Style Investing under Uncertainty

This Draft: May 15, 2009

Abstract

This paper analyzes the predictability of different style portfolio returns (a.k.a. Fama-French factors) considering time-varying sensitivities of these returns to different macroeconomic variables and own momentums. Styles, as used in this paper, can be defined as groups of securities with a common characteristic, such as value (Graham and Dodd (1934)) and size (Banz (1979)), and have been popularized by Fama and French papers. This paper specifically looks at determinants of style investing, such as style momentums and predictive variables such as macroeconomic variables (e.g. yield spread, inflation, industrial production, etc.), and show how 'learning' about these variables affects the predictability of different style portfolio returns compared to scenarios where there is no learning. A time-varying parameter model and a Kalman filter are used to take into account the effect of learning in this paper. At the end, it is found that returns of style portfolios such as value and size appear to be related, with time-varying sensitivities, to yield spread and other macroeconomic variables. This paper also finds that time-varying parameter models provide better in-sample and out-of-sample predictions than simple benchmark constant parameter models (e.g. linear models).

1 Introduction

In this paper, I present the benefits of a simple time-varying model of expected style portfolio returns that would help better solve the portfolio choice problem (e.g. of an institutional manager or a mutual fund manager) as well as contribute to the literature that searches for the potential underlying risks of Fama-French factors. I compare the in and out-of-sample forecasting ability of this time-varying parameter model to benchmark constant parameter models. Specifically, this paper looks at the time-varying effect of predictive variables such as different macroeconomic variables and style momentums in calculating the expected style portfolio returns in a univariate and multivariate sense. The macroeconomic variables used in this paper include inflation, Treasury-bill rate, yield spread, term structure, and industrial production. Style momentums used in the paper are the own short and long term momentums of style portfolios. Style portfolios are the Fama-French size, value, and momentum portfolios.

The contribution of this paper to the literature is that it analyzes the time-varying effect of macroeconomic variables and own momentums on different style portfolio returns and the predictive ability of such a specification. I conclude that macroeconomic variables affect different styles of firms in different ways (e.g. the effect of inflation on value and size firms is different in terms of magnitude and sign) and the effects change through time. I also conclude that a time-varying parameter model gives better in-sample and out-of-sample forecasts compared to the benchmark constant parameter model (using both single and multiple factors).

Finance models of expected stock returns have for a long time focused either on the predictability of individual stock returns (Avramov and Chordia (2006)) or aggregate market returns. Predictability of style returns, as can be defined as the predictability of returns of a group of securities with a common characteristic, has also been an area of research in the literature, where most of the attention is given to the groups of securities with an obvious characteristic, such as the country in which the security is traded in or the industry in which the firm operates. Predictability of returns of groups of securities with a less obvious characteristic, such as value or size, has been paid less attention to in the literature (see Barberis and Shleifer (2003) as an example of a recent paper on style investing) except for the literature which searches for potential underlying risks behind Fama-French factors.

In predicting individual stock returns (cross-section of expected returns), different style portfolio returns are used as factors, following Fama and French, with the convention that these factors have significant predictive power. But the literature has suggested that these Fama-French factors could be just proxies for some other underlying risks such as macro risks. Hahn and Lee (2003), Vassalou (2003), Petkova (2006) are some papers that try to identify these underlying risks. These papers either do not explicitly consider the possible time-varying relationship between Fama-French factors and macroeconomic variables or when they do so, are not flexible in the reasons they give behind time-variations (e.g. focusing on either business cycles or monetary policy periods, etc), yet they still support the results of this paper.

In a related strand of literature, the time-varying relationship between the market risk premium and stock returns have been analyzed using the ICAPM models (Merton (1973), Lo and Wang (2006)). ICAPM literature is an extension of the CAPM literature and realizes the changing investment opportunities whereas the CAPM literature assumes the investment opportunities to be constant. ICAPM realizes the changing investment opportunities. In this sense, motivation for ICAPM seems similar to this paper's motivation. Conditional CAPM literature in general, which includes the papers with models where market betas depend on macroeconomic variables, is more advanced but still doesn't explain the direct time-varying time-series relationship between specific macroeconomic variables and stock returns (see Lewellen and Nagel (2006) for a criticism of C-CAPM models).

Intuitively, macroeconomic variables should be excellent candidates as undiversifiable risk factors since macroeconomic developments affect many firms' cash flows and also the discount rates. Macroeconomic conditions may also affect the number and type of investment opportunities available to firms. Therefore, an understanding of the sensitivities of style portfolio returns to macroeconomic factors and the time-specific conditions surrounding these sensitivities would be of special benefit to both the finance practitioner as well as the academic. By identifying those macroeconomic variables affecting style returns and when, investment managers may be able to hedge against systematic risks stemming from particular macroeconomic variables. For instance, by identifying inflation sensitive style portfolios (those portfolios that are affected more severely when inflation goes up or down), fund managers or portfolio managers can improve their hedging activities by hedging against future inflation increases or decreases to protect these sensitive style investments.

Beginning with Chen, Roll and Ross (1986) many papers have tried to show the relationship between macroeconomic variables and stock returns. Chen, Roll and Ross (1986) note that the comovements of asset prices suggest the presence of underlying exogenous influences, but that it is yet to be determined which economic variables, if any, are responsible. Some of the macroeconomic factors they identify include the growth rate of industrial production, expected inflation, a bond default risk premium, and a term structure spread. They conclude that the default and term premia are priced risk factors; that industrial production is a strong candidate to be one; and that there's weaker evidence for inflation. Chan, Chen, and Hsieh (1985) examine other variables.

Shanken and Weinstein (2006) criticize Chen, Roll and Ross's (1986) results. But, Bodie (1976), Fama (1981), Geske and Roll (1983), Cutler, Poterba, and Summers (1989), Lo and MacKinlay (1997) show that aggregate stock returns are related to inflation, money growth, industrial production growth, and other macroeconomic variables in one way or another. Ferson and Harvey (1991) provide an analysis of the predictable components of monthly common stock and bond portfolio returns. They show that most of the predictability is associated with sensitivity to economic variables in a rational asset pricing model with multiple betas.

I claim that the impact of macroeconomic variables on stock returns has been difficult to show empirically because most of the previous studies focus on linear, time-invariant relationships between these variables and stock returns. Recent developments in theoretical econometrics show that time-variation is not something to be ignored (see Elliott and Muller (2006) among others).

Therefore, I show in this paper that the impact of macroeconomic variables on stock returns varies due to specific historical and economic events or periods (e.g. wars, monetary policy changes, business cycles, etc), albeit with a lack of pattern in plain sight. I also show that the linear models that ignore these changes have lower predictive power compared to the time-varying versions of these models.

The intuition behind these findings is that, for instance, a high inflationary period might carry different risk loadings during different monetary policy periods (depending on the credibility and transparency of the Fed Reserve, the interplay of different macroeconomic variables, etc). Inflation then will affect small and big sized firms in a time-varying manner through time. In other words, inflation will be more costly for small sized firms compared to big sized firms (due to less flexibility to negotiate with suppliers), but the magnitude and time series behavior of this cost will depend on other factors (monetary policy in this case), too.

The better predictive ability of time-varying parameter models stem from the observation that if parameters turn out to be unstable, then a good forecast of the dependent variable will be driven more by recent past than by distant past (Elliott and Muller (2006), Chernoff and Zacks (1964), Clements and Hendry (1999), and Stock and Watson (1996)). The instability, if ignored, will also affect the confidence in the accuracy of the forecast, resulting in wider confidence intervals. Technically, ignoring the time variation then will lead to biased forecasts.

Papers that draw attention to the importance of time-varying effects on stock returns include McQueen and Roley (1993) and Boyd, et al. (2005). McQueen and Roley (1993) claim that the reason why macroeconomic factors seem to have insignificant effects on stock returns is due to the constant-coefficient model used in general. They suggest that the macroeconomic developments may have different effects at different points in the business cycle. They estimate a model where the effects of different macroeconomic variables depend on overall economic conditions, defined according to the monthly growth rate of industrial production. They show that more macroeconomic developments seem to have significant effects in their model as opposed to in a constant-coefficient model. The strategy followed in this paper is restrictive in the sense that the definition used to describe the overall economic conditions is narrowed down to the monthly growth rate of industrial production. Intuitively, the results would vary considerably across alternative definitions of the economy's overall condition. The replications of this analysis with alternative definitions are carried out by Flannery and Protopapadakis (2002) giving the intuitive outcome. Also, McQueen and Roley (1993) look at the effects of different macroeconomic variables on only the S&P 500 portfolio and ignore the possibility that at the more disaggregate level different macroeconomic variables might affect different style portfolios in different ways through time.

Boyd, et al. (2005) also argues that the relationship between macroeconomic variables and stock returns is time-varying. They examine the effect of unemployment on S&P 500 portfolio returns and conclude that high unemployment raises stock prices during an economic expansion, but lowers them during an economic contraction. They claim that high unemployment predicts lower interest rates and corporate profits and conclude that the importance of these effects vary over the business cycle. Yet again, Boyd, et al. (2005) focuses on the effects of macroeconomic variables on only the aggregate (S&P 500 portfolio) stock returns and ignores the possibility that the relation might depend on also the styles of stocks in question, and that the time-varying relationship between macroeconomic variables and stock returns may also not be due to only business cycles.

Papers that focus on the link between the predictability of aggregate stock returns to changing business and monetary conditions include Fama and French (1989), Jensen, et al. (1996), Becher, et al. (2008), Patelis (1997), Thorbecke (1997), Bernanke and Kuttner (2005). The focus in this paper is broader than the relationship between monetary conditions and predictability of stock returns, e.g. we allow for a variety of alternatives to explain the predictability of returns in a time-varying sense.

Flannery and Protopapadakis (2002) estimate a GARCH model of daily equity returns, in a similar line of research, and show the effect of different macroeconomic developments on stock returns. They look at seventeen macroeconomic variables and find six candidates for priced factors among these: three nominal and three real. In their specification tests, they add explanatory variables to their original specification, e.g. a dummy variable to identify the

"Volcker" period of monetary control. The methods used in this paper fall short of addressing the time-variation problem, which they admit in their conclusion: "Unfortunately, we have been unable to model explicitly time-variation in the effects of macroeconomic announcements on returns." Including dummy variables makes sense when the points of change are known with certainty, but in real life, especially when there are so many factors affecting the overall economy it's hard to pin down the exact points of change for every relationship.

Structural break models are good for identifying the change points. Pesaran and Timmermann (2002) employ a reversed ordered CUSUM (ROC) procedure to identify structural change points and estimate a model relating S&P 500 monthly returns to a set of lagged macroeconomic variables using data only after the most recent break, arguing mounting empirical evidence indicating a time-varying relationship between state variables and returns. They find that the forecasting ability of their model improves on a similar static specification.

Besides macroeconomic variables, this paper shows that determinants such as momentum explain a big part of the predictability of different style portfolio returns. Although the style momentum idea has been put forward earlier in the literature by Barberis and Shleifer (2003), comparisons of the predictive power of these style momentums with other predictive variables (such as the macroeconomic variables) and comparisons of their time-varying effects have yet not been established. This paper also fills this gap in the literature.

Literature that focus on momentum effects that provide predictability over sorted portfolios include Barberis and Shleifer (2003), Jegadeesh and Titman (1993), Lee and Swaminathan (2000), and Moskowitz and Grinblatt (1999). These papers employ a basic strategy of buying past winners and selling past losers. Some recent papers focus on the profitability of momentum strategies during different business cycles (Antoniou, et al. (2007), Chordia and Shivakumar (2001)).

Besides its relation directly to the Fama-French model (e.g. style factors having explanatory power over individual stock returns), style analysis has also been important in the practice of professional investment management and in the theories of risk investment, and its importance has grown in recent years, as institutional investors started to dominate financial markets. Style investing is attractive to institutional investors, because it's a way for them to organize and simplify portfolio allocation decisions, and also to measure the performance of professional managers relative to benchmarks. From these agency perspectives, and also for diversification reasons, style investing is preferred to the less disciplined, more qualitative approaches. Indeed, most pension and mutual fund managers now identify themselves as following particular investment styles. Recent guidebooks on institutional portfolio management are organized around styles (Bernstein (1995)). The growing importance of style investing points to the usefulness of assessing the predictability of these different style portfolio returns that would be used in the more extensive asset allocation problem faced by professional investment managers.

The remaining part of this paper is outlined as follows. Section 2 describes the methodology, specifically the time-varying parameter model with changing conditional variance, besides the fixed-coefficient version of this model specification. The models developed in this section use lagged macroeconomic variables or style momentums as independent variables and different style portfolio returns as dependent variables. Section 3 describes the data and estimation of the models in Section 2. Section 3 also gives the empirical results and some model specification test results. Section 4 concludes and discusses some related ideas for future research.

2 Methodology

This section presents the models of expected returns used in the paper. Specifically, a linear single factor model, a linear model with multiple factors, a time-varying parameter model with changing conditional variance using a single factor and also multiple factors are used to predict different style portfolio returns. All the time series factor models in this paper are based on factors that are either lagged macroeconomic variables or the momentum factors.

2.1 A Linear Single Factor Model

The linear (non-time-varying) model with a single factor is given by:

$$r_{it} = \alpha_{0i} + \alpha_{1i} f_{t-1} + \varepsilon_{it}, \tag{1}$$

where r_{it} is the return of style portfolio *i*, in period *t*, and f_{t-1} is either a lagged macroeconomic variable or a momentum factor. ε_{it} is the error term which is normally distributed with $\varepsilon_i \sim N(0, h_i^{-1})$. Error terms are i.i.d. and the explanatory variable in the model is independent of the errors. In this model, α_{0i} and α_{1i} are assumed to be constant.

2.2 A Linear Model with Multiple Factors

The linear (non-time-varying) model with multiple factors is given by:

$$r_{it} = \alpha_{0i} + \sum_{k=1}^{K} \alpha_{1ik} f_{kt-1} + \varepsilon_{it}, \tag{2}$$

where r_{it} is the return of style portfolio *i*, in period *t*, and f_{kt-1} are lagged macroeconomic variables and/or the momentum factors in period $t-1$, $k = 1,\ldots\ldots,K$. ε_{it} is the error term which is normally distributed with $\varepsilon_i \sim N(0, h_i^{-1})$. Error terms are i.i.d. and the explanatory variables in the model are independent of the errors. α_{0i} and α_{1ik}, $k = 1,\ldots\ldots,K$ are assumed to be constant in this model.

2.3 A Time-Varying Parameter Model with Changing Conditional Variance (Using a Single Factor and Multiple Factors)

I propose in this section a time-varying parameter model with error variance conditional on past information. In other words, the assumption of constant coefficients (intercept, beta, etc) as well as constant variance of nominal shocks (h) is relaxed in this section. The error variance, as well as the other coefficients of the model, may be time-varying due to a continuously changing environment for different styles of portfolios (such as monetary policy, regulation changes, wars, etc). Then more powerful predictions will be obtained by modeling the variation in coefficients and the variation in conditional error variance through time based on a Kalman filtering estimation of recursive forecast errors and their conditional variances.

Literature on Kalman filters include Wells (1995), Harvey (2008), Andrews and Grewal (2008), Chui and Chen (2008), Hamilton (1994). Kalman filter is a recursive method to construct forecasts and forecast variances. In each step of the process, next observation is forecast based on the previous observation and the forecast of the previous observation. In other words, each consecutive forecast is found by updating the previous forecast. Updating rule for each forecast can then be considered as a weighted average of the previous observation and the previous forecast error. These weights are chosen to ensure that the forecast variance (uncertainty) is minimized.

Specifically, the model used in this section with a single factor takes the form:

$$r_{it} = \alpha_{0it} + \alpha_{1it} f_{t-1} + \varepsilon_{it}, \tag{3}$$

where r_{it} is the return of style portfolio *i*, in period *t*, and f_{t-1} is either a lagged macroeconomic variable or the momentum factor. α_{jit} is not observed and is assumed to follow a random walk:

$$\alpha_{jit+1} = \alpha_{jit} + u_{jit}, \qquad \text{where } j=0,1. \tag{4}$$

α_{ji1} is referred as an initial condition. The initial conditions used in the estimations are given in Appendix 1.

To check the specification of this model, I performed ARCH/Serial Correlation tests, the results of which are given at the end of the paper, and showed that the assumption of random walk is plausible in this context. Specifically, I performed ARCH tests on fixed-coefficient versions of the model and found strong evidence of ARCH effects. Then when I checked to see if the serial correlation still exists in the squared forecast error terms (of the time-varying specification), it wasn't possible to reject the null hypothesis that there's no serial correlation. This suggests that the ARCH effects found in the fixed-coefficient versions of the model (OLS regression) were due to evolutionary coefficients of the model.

The time-varying parameter model with changing conditional variance using multiple factors follows:

$$r_{it} = \alpha_{oit} + \sum_{k=1}^{K} \alpha_{1ikt} f_{kt-1} + \varepsilon_{it}, \tag{5}$$

where r_{it} is the return of style portfolio *i*, in period *t*, and f_{kt-1} are either lagged macroeconomic variables and/or the momentum factors. α_{0it} and α_{1ikt} for $k = 1,\ldots\ldots\ldots, K$ are not observed and are assumed to follow a random walk:

$$\alpha_{0it+1} = \alpha_{0it} + u_{0it}, \tag{6}$$

$$\alpha_{1ikt+1} = \alpha_{1ikt} + u_{1ikt}, \qquad \text{where } k = 1,\ldots\ldots K. \tag{7}$$

α_{0i1} and α_{1ik1} are referred as initial conditions. The initial conditions used in the estimations are given in Appendix 1.

These specifications assume the intercept term to be time-varying as well as the factor loadings. This type of approach is intuitive because uncertainty about the future may arise not only because of future random terms but also because of changes to parameter values. A time-varying parameter model estimated by a Kalman filtering algorithm does a good job of capturing these uncertainties. The equation for the conditional variance of forecast errors, as well as the updating rules of coefficients and their conditional variances reveal the incorporation of these uncertainties in the Kalman filtering algorithm (see Appendix 1 for details).

Kalman filtering gives insight into how a rational economic agent would revise estimates of model coefficients as new information comes in. This new information can be due to monetary policy changes, regulation changes, outbreaks of wars, etc. In this sense, a Kalman filter is also Bayesian since it is an updating procedure, where preliminary guesses about the model coefficients and their variances are formed initially. Then corrections to these guesses are added, where the corrections are determined by how well the guesses have performed.

It should also be noted here that there are other methods suggested in the literature to incorporate changing conditional variances than the method suggested in this paper. One of these methods is to calculate a moving variance based on several past observations. Another method is to use an ARCH specification (Autoregressive Conditional Heteroskedasticity) known by Engle (1982). Neither of these methods specifies the source of changing conditional variance whereas the time-varying parameter model does (e.g. see the equation for the conditional variance of forecast errors and coefficients in Appendix 1). Indeed, Kim and Nelson (1989) consider the assumption underlying the ARCH specification to be ad hoc. Other benefits of using the Kalman filter include that it's a recursive method, and also that it converges quickly no matter what the underlying model is. Faff, et al. (2000) compare different types of ARCH models versus the Kalman filter approaches to estimating beta and conclude that the Kalman filter approaches, unlike the other models, consistently dominate the benchmark OLS beta under the MSE criterion when forecasting asset returns. They also note that the different models they analyze might be capturing different aspects of the time varying characteristics of beta. Faff, et al. (2000) consider only the behavior of systematic risk and ignore the relationship between asset returns and different macroeconomic variables.

Some of the papers that discuss the case for time-varying second moments of equity market portfolio returns include French, Schwert and Stambaugh (1987), Schwert and Seguin (1990). French, et al. (1987) use daily returns to the S&P composite to estimate monthly volatility from 1928 to 1984. Schwert and Seguin (1990) use predictions of aggregate stock return variances from daily data to estimate time-varying monthly variances for size-ranked portfolios.

On a yet different strand of literature, some papers (Hamilton and Susmel (1994), Errunza and Hogan (1998), Schwert (1989)) analyze the effects of macroeconomic variables on stock return volatility, which is beyond the scope of this paper.

Finally, in this section, it should be mentioned that there is a line of research that focuses on the time-varying properties of systematic risk of individual stock returns. This literature includes Blume (1971, 1975), Brenner and Smidt (1977), Francis (1979), Sunder (1980), Simonds, et al. (1986), Ohlson and Rosenberg (1982), Collins, et al. (1987), Fabozzi and Francis (1978), Bos and Newbold (1984), Kim (1993) besides others. The findings of these papers support the methodology in this paper, yet are restricted to the behavior of systematic risk of individual stock returns. This paper focuses on predicting different style portfolio returns and explaining the time-varying relationship between these style returns and different macroeconomic variables.

In relation to the papers just mentioned, it should also be noted that the primary objective of this paper is not to investigate the problem of choosing a best possible time-varying coefficient model for each style portfolio in question. The primary objective of this paper is to show that a relationship between macroeconomic variables and style returns exist when one refrains from using a linear model to capture that relationship, e.g. the linear models have very low predictive power. An econometrician, on the other hand, could suggest modeling the time varying coefficients of different macroeconomic variables using maybe a random coefficient, an AR, or an ARMA specification, instead of the random walk specification used in this paper. But, it's more reasonable to assume that any shock to a style portfolio's coefficients persist indefinitely into the future (random walk), rather than assume that a shock in any one period has no effect on future coefficient values (random coefficients) or assume that coefficients follow a stationary process (AR or ARMA). Sunder (1980), Simonds et al. (1986), Faff, et al. (2000) support the assumptions in this paper and suggest that a random walk specification for coefficients has its advantages and consistently performs better than other specifications for coefficients. This paper also suggests a more direct way than explaining the systematic risk by macroeconomic variables. In other words explicitly looking at the relationship between macroeconomic variables and asset returns is a more direct way than specifying the coefficient on market returns (systematic risk) to depend on macroeconomic variables.

3 Empirical Results

This section gives description of the data used in the paper, estimations of the models of expected returns explained in Section 2, and empirical results.

3.1 Data

In estimation of the models used in this paper, I use returns of different style portfolios that are obtained from Ken French's website:

http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The different style portfolios include portfolios formed on size, book-to-market, and momentum. Size investing emerged following the work of Banz (1979) and value investing emerged as a distinctive style following the work of Graham and Dodd (1934). Momentum literature is extensive including papers by Jegadeesh and Titman (1993), Barberis and Shleifer (2003), etc.

The frequency of data (returns) is monthly (as in Pesaran and Timmermann (2002)) as opposed to daily (announcements/surprises) since interest here is more on identifying general patterns for the long-term investor, such as the institutional investor or a private investor who doesn't update daily.

Descriptive statistics of different style portfolio returns are given in Table 1. This table shows that mean returns for *Mom* portfolios are the largest and mean returns for SMB portfolios are the smallest in both sample periods analyzed. But standard deviations for *Mom* portfolios are also the largest, the smallest standard deviations belonging to HML portfolios in the two samples.

Specifically, SMB (Small Minus Big) and HML (High Minus Low) factors are constructed using six value-weighted portfolios formed on size and book-to-market by Fama and French. These portfolios are intersections of two portfolios formed on size (market equity, ME) and three portfolios formed on the ratio of book equity to market equity (BE/ME). Size breakpoint is the median and BE/ME breakpoints are the 30th and 70th percentiles. Portfolios include all NYSE, AMEX, and NASDAQ stocks in the CRSP database.

SMB is the average return on the three small portfolios minus the average return on the three big portfolios,

SMB=1/3 (Small Value + Small Neutral + Small Growth)-1/3 (Big Value + Big Neutral + Big Growth).

HML is the average return on the two value portfolios minus the average return on the two growth portfolios,

HML=1/2 (Small Value + Big Value)-1/2 (Small Growth + Big Growth).

The momentum factor is constructed using six value-weighted portfolios formed on size and prior (2-12) returns. Portfolios include NYSE, AMEX, and NASDAQ stocks in the CRSP database. These portfolios are intersections of two portfolios formed on size (market equity, ME) and three portfolios formed on prior (2-12) return. Size breakpoint is the median and prior (2-12) breakpoints are the 30th and 70th percentiles.

Mom is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios,

Mom=1/2 (Small High + Big High) -1/2 (Small Low + Big Low).

I obtain the macroeconomic variables from CRSP, DATASTREAM, and FACTSET databases depending on availability. Macroeconomic variables used in this paper include inflation, treasury-bill rate, term structure (=yield curve, =term spread), industrial production, and risk premium (=yield spread).

Time-series behavior of these macroeconomic variables can be seen in Figure 1 at the end of the paper. Details of these macroeconomic variables are given in Table 2 and descriptive statistics of these macroeconomic variables are given in Table 3.

I also derive style momentums as additional explanatory variables besides macroeconomic variables. Details (derivation, etc) of these style momentums and of different style portfolio returns are given in Table 4. The short-term momentum calculated is the 6-month style price momentum (p(t)/p(t-6)-1) and the long-term momentum calculated is the 24-month style price momentum (p(t)/p(t-24)-1). Time-series behavior of these momentums can be seen in Figure 2 at the end of the paper. Descriptive statistics of these short-term and long-term momentums for each style portfolio are given in Table 5.

3.2 Estimation of Models of Expected Returns

This section explains estimations of the models of expected returns, namely the linear single factor model, the linear model with multiple factors, and the time-varying parameter model with changing conditional variance using either a single factor or multiple factors. Specifically, the linear models are estimated by the OLS, and the time-varying parameter models are estimated using the Kalman filtering algorithm, which allows updating the model parameters.

3.2.1 Estimation of the Linear Single Factor Model

The estimator of expected returns for each style portfolio by a linear (non-time-varying) single factor model is given by:

$$E(r_i) = \hat{\alpha}_{0i} + \hat{\alpha}_{1i} E(f), \tag{8}$$

where $E(r_i)$ is the expected return of style portfolio i and $E(f)$ is the value of the macroeconomic variable or the momentum factor at the time of estimation. $\hat{\alpha}_{oi}$ is the estimate of the intercept and $\hat{\alpha}_{1i}$ is the estimate of the beta of style portfolio i relative to the macroeconomic variable or momentum factor in question.

3.2.2 Estimation of the Linear Model with Multiple Factors

The estimator of expected returns for each style portfolio by a linear (non-time-varying) model with multiple factors when $k = 1,\ldots\ldots,K$ is given by:

$$E(r_i) = \hat{\alpha}_{0i} + \sum_{k=1}^{K} \hat{\alpha}_{1ik} E(f_k), \tag{9}$$

where $E(r_i)$ is the expected return of style portfolio i and $E(f_k)$ is the value of kth macroeconomic variable and/or the momentum factors at the time of estimation. $\hat{\alpha}_{oi}$ is the estimate of the intercept and $\hat{\alpha}_{1ik}$ is the estimate of the beta of style portfolio i relative to the predictive variable k.

3.2.3 Estimation of the Time-Varying Parameter Model with Changing Conditional Variance (Using a Single Factor and Multiple Factors)

The estimator of expected returns for each style portfolio by a single factor model is given by:

$$E(r_i) = \hat{\alpha}_{0i} + \hat{\alpha}_{1i} E(f), \tag{10}$$

where $E(r_i)$ is the expected return of each style portfolio i and $E(f)$ is the value of each predictive variable (macroeconomic variable or momentum) at the time of estimation. $\hat{\alpha}_{0i}$ is the estimate of the intercept and $\hat{\alpha}_{1i}$ is the estimate of the beta of style portfolio i relative to the predictive variable.

Estimation of the time-varying parameter model with changing conditional variance using multiple factors follows. In estimation of the time-varying parameter model with multiple factors, all parameters of the model are assumed to be time-varying.

The estimations are carried out using a Kalman filtering algorithm in this section, the details of which are given in Appendix 1. Specifically, Appendix 1 gives the prediction and updating steps of the Kalman filtering algorithm. Initial guesses for the coefficients are taken to be 0 and initial guesses for the standard deviations are taken to be 0.1. When other initial guesses were tried for comparison, the nature of results did not change significantly.

3.3 Empirical Results

This section gives estimation results for the models of expected returns discussed in the previous section. Some of the possible candidates for explaining the time-variation in style portfolio return sensitivities to different macroeconomic variables include business cycles, monetary policy periods (according to different chairman of Fed Reserve), wars, etc. Specifically, expansionary periods in US include 11/1970-11/1973, 3/1975-1/1980, 7/1980-7/1981, 11/1982-7/1990, 3/1991-3/2001; remaining time periods correspond to recessionary periods. 1990-1991 is the First Iraq War, 2003 is the Second Iraq War. There's the effect of fear of Y2K before 2000, and the effect of 9/11 terrorist attacks in 2001. Monetary policy periods (simply by the change of the Fed Reserve chairman) include Burns years (2/1970-1/1978), Miller years (3/1978-8/1979), Volcker years (8/1979-8/1987), Greenspan years (8/1987-1/2006), Bernanke years (2006-…). Another possible cause of time-variation in US is different political periods, e.g. Republican versus Democratic years, because of the regulatory impact they might have on different styles of firms. Throughout the samples used in this paper, 1969-1977, 1981-1993, 2001-2009 correspond to Republican years; remaining periods correspond to Democratic years.

There might be other explanations of time-variations in style return sensitivities to macroeconomic variables that are not mentioned here. The time-varying parameter model used in this paper is flexible enough to allow for all kinds of explanations. Specifications of time-variations that focus on individual explanations (e.g. only monetary policy changes, or business cycles, etc) are limiting since there might be omitted variables in these specifications and these unidentified explanations of time-variations in parameters might change results drastically.

3.3.1 Results with the Linear Single Factor Model

Estimates of the intercepts and betas using the period 1974/12-2003/12 dataset (to be later comparable with the time-varying parameter model) are given in Table 6 at the end of the paper. These estimates are derived by regressing each style portfolio returns (SMB, HML, *Mom*) on each one of the macroeconomic variables (monthly and annual growth of inflation, returns on

1-month T-bill rates, term structure, monthly and annual growth of industrial production) in a non-time-varying fashion (using OLS). These results reveal that most of the macroeconomic variables (except industrial production for size style portfolios) seem to be insignificant when a linear single factor model is used (as would be expected) and the R-squareds of these regressions are very small.

Similar results are found when the estimates of the intercepts and betas are obtained using the period 1992/03-2003/12 dataset (again to be later comparable with the time-varying version of the model) using risk premium 1 and 2 as the explanatory variables. These estimates are also given in Table 6 and derived again by regressing each style portfolio returns on each of the macroeconomic variables in a non-time-varying fashion (using OLS).

Preliminary tests (with a fixed-coefficient version of the model) on the effects of momentum show that momentum factors (especially short-term momentum) are statistically and economically significant for different style portfolio returns. These momentums (short-term and long-term) also seem to have significant predictive power compared to macroeconomic variables.

Estimates of the intercepts and betas using the period 1976/12-2003/12 and momentum factors are given in Table 7. These results show that both short-term and long-term momentums of each style portfolio are highly significant and that the regressions have higher R-squareds (in the range 0.019-0.18) than the R-squareds of the previous regressions with macroeconomic variables as independent variables.

3.3.2 Results with the Linear Model with Multiple Factors

Estimates of intercepts and other coefficients obtained with three different specifications of the linear model with multiple factors are given in Table 8 at the end of the paper.

These three different specifications differ in the number and type of independent variables they have. In the first specification, monthly growth of inflation and industrial production are used as explanatory variables besides the returns on 1 month T-bill rates, term structure, risk premium 1, and short-term and long-term momentums. In the second specification, annual growth of inflation and industrial production are used as explanatory variables besides the returns on 1 month T-bill rates, term structure, risk premium 2, and short-term and long-term momentums. In the third specification, momentum factors are dropped and only macroeconomic variables are used on the right-hand side of the regression (annual growth of inflation and industrial production, returns on 1 month T-bill rates, term structure, and risk premium 2).

These regressions show that almost all macroeconomic variables are insignificant (except annual growth of inflation for value stocks) when a linear multifactor model is used as opposed to a time-varying parameter model. But, in all regressions, own short-term momentums of style portfolios remain statistically significant. The R-squareds are in the range 0.14-0.22 for the first two types of specifications and are in the range 0.01-0.06 for the third type of specification. These results, not surprisingly, are not too promising for the use of macroeconomic variables as predictive variables in linear models.

3.3.3 Results with the Time-Varying Parameter Model with Changing Conditional Variance (Using a Single Factor and Multiple Factors)

Graphs showing estimates of evolutionary coefficients, intercept and beta for each variable, derived using the time-varying parameter model with a single factor with changing conditional variance, for the Fama-French style portfolios are given in Figures 3-6 at the end of the paper. Specifically, time series of coefficient estimates for size (SMB), value (HML), and momentum (*Mom*) styles are given. Figures 3-5 look at the relationship between each style portfolio return and macroeconomic variable in question, and show how this relationship changes through time. Figure 6 looks at the relationship between each style portfolio return and own short term and long term momentums of these style portfolios, and again shows how these relationships change through time.

Figure 3 gives the relationship between monthly growth of inflation, annual growth of inflation, 1 month T-bill rate, term structure, monthly growth of industrial production, annual growth of industrial production, risk premium 1, risk premium 2 and size (SMB) style portfolio returns. According to Figure 3, the relationship between these macroeconomic variables and size style portfolio returns does not stay constant throughout the sample periods. For example, the relationship between inflation and size style portfolio returns changes significantly around the changes of the Fed Reserve chairman. Beta of annual growth of inflation stays somewhat constant during the Greenspan period (1987-2006) compared to the previous periods. Beta for 1 month T-bill rate also seems like staying somewhat constant during the Greenspan period (1987-2006). Figure 3 also shows a change in the relationship between most macroeconomic variables (such as monthly growth of inflation, 1 month T-bill rate, term structure, and monthly growth of industrial production) and size style portfolio returns after the Dot-Com Crash in 2000. Beta of term structure for instance, which is positive up until the Dot-Com Crash, stays negative after 2000. Betas for both risk premium1 and 2 show a dip around 2000, picking up the effect of Dot-Com Crash as well.

Figure 4 gives the relationship between monthly growth of inflation, annual growth of inflation, 1 month T-bill rate, term structure, monthly growth of industrial production, annual growth of industrial production, risk premium 1, risk premium 2 and value (HML) style portfolio returns. According to Figure 4, as in Figure 3, the relationship between these macroeconomic variables and value style portfolio returns does not stay constant throughout the sample periods. All the variables in this figure pick up the Dot-Com Crash. Beta of monthly growth of inflation for instance seems to be positive after 2000, while it is negative in every previous period. There are peaks in the time series of betas of annual growth of inflation, 1 month T-bill rate, and term structure around 2000. Betas of risk premiums 1 and 2 show a dip around 2000; somewhat constant behavior of these betas seems to change after 2000. Betas for monthly growth of industrial production and annual growth of industrial production seem to be stable in most part of the 80s and 90s. When it comes to the behaviors of betas of nominal variables, they seem to be unstable due to causes besides the changes of the Fed Reserve chairman (although one can still distinguish the pre-Volcker (before 1979) and Volcker periods (1979-1987)), such as the First Gulf War in 1991 (see betas of monthly growth rate of inflation, annual growth rate of inflation, and 1 month T-bill rate).

Figure 5 gives the relationship between monthly growth of inflation, annual growth of inflation, 1 month T-bill rate, term structure, monthly growth of industrial production, annual growth of industrial production, risk premium 1, risk premium 2 and momentum (*Mom*) style portfolio returns. According to Figure 5, as in Figures 3 and 4, the relationship between these macroeconomic variables and momentum style portfolio returns does not stay constant throughout the sample periods. The course of beta seems to be shifted around 1979, 1987 (crash), and 2000 for all the nominal variables (monthly growth rate of inflation, annual growth rate of inflation, 1 month T-bill rate, and term structure). Beta of both monthly growth of industrial production and annual growth of industrial production seem to be increasing before 1979, decreasing in the period 1979-1983 and more or less stable in the periods 1983-1987, 1987-1991, and 1991-2000 with different means. Biggest changes in the betas of the two types of risk premiums again happen around and after 2000 (volatilities of betas increase after 2000).

Figure 6 gives the relationship between short-term and long-term momentums of different Fama-French style portfolios and the returns of these different style portfolios. Specifically, relationship between short-term and long-term momentums and size (SMB), value (HML), and momentum (*Mom*) style portfolio returns are given. Betas of the short-term and long-term momentums (used instead of the macroeconomic variables as explanatory variables) still exhibit time-varying behavior, but these variations are not as pronounced as the variations in the betas of the macroeconomic variables analyzed before. Effect of the Dot-Com Crash in 2000 can still be observed in the beta of short-term momentum for size style portfolios; but otherwise, betas of both short-term and long-term momentums seem to be positive and increasing with respect to the size style portfolio returns. Betas of short-term and long-term momentums for value portfolios seem to have a change of course around 1980 but are somewhat stable after 1980. The same conclusion holds true for betas of short-term and long-term momentums of momentum style portfolios. Both for value and momentum style portfolios, one can see the effect of Dot-Com Crash in 2000 in betas of short-term and long-term momentums. For each of these style portfolios, betas of short-term momentums seem to be more economically significant than betas of long-term momentums.

To sum it up, time-varying changes in betas pick up significant historical, economic, financial developments in US history. These changes also prove that the univariate relationship between different macroeconomic variables, short-term momentums, long-term momentums (as predictive variables), and different style portfolio returns (returns of size, value, and momentum portfolios) is far from being constant.

Figure 7 at the end of the paper shows the effect of different macroeconomic variables and momentum factors (collectively) on size style portfolio returns using the time-varying multifactor model with changing conditional variance. Effects of macroeconomic variables and momentum factors on other style portfolio returns (value and momentum style portfolio returns), using the time-varying multifactor model with changing conditional variance, are not presented here not to take too much space but are available on request. Specifically, Figure 7 shows the effect of annual growth of inflation, annual growth of industrial production, 1-month T-bill rate, term structure, risk premium 2, and short-term and long-term momentums (using the 1992/3-2003/12 sample period) on SMB portfolio returns. The time-varying behavior of different betas and intercept term can be observed in these graphs (as was the case with the time-varying single factor models). For example, change in the behavior of betas of all the variables in the model can be seen around year 2000. To name a few variables, beta of term structure drops sharply around 2000 and stays in negatives until 2003; beta of short-term momentum increases about 100% from its previous level around 2000 and stays at that level.

Means and standard errors of coefficients with the time-varying parameter model with multiple factors are given in Table 12 (these coefficients correspond to the coefficients whose time-varying behaviors are given in Figure 7). Specifically we can see that almost all of the standard errors are low and the means of the coefficients make much more economic sense than the results with the benchmark linear model, e.g. all the coefficients with both the time-varying parameter model and the linear model have the same sign, but the magnitude of the effect seems less extreme with the time-varying parameter model. In general, annual growth of inflation, term structure, and annual growth of industrial production have negative relationships with small size firms. Return on 1 month T bill rates, risk premium 2, short-term and long-term momentums have positive relationships with small size firms. Short-term and long-term momentum coefficients with the time-varying parameter model and the linear model are more consistent because of the more linear structure of these momentum variables. In Figure 7, we could also look at the values of coefficients at the time of prediction and note the error we would make if we had used the coefficients from the linear model instead of these values. For instance, annual growth of inflation has a coefficient value of about negative 0.4 on 12/2003 using the time-varying parameter model, whereas the coefficient value obtained using the linear model is about negative 189.01.

3.3.4 Comparisons of the Models

This section gives the comparisons of in-sample and out-of-sample fits of some of the models analyzed in the previous section. Table 9 gives comparisons of in-sample and out-of-sample fits of a linear (non-time-varying) single factor model with a time-varying parameter model with a single factor. The MAEs calculated for SMB portfolios using different macroeconomic variables on the right-hand side of the regressions show that the errors are smaller for time-varying versions of the models, whereas the MSEs give conflicting conclusions. But when we look at the out-of-sample fits of the two models, we can see that the MSEs are in general smaller for time varying parameter models than linear models.

Table 10 gives comparisons of in-sample and out-of-sample fits of a linear (non-time-varying) multifactor model with a time-varying parameter model with multiple factors. In this table, for both models, SMB portfolio return is the dependent variable and an intercept, annual growth of inflation, annual growth of industrial production, 1-month T-bill rate, term structure, risk premium 2, and short-term and long-term momentums are the independent variables. Both the MAEs and MSEs of these models show that the errors are smaller for time-varying versions of the multifactor model. And this result is true for both in-sample and out-of-sample fits of the two models. χ^2 tests carried out to test if the MSEs are different from each other show that MSEs for the linear and time-varying multifactor model (using in-sample-fits of the data) are statistically significantly different from each other when 90% critical values are used. χ^2 tests for the out-of-sample-fits of the data show that MSEs for the linear and time-varying multifactor model are statistically significantly different from each other when 75% critical values are used. These results show the strength of the time-varying parameter models in general compared to the linear versions of these models.

From a utility perspective, there is reason to believe that utilities produced by the time-varying parameter models will be higher than the utilities produced by the linear models in light of West, Edison, Cho (1993). According to West, Edison, Cho (1993), GARCH models (which are also types of time varying models) produce higher utilities on average then homoskedastic, AR, non-parametric models. They claim that this is true even if MSE criterion favors GARCH only slightly.

A further analysis of the errors shows that on average, time-varying parameter model overestimates the mean, but it also overestimates the variance in in-sample fits. In out-of-sample fits, on average, time-varying parameter model overestimates the mean, but linear model estimates are more off (linear model underestimates) than the time-varying parameter model estimates. In out-of-sample fits, on average, variance is underestimated by both models.

In out-of-sample tests, underestimation of the returns decreases by about 40% (if we look at the sign of errors) if we use the time-varying parameter model. This suggests that the problem might arise from not investing enough in style stocks when a linear model is used in predictions.

3.3.5 Additional Specification Tests

To see whether the time-varying parameter model with changing conditional variance is correctly specified, I also checked for whiteness or lack of serial correlation in one-period-ahead forecast errors. I first performed ARCH tests on fixed-coefficient versions of the models. I specifically performed ARCH tests on the linear single factor models with each style portfolio (size, value, momentum) and different macroeconomic variables (monthly growth of inflation, annual growth of inflation, term structure, 1 month T-bill rate, monthly growth of industrial production, annual growth of industrial production). Table 11 shows the results of these ARCH tests: All specifications in question show ARCH effects, as can be seen from the Prob. Chi-Squares being too small. To determine if sources of the ARCH effects, seen in these cases using fixed-coefficient versions of the models, could be varying coefficients of the models; when I checked to see if serial correlation still remains in forecast error terms after adjusting them for conditional heteroskedasticity as implied by the time-varying parameter model, it could be seen that serial correlations in all of the specifications in question were corrected. Results of ARCH and corresponding serial correlation tests with other macroeconomic variables and other models analyzed in this paper are not included here due to space concerns but are available on request.

4 Conclusions

Although macroeconomic variables seem like good candidates to explain the Fama-French risk factors, previous researchers have found limited evidence that stock returns respond to macroeconomic developments. In this paper, I identify macroeconomic variables that affect the predictability of different style portfolio returns (Fama-French risk factors). I show that if the relationship between macroeconomic variables and stock returns is modeled as being time-varying as opposed to fixed through time, we can identify significant relationships due to taking into account the effect of learning. I also find that short-term and long-term momentums of these different style portfolios are significant predictive variables besides different macroeconomic variables.

Specifically, this paper proposes time-varying parameter models with a single factor and multiple factors, and applies the Kalman filtering algorithm to estimate the model. This paper uses an algorithm that provides recursive forecast errors and their conditional variances for a changing conditional variance model. Kalman filter shows how agents would combine past and new information to form a new expectation. Estimating a time-varying parameter model with a Kalman filter as such allows taking into account the effects of updating.

This paper finds that different macroeconomic variables affect different style portfolio returns in different ways among each other and through time. Using time-varying parameter models helps capture the changing relationships between macroeconomic variables and different style portfolio returns. These changes correspond to important historical, economic periods such as the changes of the Fed Reserve chairman (changes of monetary policy), business cycles, wars, etc.

This paper also gives comparisons of non-time-varying (linear) and time-varying versions of the models, in terms of their in-sample and out-of-sample fits; and shows that time-varying versions of the models have better fits in general. We can then conclude that previous tests of the effects of macroeconomic variables on stock returns may have failed to detect any significant effects because in general non-time-varying models were utilized and non-time-varying models impose too much structure on the data. Finally, I demonstrate the need for time-varying parameter models also doing some tests such as ARCH tests on the fixed-coefficient versions of the models.

Then I check to see if serial correlations still exist in forecast errors after using time-varying models and conclude that all ARCH effects that were found in the pre-tests are corrected for in the after-tests.

Also, to sum it up, the reason why finding out the determinants of style investing is important can be given in two points. First, most investment companies (because of concerns of otherwise too much coverage and other reasons) have started focusing their attention more and more on dividing the stocks into different groups (such as styles), and appointing different analysts to work with different styles of portfolios. These analysts specifically focus on small cap, large cap, value, growth, and other styles of stocks (besides other analysts that focus on indexes, industry, and country stocks). These style recommendations (depending on the sensitivities of each style to different macroeconomic variables) could serve as the 'prior' to individual stock recommendations within these styles. Second, in predicting individual stock returns, different style portfolio returns are used as factors, following work of Fama and French, with the convention that these factors have significant predictive power. But, one of the problems with depending on these Fama and French factors (if nothing else) is that, to obtain more realistic forecasts of individual stock returns, we also need to be able to forecast these factor returns. In this case, forecasting different style portfolio returns with better in-sample and out-of-sample fits will improve multiple-step ahead forecasts of individual stock returns.

Some further analysis could include the time-varying effect of liquidity on style portfolio returns. Non-time-varying relationship between expected returns and liquidity has been a concern in the literature (Bekaert, et al. (2006), Pastor and Stambaugh (2002), Chordia and Shivakumar (2002)), but none of these papers explicitly model the time-varying parameters in the relation between expected returns and liquidity.

Table 1: Descriptive Statistics of Fama-French Style Portfolio Returns (Monthly)

Descriptive Statistics of Fama-French Factors (in percentage)						
	1974/12-2003/12			1992/3-2003/12		
	SMB	HML	Mom	SMB	HML	Mom
Mean	0.308	0.417	0.845	0.190	0.460	0.940
Standard Error	0.177	0.169	0.230	0.342	0.319	0.447
Median	0.210	0.430	0.840	0.080	0.510	1.245
Standard Deviation	3.302	3.151	4.299	4.070	3.798	5.328
Kurtosis	7.240	2.332	5.862	6.896	1.993	4.954
Skewness	0.563	0.118	-0.663	0.808	0.046	-0.715
Minimum	-16.580	-12.660	-25.050	-16.580	-12.660	-25.050
Maximum	21.870	13.710	18.400	21.870	13.710	18.400
Count	349	349	349	142	142	142

Table 2: Details of Macroeconomic Variables

DATA	MACROECONOMIC VARIABLES		
Glossary and Definition of Observed Variables			
Symbol	Variable	Definition of Source	File name
1974/12-2003/12-Monthly			
Inf	Inflation	log CPI (CPI, price index, seasonally adjusted) monthly growth: monthly first difference in the log of CPI annual growth: annual difference in the log of CPI Datastream	CPI__Time_Series_Data CPI__Time_Series_Data
Tbill	Treasury-bill Rate	Return on 1 month T-bills CRSP	1mTbill
LGB	Long-term Government Bonds	Return on 10 year Government Bonds CRSP	10yBond
TS	Term Structure (=Yield Curve, =Term Spread)	LGB(t)-Tbill(t-1) Derived from CRSP Tbill and LGB	
IP	Industrial Production	Industrial Production Total Index monthly growth: ln[IP(t)/IP(t-1)] annual growth: ln[IP(t)/IP(t-12)] Datastream	INDUSTRIAL_PRODUCTION
1992/3-2003/12-Monthly			
BAA-IYA	Low-grade index	Moody's BAA Index Yield Average Factset	MoodysYieldAverages
BAA-CBYA	Low-grade bond	Moody's BAA Corporate Bond Yield Average Factset	MoodysYieldAverages
AAA-IYA	High-grade index	Moody's AAA Index Yield Average Factset	MoodysYieldAverages
AAA-CBYA	High-grade bond	Moody's AAA Corporate Bond Yield Average Factset	MoodysYieldAverages
RP1	Risk Premia-1 (=Yield Spread)	Moody's BAA-AAA-IYA Derived from Factset	
RP2	Risk Premia-2 (=Yield Spread)	Moody's BAA-AAA-CBYA Derived from Factset	

Table 3: Descriptive Statistics of Macroeconomic Variables

Descriptive Statistics of Macroeconomic Variables (Monthly)							
	1974/12-2003/12					1992/3-2003/12	
	CPI	Mret-1mTbill	Mret-10yGovBond	Term Structure	Industrial Production	RP1	RP2
Mean	71.3	0.005	0.007	0.002	71.6	0.730	0.950
Standard Error	1.2	0.000	0.001	0.001	0.9	0.017	0.018
Median	72.1	0.005	0.006	0.002	68.5	0.711	0.873
Standard Deviation	22.9	0.003	0.024	0.024	17.4	0.207	0.215
Kurtosis	-1.1	1.559	1.094	0.951	-1.0	-0.946	0.748
Skewness	-0.2	1.002	0.271	0.140	0.5	-0.045	1.222
Minimum	30.1	0.001	-0.067	-0.074	44.6	0.172	0.688
Maximum	107.5	0.015	0.100	0.095	104.2	1.161	1.569
Count	349	349	349	349	349	142	142

Table 4: Details of Fama-French Style Portfolio Returns and Their Momentums

DATA	NON-MACRO VARIABLES			
Glossary and Definition of Observed Variables				
Frequency: Monthly				
Symbol	Variable	Definition of Source	Time Interval	File name
FF-Size	Fama-French Factor SMB	Kenneth R. French-Data Library* Factor Returns constructed using the 6 value-weighted portfolios formed on size and book-to-market.	1974/12-2003/12 1992/3-2003/12	F-F_Research_Data_ Factors_size&book-to-market
FF-Value	Fama-French Factor HML	Kenneth R. French-Data Library* Factor Returns constructed using the 6 value-weighted portfolios formed on size and book-to-market.	1974/12-2003/12 1992/3-2003/12	F-F_Research_Data_ Factors_size&book-to-market
FF-Momentum	Fama-French Factor Mom	Kenneth R. French-Data Library* Factor Returns constructed using the 6 value-weighted portfolios formed on size and prior (2-12) returns.	1974/12-2003/12 1992/3-2003/12	F-F_Momentum_Factor
FF-Factor-SM	Fama-French Factor Short-term Momentum	6 month Factor Price Momentums p(t)/p(t-6)-1 Derived	1976/12-2003/12	
FF-Factor-LM	Fama-French Factor Long-term Momentum	24 month Factor Price Momentums p(t)/p(t-24)-1 Derived	1976/12-2003/12	
* http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html				

Table 5: Descriptive Statistics of Fama-French Style Portfolio Returns (Monthly) and Their Momentums

Descriptive Statistics for Different Style Returns and Their Momentums									
1976/12-2003/12									
	Portfolio Returns			Short-Term Momentum			Long-Term Momentum		
	SMB	HML	Mom	SMB-STM	HML-STM	Mom-STM	SMB-LTM	HML-LTM	Mom-LTM
Mean	0.281	0.373	0.928	0.017	0.023	0.057	0.063	0.106	0.245
Standard Error	0.183	0.175	0.242	0.004	0.005	0.006	0.010	0.012	0.009
Median	0.260	0.400	1.280	0.007	0.017	0.049	0.051	0.089	0.245
Standard Deviation	3.290	3.160	4.361	0.080	0.093	0.107	0.179	0.208	0.169
Kurtosis	7.744	2.372	5.638	1.080	3.393	3.071	-0.303	1.820	0.639
Skewness	0.516	0.078	-0.622	0.404	0.646	0.837	0.447	0.700	0.272
Minimum	-16.580	-12.660	-25.050	-0.200	-0.311	-0.208	-0.266	-0.400	-0.159
Maximum	21.870	13.710	18.400	0.409	0.435	0.617	0.609	0.938	0.914
Count	325	325	325	325	325	325	325	325	325

Table 6: Estimation Results with the Linear Single Factor Model (Using Macroeconomic Variables as Factors)

Dependent Variable			Independent Variable		
Portfolio Returns			Macroeconomic Variable		
	Intercept	T-stat		Coefficient	T-stat
1974/12-2003/12					
SMB					
	0.321	1.147	Monthly Growth of Inf	1.552	0.011
	-0.180	-0.548	Annual Growth of Inf	25.357	1.812
	0.535	1.322	1 month T-bill Rate	-41.217	-0.582
	0.304	1.716	Term Structure	8.214	1.117
	0.455	2.480	Monthly Growth of IP	-61.835	-2.469
	0.552	2.778	Annual Growth of IP	-9.654	-2.457
HML					
	0.363	1.357	Monthly Growth of Inf	34.495	0.265
	0.521	1.648	Annual Growth of Inf	-5.189	-0.386
	0.225	0.581	1 month T-bill Rate	37.614	0.555
	0.397	2.340	Term Structure	9.315	1.324
	0.420	2.373	Monthly Growth of IP	-0.893	-0.037
	0.322	1.683	Annual Growth of IP	4.058	1.071
Mom					
	0.618	1.694	Monthly Growth of Inf	138.672	0.783
	0.805	1.866	Annual Growth of Inf	1.713	0.093
	0.882	1.669	1 month T-bill Rate	-8.343	-0.090
	0.874	3.781	Term Structure	-15.568	-1.625
	0.710	2.955	Monthly Growth of IP	60.439	1.841
	0.854	3.267	Annual Growth of IP	-0.655	-0.127
1992/3-2003/12					
SMB					
	-1.156	-0.919	RP1	1.858	1.120
	-1.878	-1.210	RP2	2.188	1.372
HML					
	0.121	0.103	RP1	0.433	0.279
	0.383	0.263	RP2	0.057	0.038
Mom					
	2.100	1.271	RP1	-1.577	-0.724
	1.878	0.919	RP2	-0.979	-0.466

Table 7: Estimation Results with the Linear Single Factor Model (Using Momentum Factors)

Dependent Variable			Independent Variable		
Portfolio Returns			Momentum Factor		
	Intercept	T-stat		Beta	T-stat
1976/12-2003/12					
SMB					
	-0.010	-0.060	STM	17.239	8.288
	-0.002	-0.011	LTM	4.525	4.557
HML					
	0.024	0.148	STM	15.105	8.920
	0.154	0.789	LTM	2.075	2.482
Mom					
	0.046	0.179	STM	15.500	7.382
	-0.206	-0.491	LTM	4.634	3.281

Table 8: Estimation Results with the Linear Multifactor Models (With Three Different Specifications)

1992/3-2003/12									
Independent Variables	Dependent Variables and Specifications								
	SMB-1	SMB-2	SMB-3	HML-1	HML-2	HML-3	Mom-1	Mom-2	Mom-3
Intercept	-1.71	-0.79	0.74	1.39	-4.45	-4.02	0.40	1.66	3.19
T-stats	-0.78	-0.21	0.18	0.62	-1.08	-1.05	0.14	0.32	0.58
Monthly Growth of Inf	-537.89			463.25			269.75		
T-stats	-1.19			1.10			0.43		
Annual Growth of Inf		-189.01	33.83		226.00	325.44		-67.91	-111.67
T-stats		-1.25	0.24		1.52	2.47		-0.34	-0.59
1 month T-bill Rate	514.64	784.80	-32.29	-221.52	-29.83	62.97	-140.85	-44.46	131.65
T-stats	1.47	1.79	-0.08	-0.62	-0.07	0.17	-0.34	-0.09	0.24
Term Structure	-17.01	-15.44	-25.75	-8.88	-11.70	4.05	-37.83	-38.21	-24.84
T-stats	-1.06	-0.97	-1.51	-0.59	-0.79	0.26	-1.72	-1.76	-1.09
Monthly Growth of IP	-50.27			7.85			16.17		
T-stats	-0.72			0.12			0.17		
Annual Growth of IP		-4.42	-23.50		16.17	-9.26		-6.62	-3.54
T-stats		-0.30	-1.56		1.16	-0.66		-0.35	-0.18
Risk Premium-1	0.79			-1.42			-0.69		
T-stats	0.43			-0.82			-0.26		
Risk Premium-2		0.31	0.04		1.55	1.05		-0.93	-1.34
T-stats		0.13	0.01		0.69	0.43		-0.28	-0.38
Short-Term Momentum	18.99	17.77		16.64	14.40		14.34	14.37	
T-stats	4.35	4.10		5.36	4.19		3.11	3.07	
Long-Term Momentum	3.50	5.92		-0.80	1.09		1.95	2.07	
T-stats	1.15	1.71		-0.46	0.53		0.53	0.56	
R-squared	0.21	0.21	0.05	0.22	0.22	0.06	0.15	0.14	0.01

Table 9: Comparing the In-Sample and Out-of-Sample Fits of a Linear Single Factor Model and a TVP Model with a Single Factor

Model Comparisons Using In-Sample Fits of Data:			
1974/12-2003/12			
Dependent Variable	Independent Variable		
		Linear Single Factor Model Mean Squared Errors	TVP Model with a Single Factor Mean Squared Errors
SMB	Monthly Growth of Inf	10.634	10.677
SMB	Annual Growth of Inf	10.576	10.677
SMB	1 month T-bill Rate	10.620	10.677
SMB	Term Structure	10.603	10.544
SMB	Monthly Growth of IP	10.613	10.643
SMB	Annual Growth of IP	10.475	10.538
		Linear Single Factor Model Mean Absolute Errors	TVP Model with a Single Factor Mean Absolute Errors
SMB	Monthly Growth of Inf	2.305	2.287
SMB	Annual Growth of Inf	2.277	2.287
SMB	1 month T-bill Rate	2.303	2.287
SMB	Term Structure	2.298	2.292
SMB	Monthly Growth of IP	2.290	2.280
SMB	Annual Growth of IP	2.270	2.253
Model Comparisons Using Out-of-Sample Fits of Data:			
2004/01-2006/03			
Dependent Variable	Independent Variable		
		Linear Single Factor Model Mean Squared Errors	TVP Model with a Single Factor Mean Squared Errors
SMB	Annual Growth of Inf	5.538	5.516
SMB	Annual Growth of IP	5.487	5.479
SMB	RP1	5.129	5.132
SMB	RP2	5.248	5.243
		Linear Single Factor Model Mean Absolute Errors	TVP Model with a Single Factor Mean Absolute Errors
SMB	Annual Growth of Inf	1.969	2.037
SMB	Annual Growth of IP	1.965	1.967
SMB	RP1	1.925	1.927
SMB	RP2	1.917	1.920

Table 10: Comparing the In-Sample and Out-of-Sample Fits of a Linear Multifactor Model and a TVP Model with Multiple Factors. In this table, both these models have SMB portfolio returns as the dependent variable, and an intercept, AG-Inf, AG-IP, TS, 1 month T-bill rate, RP2, SMB-STM, SMB-LTM as the independent variables.

Model Comparisons Using In-Sample and Out-of-Sample Fits of Data:	
2004/01-2006/03	
Comparisons Using In-Sample Fits of Data:	
Linear Multifactor Model Mean Squared Errors 15.636	TVP Model with Multiple Factors Mean Squared Errors 13.543
Linear Multifactor Model Mean Absolute Errors 2.780	TVP Model with Multiple Factors Mean Absolute Errors 2.639
Comparisons Using Out-of-Sample Fits of Data:	
Linear Multifactor Model Mean Squared Errors 9.142	TVP Model with Multiple Factors Mean Squared Errors 6.972
Linear Multifactor Model Mean Absolute Errors 2.378	TVP Model with Multiple Factors Mean Absolute Errors 2.224

Table 11: ARCH Tests on Fixed Coefficient Version of a Single Factor Model

Dependent Variable	Independent Variable	Prob. Chi-Square	Original ARCH Effects	Serial Correlation Remaining
SMB	Monthly Growth of Inf	0	Yes	None
SMB	Annual Growth of Inf	0	Yes	None
SMB	1 month T-bill Rate	0	Yes	None
SMB	Term Structure	0	Yes	None
SMB	Monthly Growth of IP	0	Yes	None
SMB	Annual Growth of IP	0	Yes	None
HML	Monthly Growth of Inf	0	Yes	None
HML	Annual Growth of Inf	0	Yes	None
HML	1 month T-bill Rate	0	Yes	None
HML	Term Structure	0	Yes	None
HML	Monthly Growth of IP	0	Yes	None
HML	Annual Growth of IP	0	Yes	None
Mom	Monthly Growth of Inf	0.000001	Yes	None
Mom	Annual Growth of Inf	0.000002	Yes	None
Mom	1 month T-bill Rate	0.000002	Yes	None
Mom	Term Structure	0.000001	Yes	None
Mom	Monthly Growth of IP	0	Yes	None
Mom	Annual Growth of IP	0.000002	Yes	None

Table 12: TVP Model with Multiple Factors (Size on Macro Variables)

	μ_TVP	s.e. _TVP	μ_linear
Intercept	-0.23	0.07	-0.79
Annual Growth of Inflation	-0.19	0.02	-189.01
Return on 1 month T-bill rate	0.05	0.00	784.80
Term Structure	-3.77	0.85	-15.44
Annual Growth of Industrial Production	-0.81	0.06	-4.42
Risk Premium 2	0.14	0.09	0.31
Short Term Momentum	11.21	0.67	17.77
Long Term Momentum	4.31	0.09	5.92

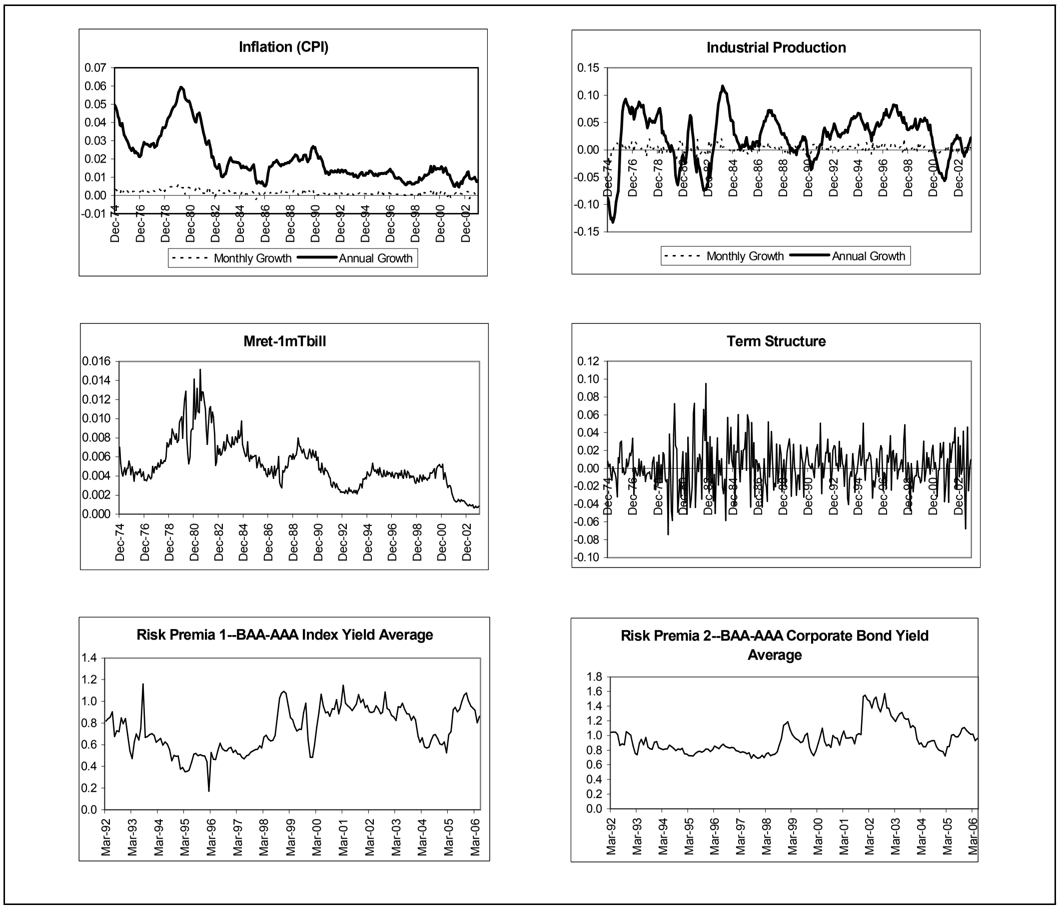

Figure 1: Time Series Behavior of Macroeconomic Variables.

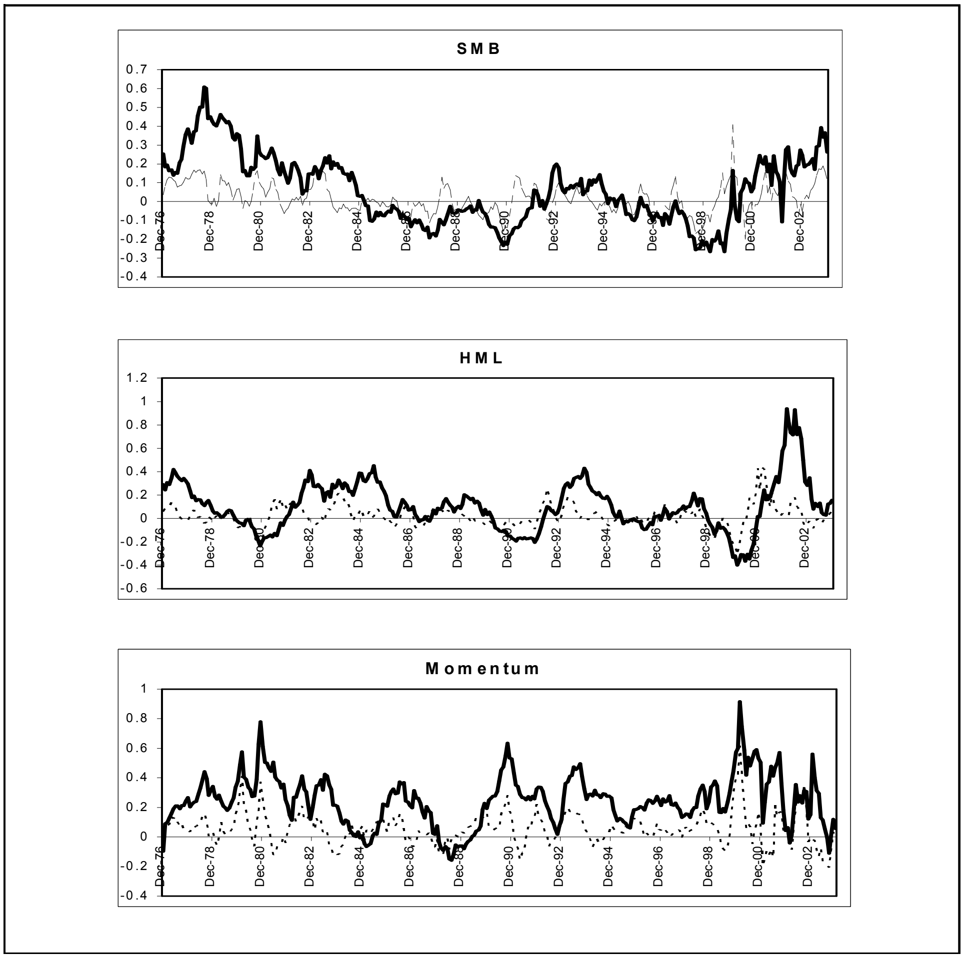

Figure 2: Time Series Behavior of Style Momentums. The dotted lines represent the short-term and the undotted lines represent the long-term momentums.

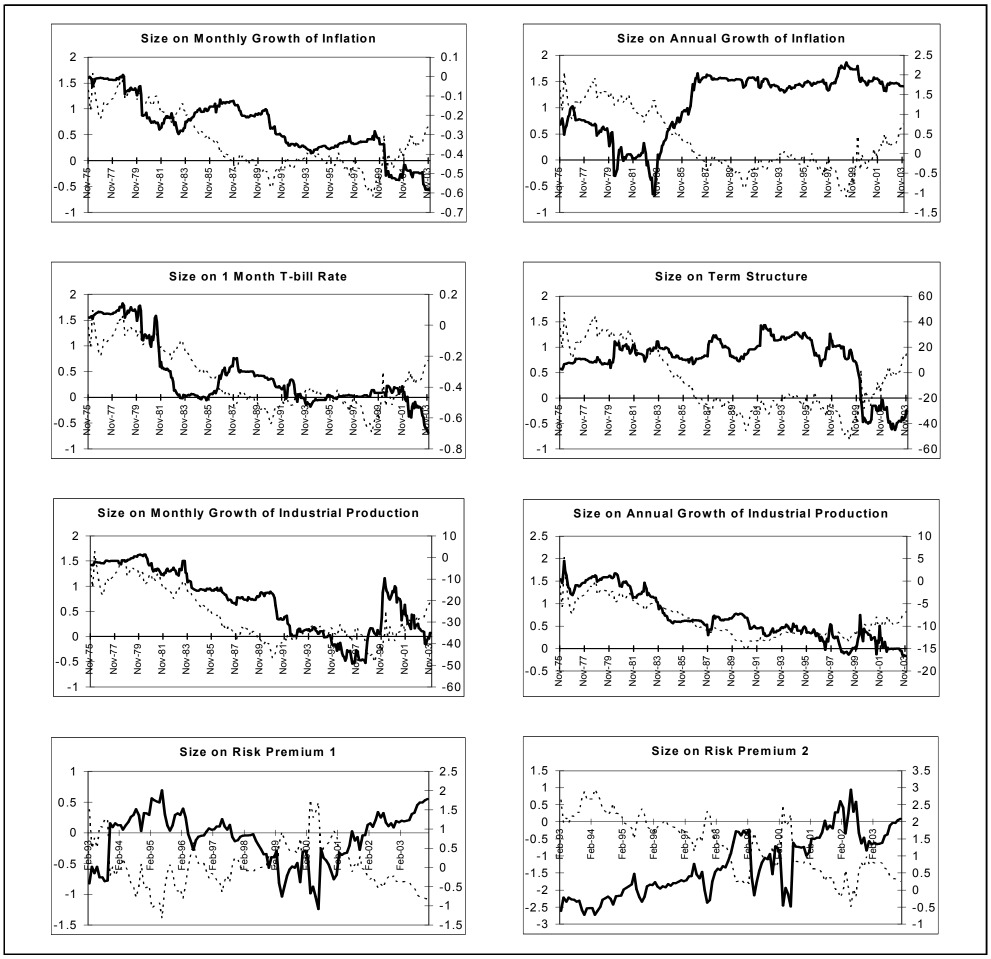

Figure 3: The Effect of Different Macroeconomic Variables on Size Style Portfolio Returns Using the TVP Model with a Single Factor. The dotted lines in all graphs represent the intercept and the undotted lines represent the coefficient. Also, the left scale in all graphs is for the intercept and the right scale is for the coefficient.

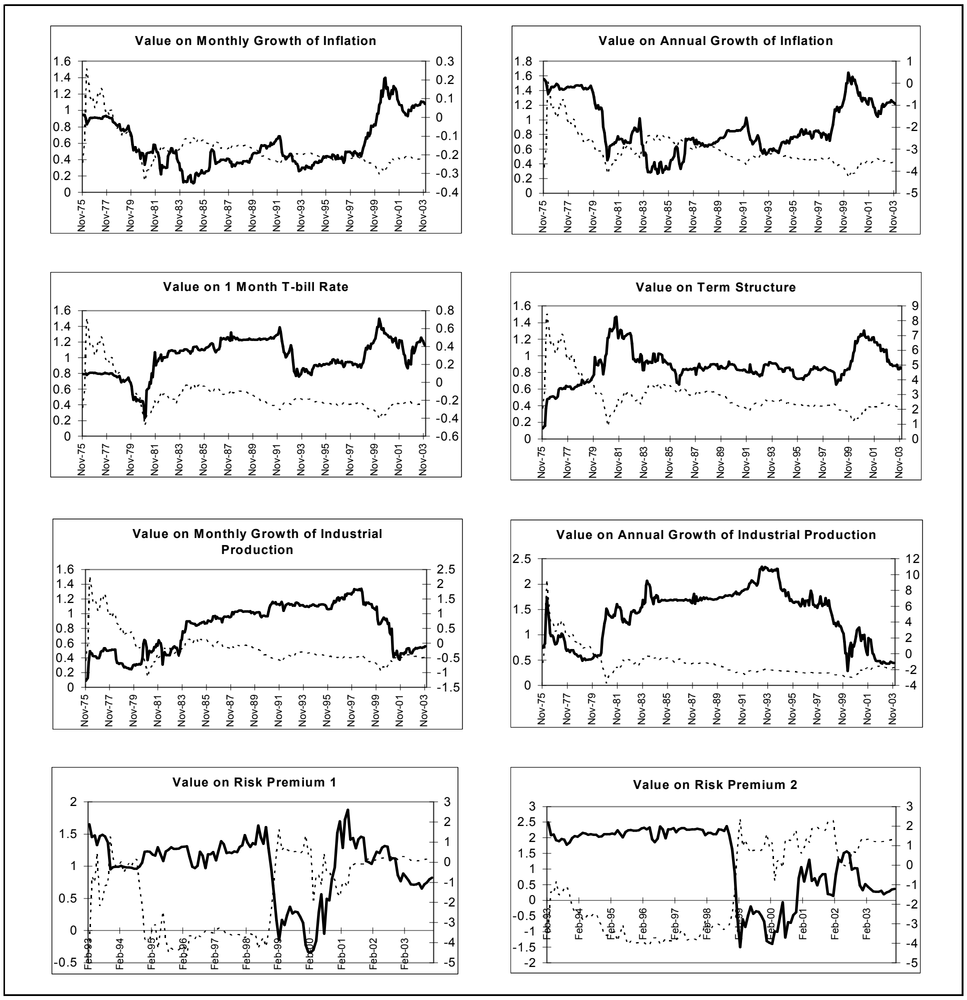

Figure 4: The Effect of Different Macroeconomic Variables on Value Style Portfolio Returns Using the TVP Model with a Single Factor. The dotted lines in all graphs represent the intercept and the undotted lines represent the coefficient. Also, the left scale in all graphs is for the intercept and the right scale is for the coefficient.

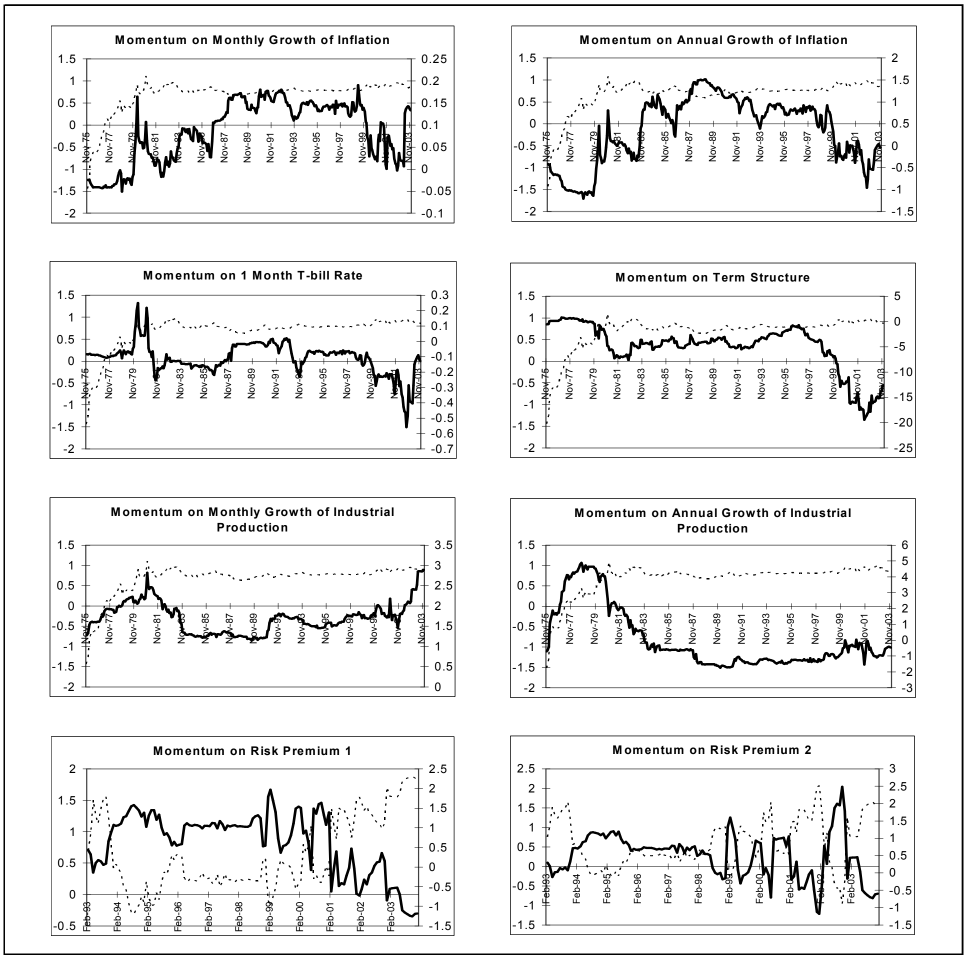

Figure 5: The Effect of Different Macroeconomic Variables on Momentum Style Portfolio Returns Using the TVP Model with a Single Factor. The dotted lines in all graphs represent the intercept and the undotted lines represent the coefficient. Also, the left scale in all graphs is for the intercept and the right scale is for the coefficient.

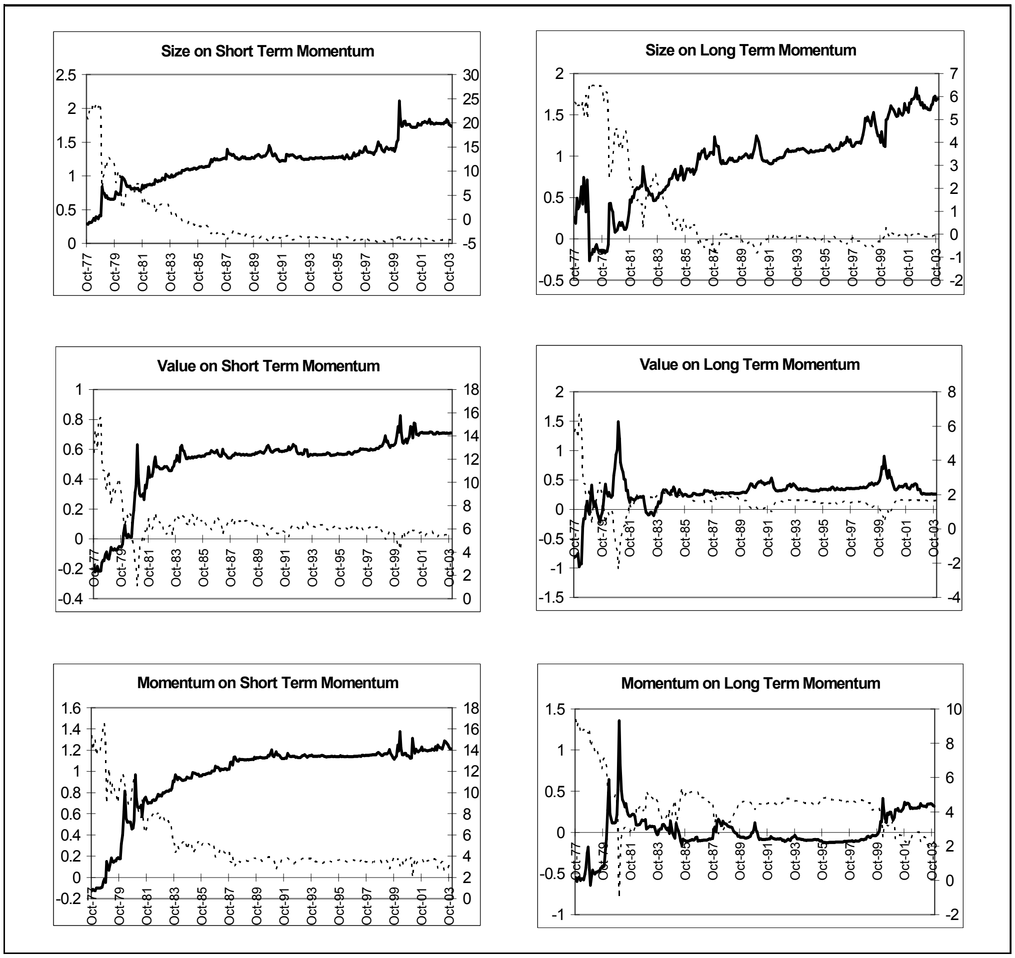

Figure 6: The Effect of Own Short-Term and Long-Term Momentums on Different Styles of Portfolio Returns (Size, Value, Momentum) Using the TVP Model with a Single Factor. The dotted lines in all graphs represent the intercept and the undotted lines represent the coefficient. Also, the left scale in all graphs is for the intercept and the right scale is for the coefficient.

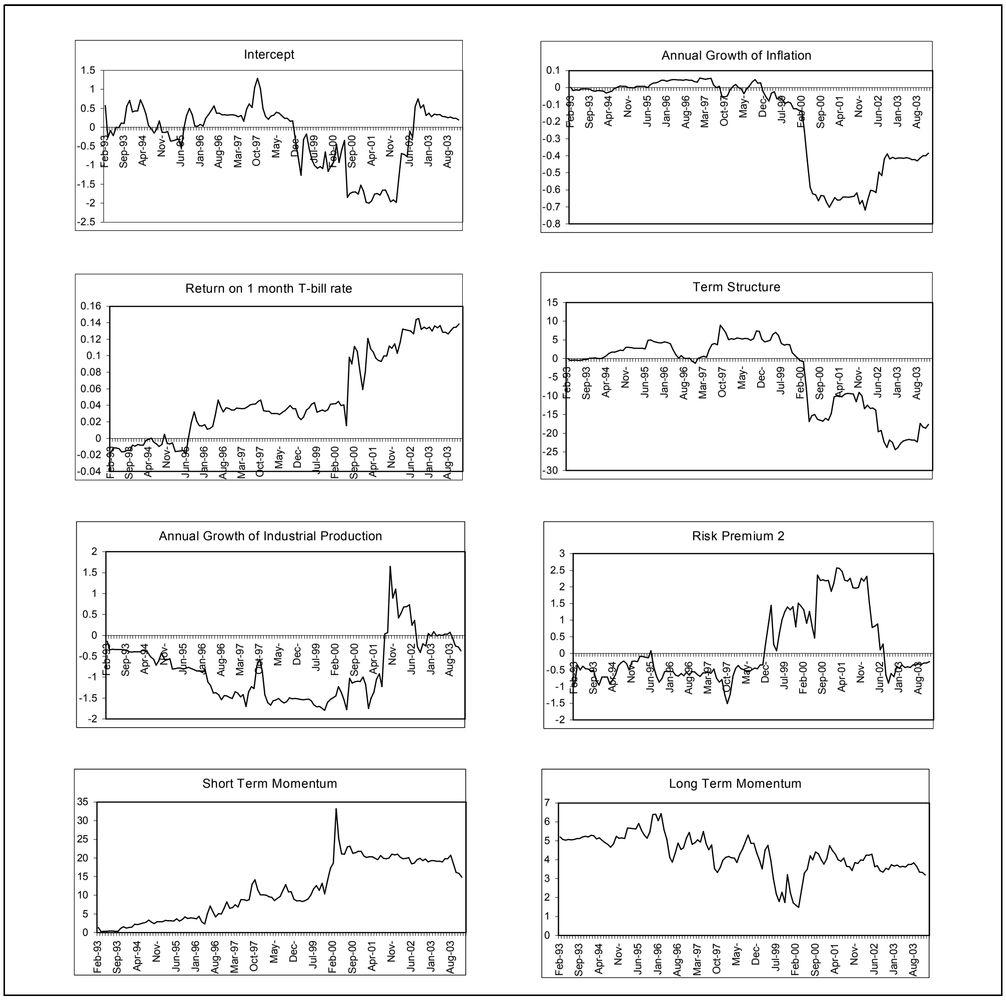

Figure 7: The Effect of Different Variables on Size Style Portfolio Returns Using the Time-Varying Multifactor Model.

Appendix 1: Time-Varying Parameter Model with Changing Conditional Variance

This paper closely follows the approach that is used in Kim and Nelson (1989) and the other papers written in the time-varying parameter model literature using Kalman filters.

First the non-time-varying parameters of the model are estimated using a maximum likelihood method. Then, given these estimates, as well as initial values for coefficients and their variances, evolutionary coefficients of the model are estimated. See Wells (1996) for OLS estimates as initial conditions.

The prediction step of the Kalman filtering algorithm is given as:

When $t-1$ is the initial period, estimates of the coefficients and their variance-covariance matrix at time t, conditional on information available at time t-1, are:

$$\alpha_{t|t-1} = \phi\alpha_{t-1|t-1},$$

$$V_{t|t-1} = \phi V_{t-1|t-1}\phi' + Q,$$

where ϕ is the identity matrix in case of a random walk.

The updating step of the Kalman filtering algorithm is given as follows:

$$\alpha_{t|t} = \alpha_{t|t-1} + \frac{V_{t|t-1} f'_{t-1}}{H_{t|t-1}} e_{t|t-1},$$

$$V_{t|t} = V_{t|t-1} - \frac{V_{t|t-1} f'_{t-1}}{H_{t|t-1}} f_{t-1} V_{t|t-1},$$

where $e_{t|t-1}$ is the forecast error and $H_{t|t-1} = f_{t-1} V_{t|t-1} f'_{t-1} + \sigma^2$ is the conditional variance of the forecast error.

In words, coefficients will be updated using the initial guesses for coefficients and their variance-covariance matrix as well as the forecast errors and the conditional variances of the forecast errors.

Variances of the coefficients will be updated using the initial guesses for the variances of coefficients and the conditional variances of the forecast errors.

References

1. Adrian, T., and Franzoni, F., 2005, "Learning about Beta: Time-varying Factor Loadings, Expected Returns, and the Conditional CAPM," Working Paper, Federal Reserve Bank.

2. Andrews, Angus P., and Mohinder S. Grewal, 2001, “Kalman Filtering: Theory and Practice Using MATLAB,” Wiley, John & Sons.

3. Antoniou, A., Herbert Y. T. Lam, Krishna Paudyal, 2007, “Profitability of Momentum Strategies in International Markets: The Role of Business Cycle Variables and Behavioral Biases,” Journal of Banking and Finance, 31, 955-972.

4. Avramov, D., and Chordia, T., 2006, “Asset Pricing Models and Financial Market Anomalies,” Review of Financial Studies, 19:1001–40.

5. Banz, R., 1979, "The Relationship between Return and Market Value of Common Stocks," Journal of Financial Economics 9, 3-18.

6. Barberis, N., and Shleifer, A., 2003, "Style Investing," Journal of Financial Economics, Vol: 68(2), pp. 161-199.

7. Bekaert, G., Harvey, C. R., and Lundblad, C., 2007, “Liquidity and Expected Returns: Lessons from Emerging Markets,” Review of Financial Studies, 20(6), 1783-1831.

8. Becher, D.A., G.R. Jensen, and J.M. Mercer, 2008, “Monetary Policy Indicators as Predictors of Stock Returns,” Journal of Financial Research, Vol. XXXI, No. 4, 357-379.

9. Bernanke, B.S. and K.N. Kuttner, 2005, “What explains the stock market’s reaction to Federal Reserve Policy?” Journal of Finance, 60, 1221-57.

10. Bernstein, R., 1995, “Style Investing,” New York: Wiley.

11. Blume, M.E., 1971, “On the Assessment of Risk,” Journal of Finance, Vol. 26, No. 4, 275-88.

12. Blume, M.E., 1975, “Betas and the Regression Tendencies,” Journal of Finance, Vol. 30, No. 3, 785-95.

13. Bodie, Z., 1976, "Common Stocks as a Hedge against Inflation," Journal of Finance, 31(2), 459-470.

14. Bos, T., and Newbold, P., 1984, “An Empirical Investigation of the Possibility of Stochastic Systematic Risk in the Market Model,” Journal of Business, Vol. 57, No. 1, 35-42.

15. Boyd, J. H., Ravi Jagannathan, Jian Hu, 2005, "The Stock Market's Reaction to Unemployment News: Why Bad News is Usually Good for Stocks," Journal of Finance, Vol. LX, No. 2, April.

16. Brenner, M., and Smidt, S., 1977, “A Simple Model of Non-Stationarity of Systematic Risk,” Journal of Finance, Vol. 32, No. 4, 1081-92.

17. Chan, K. C., Nai-Fu Chen, and David A. Hsieh, 1985, "An Explanatory Investigation of the Firm Size Effect," Journal of Financial Economics, 14 (3), 451-471.

18. Chen, Nai Fu, Richard Roll, and Steve Ross, 1986, "Economic Forces and the Stock Market," Journal of Business, 59(3), 383-403.

19. Chernoff, H., and Zacks, S., 1964, "Estimating the Current Mean of a Normal Distribution which is Subject to Changes in Time," Annals of Mathematical Statistics, 35, 999-1028.

20. Chordia, Tarun, and L. Shivakumar, 2002, “Momentum, Business Cycle and Time-Varying Expected Returns,” Journal of Finance, 57, 985–1019.

21. Chui, C. K., and G. Chen, 1998, “Kalman Filtering: with Real-Time Applications,” Springer-Verlag, New York.

22. Clements, M., and Hendry, D., 1999, "Forecasting Non-Stationary Economic Time Series," MIT Press, Cambridge, Mass.

23. Collins, D.W., Ledolter, J., and Rayburn, J., 1987, “Some Further Evidence on the Stochastic Properties of Systematic Risk,” Journal of Business, Vol. 60, No. 3, 425-48.

24. Cutler, D. M., J. M. Poterba, and L. H. Summers, 1989, "What Moves Stock Prices?" Journal of Portfolio Management, 15 (3), 4-12.

25. Elliott, G., and Muller, U.K., 2006, "Efficient Tests for General Persistent Time Variation in Regression Coefficients," Review of Economic Studies, 73, 907-940.

26. Engle, Robert F., 1982, “Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation,” Econometrica, Vol. 50, Issue: 4, 987-1007.

27. Errunza, Vihang, and Ked Hogan, 1998, "Macroeconomic Determinants of European Stock Market Volatility," European Financial Management, 4(3), 361-377.

28. Fabozzi, F., and Francis, J., 1978, “Beta as Random Coefficient,” Journal of Financial and Quantitative Analysis, Vol. 13, No. 1, 106-16.

29. Faff, Robert W., D. Hillier, J. Hillier, 2000, “Time Varying Beta Risk: An Analysis of Alternative Modelling Techniques,” Journal of Business Finance and Accounting, 27(5) & (6), June/July, 523-554.

30. Fama, Eugene F., 1981, "Stock Returns, Real Activity, Inflation, and Money," American Economic Review, 71 (4), 545-565.

31. Fama, E.F., and K.R. French, 1989, “Business Conditions and Expected Returns on Stocks and Bonds,” Journal of Financial Economics, 25, 23-49.

32. Ferson, Wayne E., and Campbell R. Harvey, 1991, "The Variation of Economic Risk Premiums," Journal of Political Economy 99, 385-415.

33. Flannery, M. J., and A. A. Protopapadakis, 2002, "Macroeconomic Factors Do Influence Aggregate Stock Returns," Review of Financial Studies, Volume: 15, Number: 3, 751-782.

34. Francis, J.C., 1979, “Statistical Analysis of Risk Surrogates for NYSE Stocks,” Journal of Financial and Quantitative Analysis, Vol. 14, 981-97.

35. French, Kenneth R., G. William Schwert, and Robert F. Stambaugh, 1987, "Expected Stock Returns and Volatility," Journal of Financial Economics 19, 3-29.

36. Geske, Robert, and Richard Roll, 1983, "The Fiscal and Monetary Linkage between Stock Returns and Inflation," Journal of Finance, 38 (1), 1-34.

37. Graham, B., and D. Dodd (1934), Security Analysis, New York: McGraw Hill.

38. Hamilton, J. D., and R. Susmel, 1994, "Autoregressive Conditional Heteroskedasticity and Changes in Regime," Journal of Econometrics, 54 (1-2), 307-333.

39. Hamilton, J. D., 1994, “Time Series Analysis,” Princeton University Press.

40. Hahn, J., and H. Lee, 2006, “Yield Spreads as Alternative Risk Factors for Size and Book-to-Market,” Journal of Financial and Quantitative Analysis, vol. 41, issue 02, 245-269.

41. Harvey, Andrew C., 1991, “Forecasting, Structural Time Series Models and the Kalman Filter,” Cambridge University Press.

42. Jegadeesh, Narasimhan and Sheridan Titman, 1993, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," Journal of Finance 48, 65-91.

43. Jensen, G.R., J.M. Mercer, and R.R. Johnson, 1996, “Business Conditions, Monetary Policy and Expected Security Returns,” Journal of Financial Economics, 40, 213-37.

44. Kim, C. J., and Nelson, C. R., "The Time-Varying-Parameter Model for Modeling Changing Conditional Variance: The Case of the Lucas Hypothesis," Journal of Business and Economic Statistics, October 1989, Vol. 7, No. 4.

45. Kim, D., 1993, “The Extent of Non-Stationarity of Beta,” Review of Quantitative Finance and Accounting, Vol. 3, 241-54.

46. Lewellen, Jonathan, and Stefan Nagel, 2006, “The Conditional CAPM Does Not Explain Asset-Pricing Anomalies,” Journal of Financial Economics, Vol. 82, No. 2, 289-314, Nov.

47. Lee, Charles M. C., and Bhaskaran Swaminathan, 2000, "Price Momentum and Trading Volume," Journal of Finance 55, 2017-2069.

48. Lo, Andrew W., and Craig MacKinlay, 1997, "Maximizing Predictability in the Stock and Bond Markets," Macroeconomic Dynamics 1, 102-134.

49. Lo, Andrew W., and Jiang Wang, 2006, “Trading Volume: Implications of an Intertemporal Capital Asset Pricing Model,” Journal of Finance, Vol. LXI, No. 6, Dec.

50. Markowitz, H., 1952, "Portfolio Selection," Journal of Finance, VII, 77-91.

51. McQueen, Grant, and Vance Roley, 1993, "Stock Prices, News, and Business Conditions," The Review of Financial Studies, 6 (3), 683-707.

52. Merton, Robert C., 1973, “An Intertemporal Capital Asset Pricing Model,” Econometrica, Vol. 41, No. 5 (Sep), 867-887.

53. Moskowitz, T. J., and M. Grinblatt, 1999, "Do Industries Explain Momentum?" Journal of Finance, Vol. 54, No. 4, August, 1249-90.

54. Ohlson, J., and Rosenber, B., 1982, “Systematic Risk of the CRSP Equal-Weighted Common Stock Index: A History Estimated by Stochastic Parameter Regression,” Journal of Business, Vol. 55, No. 1, 121-45.

55. Pastor, L., and R. F. Stambaugh, 2003, “Liquidity Risk and Expected Stock Returns,” Journal of Political Economy, Vol. 111(3), 642-685.

56. Patelis, A.D., 1997, “Stock Return Predictability and the Role of Monetary Policy,” Journal of Finance, 52, 1951-72.

57. Pesaran, Hashem M., and Allan Timmermann, 2002, "Market Timing and Return Prediction under Model Instability," Journal of Empirical Finance, Volume 9, Issue 5, 495-510.

58. Petkova, Ralitsa, 2006, “Do the Fama-French Factors Proxy for Innovations in Predictive Variables?” Journal of Finance, Vol. LXI, No. 2, April.

59. Schwert, G. William, 1989, "Why Does Stock Market Volatility Change over Time?" Journal of Finance, 44(5), 1115-1145.

60. Schwert, William G., and Paul J. Seguin, 1990, "Heteroskedasticity in Stock Returns," Journal of Finance 45, 1129-1155.

61. Shanken, Jay, and Mark I. Weinstein, 2006, "Economic Forces and the Stock Market Revisited," Journal of Empirical Finance, 13, 129-144.

62. Simonds, R.R., LaMotte, L.R., and McWhorter, A. Jr., 1986, “Testing For Non-Stationarity of Market Risk: An Exact Test and Power Consideration,” Journal of Financial and Quantitative Analysis, Vol. 21, No. 2, 209-20.

63. Stock, J., and Watson, M., 1996, "Evidence on Structural Instability in Macroeconomic Time Series Relations," Journal of Business and Economic Statistics, 14, 11-30.

64. Sunder, S., 1980, “Stationarity of Market Risk: Random Coefficients Test for Individual Stocks’, Journal of Finance, Vol. 35, No. 4, 883-96.

65. Thorbecke, W., 1997, “On Stock Market Returns and Monetary Policy,” Journal of Finance, 52, 635-54.

66. Vassalou, M., 2003, “News Related to Future GDP Growth as a Risk Factor in Equity Returns,” Journal of Financial Economics, 68, 47-73.

67. Wells, Curt, 1996, “The Kalman Filter in Finance,” Springer-Verlag, New York.

68. West, K. D., H. J. Edison, and D. Cho, 1993, “A Utility Based Comparison of Some Models of Exchange Rate Volatility,” Journal of International Economics, 35, 23-45.