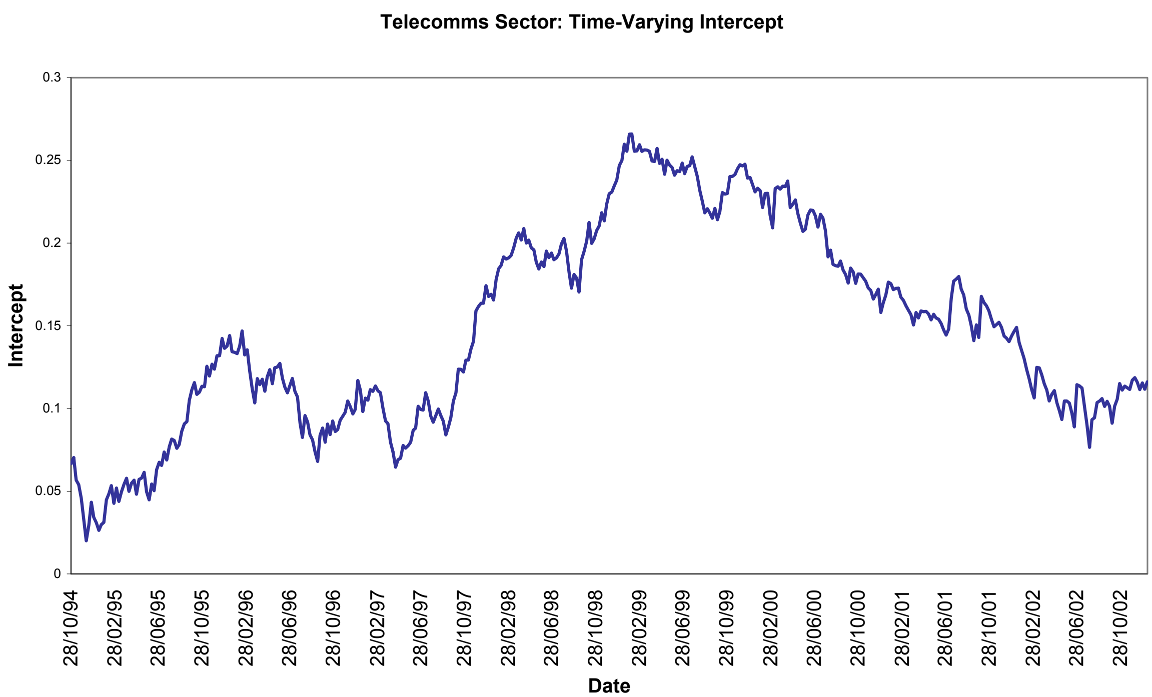

Figure 3

Returns on Dynamic Sector Allocation Model

Cummulative returns for a dynamic sector allocation model using 5 different econometric specifications are charted. For each case, total available capital is split evenly between a long portfolio based on the highest predicted sector return and a short portfolio based on the lowest predicted sector return. For the expanding sample strategy, parameters are updated by OLS every period beginning at T = 250 using the full available sample through time t. For the discrete rolling strategy, parameters are updated by OLS every 50 periods for the sample from *t-T* to *t*. For the 5yr rolling sample strategy, parameters are updated by OLS weekly using a sample from *t-T* to *t*. For the 1yr rolling sample strategy, parameters are updated by OLS weekly using a sample from *t-49* to *t*.For the Bayesian beta strategy, variance parameters are estimated every 50 periods and the beta parameters are updated using the Kalman filter. All results are based on forecasts for period *t+1* using parameters and data estimated through period *t*. The total sample is 429 observations. Estimation results for each strategy begin in period 250 (October 14, 1994). The starting capital level for the strategy is normalized at 100.

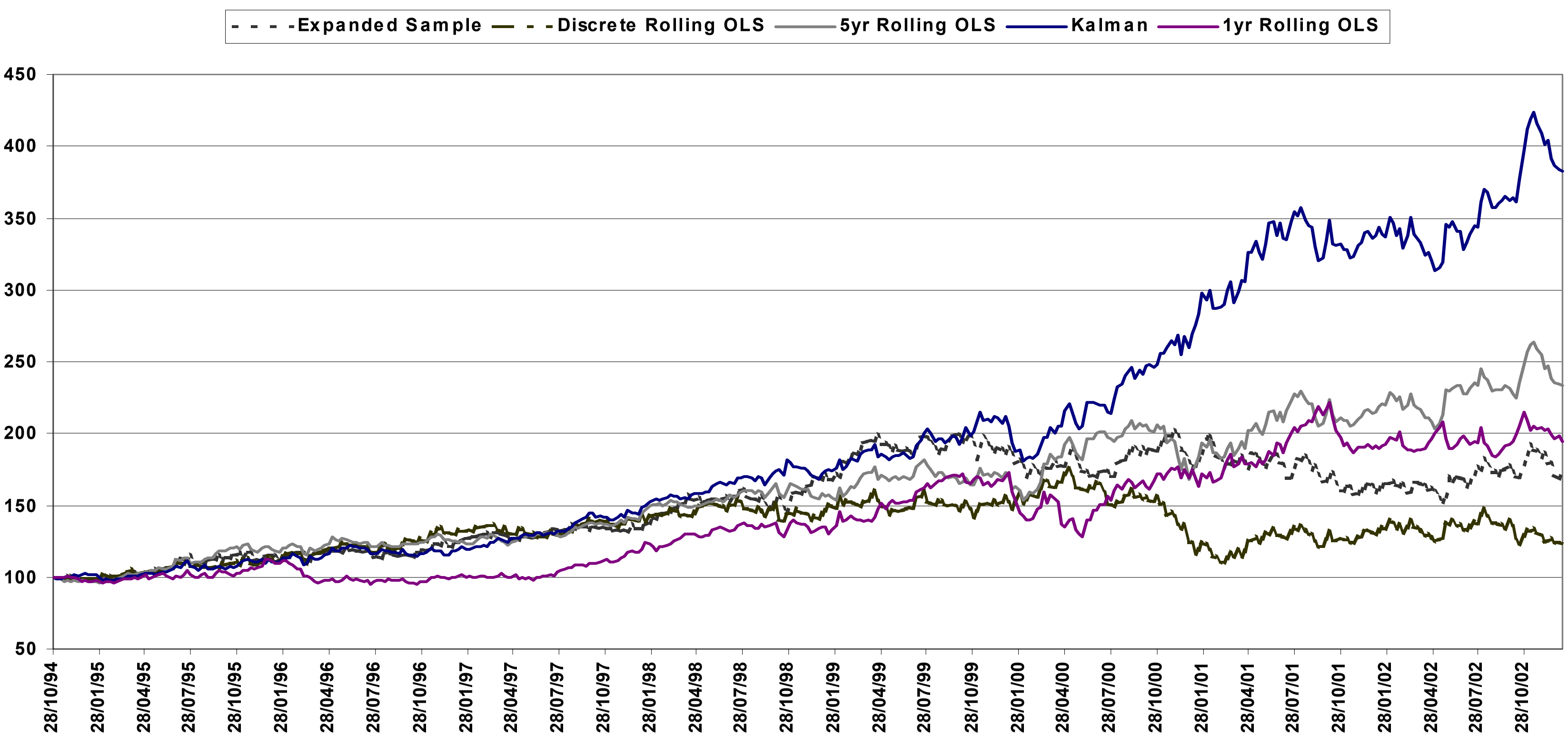

Figure 4

Expected and Actual Geometric Returns

The solid line in the figure below indicates the expected average annualized geometric return over the 1995-2002 period based on a Monte Carlo Simulation. The simulation is designed so that we assume only long-positions for a specified number of months that are selected randomly. The actual returns based on the different econometric specifications used are signified by uniquely colored triangles on the same figure.